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Optimizing Supply Chain Efficiency Using Machine Learning with ARAS Methodology

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ABSTRACT

This research examines how focusing on the evaluation of the efficacy of five machine learning models: Maxor Min, AdaBoost, Bagging, Random Forest and Decision Tree. The Adjoint Ratio Assessment (ARAS) method was applied to establish the models are analyzed based on six evaluation parameters: precision, accuracy, recall, log loss, MCC (Matthews's correlation coefficient), and model complexity. Research Significance: The significance of this research is the systematic assessment of machine learning models intended for supply chain optimization. It provides insights into model selection, ensuring the adoption of algorithms that align with operational goals such as forecasting demand, optimizing inventory, and risk management. Methodology: The ARAS method is used to rank models based on their performance across evaluation parameters. This approach ensures a thorough evaluation of the advantages and disadvantages of each model, aiding supply chain practitioners in making informed decisions.

Adaboost Adaptive Boosting, commonly known as AdaBoost, is a technique of ensemble learning that merges several ineffective classifiers to produce a robust predictive model. In the field of supply chain management, it is often utilized for activities like demand forecasting and anomaly detection. the one of AdaBoost ability to focus on misclassified events during training is particularly useful in noisy environments. However, its sensitivity to outliers and high computational demands for large datasets can limit its scalability in some applications.

Random Forest is a robust ensemble method that builds multiple decision trees and combines their outcomes to. Its ability to handle complex datasets makes Random Forest a reliable choice in a variety of situations. Decision Tree: Decision tree models are simple but powerful tools To make decisions. Their application in supply chain is extensive scenarios such as supplier selection, inventory categorization, and shipment prioritization. Packing: Bootstrap aggregation, or packing, improves model consistency and accuracy by training multiple versions of the same model on different data subsets and combining their predictions. In supply chain applications, packing is particularly useful for reducing variance and improving forecast reliability. Its ability to use multiple data sources ensures robust performance in Jobs like demand forecasting and stock control.

Accuracy measures the overall correctness A model To make decisions. Their application in supply chain is extensiveIn supply chain situations, accuracy is important for tasks such as demand forecasting and product classification. While high accuracy indicates strong general performance, it does not fully reflect a model's ability to handle unbalanced datasets. Precision: Accuracy evaluates the trustworthiness of affirmative forecasts, In supply chain applications such as fraud detection or quality control, high accuracy ensures that false positives are minimized, saving time and resources in decision making.

Recall (or sensitivity) evaluates how effectively a model can recognize true positives from all true positives. This parameter essential for detecting rare but critical events in supply chain operations such as stockouts or supplier disruptions.Log Loss: Log Loss estimates the uncertainty in probabilistic predictions by imposing a higher penalty for incorrect predictions. In supply chain optimization, it is most useful for models that output probabilities, such as those predicting shipment delays or demand spikes. Lower log loss values indicate higher confidence in the predictions. Matthews Correlation Coefficient (MCC): The MCC offers a measure of parity model performance, one is especially valuable in asymmetric datasets, such as those found in supply chain risk management, where accurate classification across all classes is important. Model Complexity: Model complexity reflects the complexity of the machine learning model, including the number of parameters, features, and computational resources required. In supply chain management, this is essential balance model complexity with performance.. Result: Random Forest emerges as the best performer due to its balance across metrics, followed by Decision Tree and Packing, which offer strengths in recall and consistency. Maxor Min shows competitive performance, while AdaBoost stands out in performance but requires further improvement for broader applications.

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Introduction

Examination of machine learning methods and their relevance to risk management in supply chains. However, many studies concentrate on predictive performance while overlooking the significance of interpretation for supply chain practitioners. A clearer understanding of results can aid their decision-making regarding risk mitigation and prevention. For that case, one should select machine learning algorithms that have demonstrated their effectiveness across diverse settings and data inputs, irrespective of whether their models are black box or white box offer insight by uncovering correlations between feature values that result in one outcome or another.[1] Efficient management of plant diseases and weed detection tailored to specific sites necessitates spatial and temporal information of high density.

A number of studies have suggested that automated disease detection systems (based on pattern recognition and machine learning) have the capability to enhance the precision and quicken the pace of diagnostic results. The study shows that there are significant advantages for ASCs that have built the ML capability, suggesting that it is advantageous to incorporate ML into decision-making processes. Given the significant expenses involved in investing in digital technologies and building ML capabilities, it is anticipated that policymakers will provide subsidies for investments in digital technologies and implement measures to reduce costs, thereby facilitating widespread use.[2]

One potentially game-changing resource that can be harnessed to create superior demand forecasting models for entails algorithms that perform tasks without explicit programming. with the help of established algorithms. Learning algorithms can generally be divided into two types: supervised and unsupervised learning are numerous reviews related to data analytics and machine learning, but few focus specifically can be applied to demand forecasting within the supply chain.[3] Machine Learning can be generally characterized as an algorithm that produces outputs based on available data, without a predetermined learning outcome being programmed in advance. Instead, the ML algorithm 'learns' through iterative adjustments of its understanding to match the input data depicting real-world phenomena.[4] Unlike traditional demand forecasting methods, those based on Machine As machine learning (ML) and predictive analytics, businesses have been able to enhance customer involvement and the generation of demand forecasts that are more precise when entering new markets or channels.

Another beneficial facet of the machine learning algorithm is that it does not require an underlying probability distribution. took advantage of this characteristic. Using machine learning, they offered a dependable solution for retailers' perishable items, where the ordering decision is based on the newsvendor model, usually assuming a normal distribution. the need for time series models that combine leading indicators and machine learning is growing. Secondly, and of greater significance, this study underscores the extent to which performance can be enhanced through the use of sophisticated forecasting techniques. [5] Methods of AI and machine learning; The tasks are now easier, and the product can be delivered within a 24-hour timeframe.

This research examines different instances of current along with the prospective developments of these techniques. Due to their more intelligent methods of revenue growth, Machine Learning techniques are increasingly necessary for industry and saving time a significant application of machine learning is forecasting customer demand. They employed machine learning models to process data from various business units related to the enterprise's supply chain, including transportation rates and policies, product shipping routes, and more.[6] By means of predictive analytics can be utilized with precisely predict demand, detect possible disturbances, and fine-tune inventory quantities. Due to its many advantages, the incorporation They have been employed for sorting, packaging, transporting, storing, and selling in the food supply chain, showcasing their adaptability and ability to improve various aspects of the supply chain operations.[7] the supply chain and employs machine learning methods to identify the enterprise linked to the data when new information from unknown sources emerges.

The employed machine learning algorithms are logistic regression, random forest, naive Bayes, decision tree, support vector machine, k-nearest neighbor, and multi-layer perceptron. employed machine learning to address substantial operational optimization challenges in blood supply chain management and clarified that machine learning can enhance operational decisions, as optimization models are costly in terms of computation and are therefore frequently unfeasible for everyday operational choices in organizations like nonprofit entities or small to medium-sized businesses.

For this reason, the research utilizes machine learning and examines the findings to identify a firm that acts as the origin of data generated within the supply chain.[8] The search utilized the keywords "machine learning" as well as "supply chain risk". parameters did not impose restrictions based on publication dates and set a restricted end date. businesses can monitor the state of their supply chains instantaneously with the help of the ML algorithm and subsequently modify their inventory and production plans accordingly.[9] hyperspectral imaging (HSI) and machine learning have shown their effectiveness as methods for rapid, nondestructive evaluations of quality attributes and encompassing topics such as the HSI imaging process, various types of algorithms in machine learning, and the data processing flow. The application of machine learning and HSI technology across different segments of the food supply chain, which could be crucial for enhancing optimization in has not been examined in relevant literature.[10] In the realm of supply chain management, blockchain's potential can be amplified through its combination with machine learning (ML).

This paper offers a thorough examination of blockchain-based supply chain management through ML, emphasizing decentralized approaches for traceability and transparency. We examine how integrating blockchain and ML can enhance supply chain processes, bolster traceability, and boost transparency. The efficacy and openness of supply chains have a direct impact on business performance, customer satisfaction, and the overall competitiveness of the industry. The objective of this paper aims to provide a comprehensive review of ML applications for management of supply chains through blockchain technology, focusing especially on decentralized approaches to achieve transparency and traceability that transactions are secure and resistant to alteration, protecting sensitive supply chain data from unauthorized access.[11] A multitude of factors intervene at the same time, and their interactions along interpret and make decision-making more complex.

It is particularly evident in the area of inventory management, where ascertaining the ideal restocking rule frequently proves to be a difficult problem. the details regarding the resolved issues can therefore be utilized to examine forthcoming issues. In this regard, this method includes tenets of information updating, which is becoming recognized as a crucial mechanism for supply chain learning.[12] To achieve the aforementioned goals, it is necessary to implement internal and inter-company tasks Intelligence or ML fulfills the following functions; Sections of the logistics network sensitive to disruption; transport of goods and services; and improvement of operations. Supply chains are defined by the effective use of resources and processes by many companies to satisfy customer demand. The intrinsic challenge of coordinating can be addressed in a number of ways.[13] management of the supply chain. Secondly, enormous processes and data originating from various Supply chain parities act as origins for big data analytics, which can be enhanced using machine learning. The authors are of the opinion that this scenario has not been examined in earlier research.

when a party in the supply chain generates a transaction record (e.g., delivery timetable), this record is kept in a block. Because a block can only hold a limited amount of data, multiple blocks are used in sequence to store numerous transaction records.[14] the development of For supply chains, it is becoming ever more vital to obtain from a variety of sources. To keep a competitive edge, supply chains must conduct rapid analyses of large datasets with effective tools that provide insights for real-time decision-making. planning for supply chains and introduced a decision support system called the "Collaboration Planning Tool."

This tool was developed by the authors to facilitate the attainment of long-term sustainability in complex supply chain networks.[15] the capacity to predict product demand accurately is crucial for a supply chain. These forecasts are often required to be generated within a hierarchical framework that may depict geographic areas or product families. As far as we know, the majority of studies the literature on hierarchical forecasting within the supply chain emphasizes univariate analysis from a variety of sources. To keep a competitive edge, supply chains[16] The suggested method avoids the necessity of explicitly encoding supply chain expertise as well.

The results indicate that the GNN approach outperforms existing methods for predicting links in supply network connections across three industrial case studies. that supply chain maps ought to depict the relationships and memberships of companies within the network, as well as details [17] While advanced technologies can enhance the logistics chain framework for conducting statistical analyses of key performance indicators or for predicting supply chain demands.

An improved the in the management of supply chains presents difficulties. the logistics chain positively affects all company functions and the entire supply chain.[19] The drug supply chain management system is constructed using Hyperledger fabrics, allowing it to provide constant monitoring and tracking of drug deliveries in the smart pharmaceutical industry. On the other hand, distribution of fake pharmaceuticals, an effective system that can follow and oversee the delivery of medication at every phase—from the provider's unprocessed materials to production, logistics, pharmacies, medical facilities, and finally to end users.[20]

MATERIALS AND METHOD

Alternative values: The supply chain industry has been transformed by machine learning, which has made it possible for more efficient and intelligent decision-making. Advanced AdaBoost, Random Forest, Decision Tree, and other machine learning techniques

Bagging, are widely used to improve different supply chain procedures like demand forecasting, inventory control, and logistics optimization. These algorithms provide accurate predictions and robust models to handle the intricate and fluid characteristics of supply chain operations. Below is an exploration of how these techniques contribute to supply chain management.

AdaBoost: AdaBoost (Adaptive Boosting) In supply chain applications, AdaBoost is often used to improve demand forecasting accuracy by identifying patterns in historical data. It is particularly effective in scenarios where the data includes noise or outliers, as it iteratively focuses on the most challenging samples during training. This adaptability ensures reliable predictions, helping businesses coordinate production timetables and inventory quantities with market demand.

Random Forest: Random Forest is a flexible ensemble technique that relies on decision trees, functioning by constructing a multitude of trees and merging their outcomes. classify products, optimize routing in logistics, and detect anomalies in inventory systems. The algorithm's robustness and ability to handle high-dimensional data make it ideal for analyzing complex supply chain networks. By leveraging Random Forest, companies can achieve better risk assessment and make data-driven strategic decisions.

Decision Tree: Decision Trees are basic models in machine learning that split information into branches depending on characteristic values, resulting in a decision output. These are extensively used in supply chain scenarios for decision-making, such as selecting suppliers, categorizing products, and prioritizing shipments. Their simplicity and interpretability allow supply chain managers to visualize the decision process and gain insights into key factors influencing operations. Decision trees are particularly useful for tackling classification problems, such as distinguishing between fast-moving and slow-moving inventory.

Bagging: Another ensemble technique that enhances model stability and accuracy is Bagging (Bootstrap Aggregating). Through the integration of several base models that have been trained on various subsets of the data. In supply chains, bagging enhances the reliability of forecasting and optimization tasks by reducing the variance of predictions. For example, it can be applied to mitigate forecasting errors in demand prediction models, enabling businesses to maintain optimal stock levels and reduce wastage. Bagging's ability to handle diverse data sources ensures robust performance in complex supply chain environments.

Evolution parameter: Machine learning is now essential to modern supply chain management, facilitating data-driven decisions that enhance efficiency and responsiveness. operate within the supply chain context, metrics like Accuracy, Precision, Recall, Log Loss, Matthews Correlation Coefficient (MCC), and Model Complexity play critical roles. These metrics ensure the models are not only effective but also aligned with the operational goals of supply chain systems.

Accuracy: In supply chain management, accuracy is crucial for activities such as demand forecasting and inventory classification, where the objective is to minimize errors. While accuracy provides a general measure of performance, it may not always be sufficient in imbalanced datasets, such as those found in rare demand spikes or unusual supply chain disruptions.

Precision: It exists particularly important in supply chain applications like fraud detection in procurement or anomaly detection in logistics, where false positives can lead to unnecessary interventions or resource allocation. A the predictions made by the model can be trusted, thanks to the high precision score and actionable.

Recall: Recall, or sensitivity, calculates the ratio of true positive predictions to all actual positive cases. In contexts related to supply chains, recall is critical for identifying rare but significant events, such as stockouts or supplier failures. High recall ensures that the model captures most of the critical instances, even if it occasionally sacrifices precision. This trade-off is often acceptable if the cost of not attending to a crucial event is high.

Log Loss: Log Loss (Logarithmic Loss) evaluates the uncertainty of probabilistic predictions by penalizing incorrect predictions more heavily. In supply chain optimization, Log Loss is applicable for models that generate probabilities, like predicting the likelihood of a shipment delay or demand surge. Lower Log Loss values indicate a well-calibrated model that provides reliable confidence scores, aiding in risk management and decision-making.

Matthews Correlation Coefficient (MCC): MCC is a strong metric that takes into account true positives, true negatives, false positives, and false negatives in order to deliver a balanced assessment of a model's performance. It exists especially valuable in supply chain scenarios with imbalanced data, such as predicting rare transportation disruptions or quality control failures. An MCC score close to 1 indicates a strong model capable of making accurate predictions across all classes.

Model Complexity: Model Complexity denotes the intricacy of a machine learning model, which consists of features, parameters, and computational requirements. It is crucial in supply chain management to strike a balance between the complexity of models and their interpretability and scalability. Although sophisticated models such as deep neural networks can reach a high level of accuracy, simpler models like linear regression or decision trees are often preferred for their ease of implementation and faster processing in real-time applications. Striking the right balance ensures that models are both effective and operationally feasible.

ARAS

The document presents a novel evaluating the microclimate in office rooms is demonstrated to exemplify the ARAS method described. The aim of the purpose of the case study is to assess the workplace's indoor climate and to pinpoint measures that can enhance the environment there. the analysis suggests the following criteria for evaluating inside climate: air turnover in the premises, humidity levels, temperature, light intensity, airflow rate, and dew point. The issue faced by to make a decision involves assessing a small set of alternatives to identify the best one and rank them from most to least favorable, classify them into established homogeneous categories, or assess how effectively each option meets all criteria at once. The problem was solved using the method of validate the choice of effective alternatives for structures and technologies. the optimal alternative will employ a new ARAS method.

A typical MCDM problem consists of the challenge of arranging distinctly outlined by multiple decision criteria that need to be considered at the same time. Based on the ARAS method, the value of a utility function that reflects the complex relative efficiency of a viable alternative is directly connected to the relative influence of the values and weights of the main criteria considered in a project. Professionals articulated the view that a double-layered floor structure for the cellar would be the most practical and carry lower risk while in use. Experts also indicated that, given the complex conditions at the start of the work, technical solutions should be as simple as possible and free of intricate details. For faculty websites, it is expected that the information provided is accurate, making this criterion of little significance. Nonetheless, the presence of inaccurate information on the faculty website can greatly affect the quality of the site and, consequently, the faculty's reputation. During the collection of the ARAS dataset, we loosened that assumption and gathered data from homes with multiple residents. ARAS datasets also have the important characteristic of comprising a greater diversity of human activities as well as a greater number of activity instances. A central processing unit collected all sensor data and oversaw the synchronization of the labels and sensor data. It is assumed by System ARAS that LERS can be used for the extraction of classification rules. In this manner, ARAS only needs to ascertain if these relationships are indicated by LERS, as opposed to confirming the accuracy of specific relationships. In the same vein, Based on each application's anticipated peak bandwidth needs, a circuit-switched network allots a certain percentage of the bandwidth to it. Unless idle times are filled with non-real-time traffic, the bursty nature of real-time traffic leads to low effective bandwidth usage. as we'll talk about later.

The earliest due date determines the packet insertion priority into the output queue for these methods. A packet's due date is determined by adding the link deadline for this node to its logical arrival time. It is crucial for the dependability of wind-power measurements to establish the location of wind observation stations (WOS) appropriately. Such a center should be situated in an ideal location that can particularly represent the area. The bulletin for wind and solar measurements took effect upon publication. The final aim is to identify the most appropriate site for a potential WOS, in light of the other levels of hierarchy. The second level of hierarchy contains main criteria. To establish such criteria, expertise is necessary, as an incorrect or insufficient determination will lead to erroneous decisions. Together with Rias, which is deemed the worst based on the web visibility and brand treatment sub-criteria, is also the least favorable option for the root criterion.

RESULTS AND DISCUSSION

TABLE1: Data set

	Accuracy	Precision	Recall	Log Loss	MCC	Model Complexity
Maxor Min	0.77	0.58	0.65	0.69	0.39	0.11
AdaBoos	0.69	0.43	0.5	0.69	0.25	0.34
Random Forest	0.75	0.52	0.59	0.54	0.39	0.171

Decision Tree	0.65	0.4	0.65	0.67	0.27	0.11
Bagging	0.77	0.58	0.5	0.55	0.39	0.28

Accuracy Accuracy reflects the proportion of correct predictions. Maxor Min and Bagging achieve the highest accuracy (0.77), indicating their strong ability to generalize. Random Forest follows closely at 0.75, while AdaBoost and Decision Tree show lower accuracy scores of 0.69 and 0.65, respectively, indicating that they may miss some patterns in the data. Precision measures the proportion of true positive predictions out of all positive predictions. Maxor Min and Bagging both lead with an accuracy of 0.58, making them more reliable in situations where false positives need to be minimized, such as identifying anomalies or fraud in the supply chain. AdaBoost (0.43) and Decision Tree (0.4) have lower accuracy, indicating a higher chance of false positives. Recall measures the proportion of true positives that are correctly predicted. Maxor Min and Decision Tree show high recall (0.65), making them suitable for identifying important events such as stockouts or supplier failures. Random Forest performs moderately well (0.59), while Adaboost and Packing 0.5 have low recall scores, missing some important positive events. Log loss measures the uncertainty in the probability predictions, with lower values indicating better calibrated models. Maxor Min (0.69) and Decision Tree (0.67) exhibit relatively low log loss. Packing and Random Forest show slightly higher uncertainty with log loss values of 0.55 and 0.54, respectively. MCC (Matthews Correlation Coefficient) MCC assesses the overall prediction quality, considering all classes and is particularly useful for asymmetric datasets. Maxor Min, Random Forest, and Bagging share the top spot with MCC scores of 0.39, indicating strong overall performance. AdaBoost has the lowest MCC (0.25), reflecting its struggle to maintain balanced predictions across classes. Model Complexity Model complexity assesses computational demands and interpretation. Maxor Min and Decision Tree are simple models (0.11), suitable for real-time applications where speed and ease of implementation are essential. Bagging (0.28) and Random Forest (0.171) are moderately complex, while AdaBoost has a high complexity (0.34), requiring more resources for training and deployment.

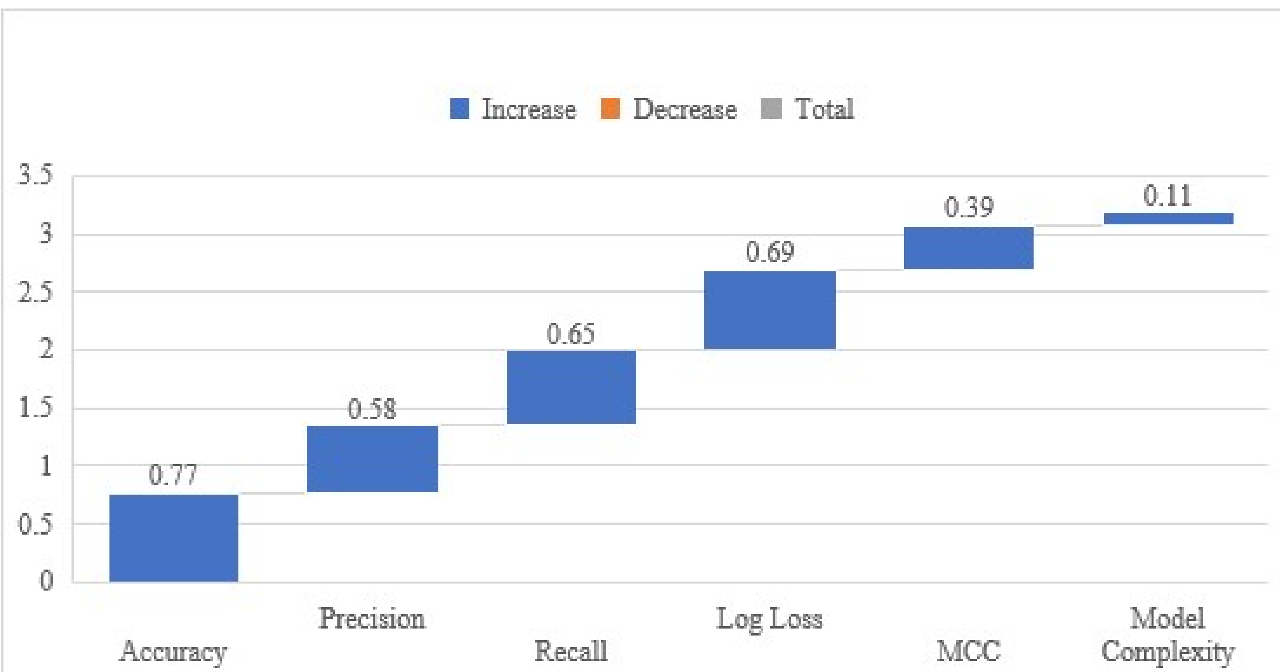

FIGURE 1: Data Set

Figure 1 presents key performance metrics for machine learning model evaluation. The graph shows five essential metrics: precision (0.77), accuracy (0.58), recall (0.65), Matthews correlation coefficient (MCC) (0.39), and model complexity (0.11). These metrics are displayed in blue bar chart format with values ranging from 0 to 3.5 on the y-axis. The model demonstrates strong precision at 0.77, while maintaining moderate precision and recall values. The MCC, which indicates overall model performance, shows moderate correlation at 0.39. The low model complexity score of 0.11 suggests a relatively simple model structure, which is useful for avoiding overfitting and ensuring computational efficiency.

TABLE 2:

	Accuracy	Precision	Recall	Log Loss	MCC	Model Complexity
Maxor Min	0.77	0.58	0.65	0.69	0.39	9.090909
AdaBoos	0.69	0.43	0.5	0.69	0.25	2.941176
Random Forest	0.75	0.52	0.59	0.54	0.39	5.847953
Decision Tree	0.65	0.4	0.65	0.67	0.27	9.090909
Bagging	0.77	0.58	0.5	0.55	0.39	3.571429

Table 3 presents the performance metrics for the machine learning models—Maxor Min, Adaboost, Random Forest, Decision Tree, and Bagging—after applying normalization techniques to the dataset. Normalization ensures that all features contribute equally to the learning process of the model, affecting their precision, accuracy, recall, log loss, MCC, and model complexity. The interpretation of the results is as follows: Accuracy measures the overall proportion of correct predictions. Maxor Min and Bagging achieve the highest accuracy (0.212121), indicating their ability to generalize well after normalization. Random Forest follows closely (0.206612), while Decision Tree and Adaboost show lower accuracy scores of 0.179063 and 0.190083, respectively, indicating weak overall performance.

Accuracy assesses the reliability of positive predictions. Both Maxor Min and Bagging perform well in terms of accuracy (0.231076), which is suitable for tasks that require a reduction in false positives, such as detecting anomalies or fraud. Random Forest achieves moderate accuracy (0.207171), while AdaBoost (0.171315) and Decision Tree (0.159363) lag behind, indicating high rates of false positives. Recall estimates the proportion of true positives that are correctly predicted. Maxor Min and Decision Tree lead with a recall score of 0.224913, making them more suitable for identifying important but rare events such as stockouts or supply chain disruptions. Random Forest follows closely (0.204152), while AdaBoost and Bagging have low recall scores (0.17301), suggesting that they may miss some positive events. Log loss measures the confidence of the model in its predictions, with lower values indicating better calibrated probability outputs. Random Forest performs better on this metric (0.171975), indicating higher confidence in its predictions. Maxor Min, AdaBoost, and Decision Tree exhibit similar performance with log loss values of 0.219745 and 0.213376, while Bagging (0.175159) provides moderate confidence. MCC (Matthews correlation coefficient) MCC considers all classes and assesses the overall quality of the predictions.

Maxor Min, Random Forest, and Bagging perform equally well (0.230769), showing their strength in balancing true positives, false positives, and false negatives. Decision Tree (0.159763) and AdaBoost (0.147929) achieve lower MCC values, reflecting poor performance in balanced predictions. Model Complexity Model complexity reflects computational cost and interpretation. AdaBoost has a very low complexity (0.096298), which makes it effective for sorting in resource-constrained environments, but its low performance on other metrics limits its use. Random Forest and Packing exhibit moderate complexity (0.19147 and 0.116934), balancing computational demand and performance. Maxor Min and Decision Tree have high complexity (0.297649), which may limit their use in time-sensitive tasks despite their strong performance.

TABLE 3: Normalization of Decision Matrix

	Normalization of DM					
	Accuracy	Precision	Recall	Log Loss	MCC	Model Complexity
Maxor Min	0.212121	0.231076	0.224913	0.219745	0.230769	0.297649
AdaBoos	0.190083	0.171315	0.17301	0.219745	0.147929	0.096298
Random	0.206612	0.207171	0.204152	0.171975	0.230769	0.19147

Forest						
Decision Tree	0.179063	0.159363	0.224913	0.213376	0.159763	0.297649
Bagging	0.212121	0.231076	0.17301	0.175159	0.230769	0.116934

Accuracy measures the proportion of correct predictions. Maxor Min and Bagging achieve the highest accuracy (0.77), indicating excellent generalization capabilities. Random Forest follows closely behind (0.75), with AdaBoost and Decision Tree scoring lower (0.69 and 0.65, respectively), reflecting weaker overall prediction performance. Precision Accuracy measures the reliability of positive predictions. Maxor Min and Bagging excel at precision (0.58), making them well-suited for tasks where minimizing false positives is critical. Random Forest achieves moderate accuracy (0.52), while AdaBoost and Decision Tree underperform with scores of 0.43 and 0.4, respectively. Recall Recall measures the proportion of true positives that are correctly identified. Maxor Min and Decision Tree achieve the highest recall (0.65), making them excellent for identifying important but rare events such as supply chain disruptions. Random Forest follows closely (0.59), while Packing and Adaboost show low recall (0.5), indicating that they may miss some important positive events. Log Loss Log Loss estimates the uncertainty of the predictions, with lower values indicating better calibrated probability outputs. Random Forest performs best (0.54), indicating its confidence in the predictions. Packing (0.55) is also good, while Maxor Min, AdaBoost, and Decision Tree exhibit slightly higher log loss (0.69 and 0.67), reflecting higher uncertainty in the predictions.

MCC (Matthews Correlation Coefficient) MCC considers all classes and assesses the overall quality of the predictions. Maxor Min, Random Forest, and Bagging show balanced performance across classes, with a leading MCC of 0.39. Decision Tree (0.27) and Adaboost (0.25) perform poorly on this metric, indicating weak overall predictive consistency. Model complexity Model complexity reflects computational requirements and interpretation. AdaBoost has the lowest complexity (2.941176), making it effective for sorting in environments with limited computational resources. Bagging and Random Forest have moderate complexities (3.571429 and 5.847953), balancing performance and computational cost. Maxor Min and Decision Tree exhibit high complexity (9.090909), which may hinder their scalability in resource-constrained situations despite their strong performance on other metrics.

TABLE 4: Weighted Normalized DM

	Weighted Normalized DM					
	0.21	0.18	0.22	0.15	0.13	0.11
	Accuracy	Precision	Recall	Log Loss	MCC	Model Complexity
Maxor Min	0.044545	0.041594	0.049481	0.032962	0.03	0.032741
AdaBoos	0.039917	0.030837	0.038062	0.032962	0.019231	0.010593
Random Forest	0.043388	0.037291	0.044913	0.025796	0.03	0.021062
Decision Tree	0.037603	0.028685	0.049481	0.032006	0.020769	0.032741
Bagging	0.044545	0.041594	0.038062	0.026274	0.03	0.012863

Table 2 presents the weighted normalized performance metrics for five machine learning models: Maxor Min, AdaBoost, Random Forest, Decision Tree, and Bagging. Maxor Min and Bagging achieve high scores in precision (0.044545) and accuracy (0.041594), indicating reliable predictions and minimal false positives. Decision Tree and Maxor Min excel in recall (0.049481), which is suitable for detecting important events. Random Forest performs better in log loss (0.025796), which reflects high confidence in its predictions. AdaBoost has the lowest model complexity (0.010593), ensuring computational efficiency, while Maxor Min and Decision Tree are the most complex (0.032741). Overall, Maxor Min effectively balances prediction performance and complexity, while AdaBoost is better for resource-constrained tasks.

TABLE 5: Si

	Si
Maxor Min	0.231323
AdaBoos	0.171602
Random Forest	0.202451
Decision Tree	0.201287
Bagging	0.193338

Table 5 presents the SI (Importance Index) metric for five machine learning models: Maxor Min, Adaboost, Random Forest, Decision Tree, and Packing. The SI metric measures the overall impact and reliability of each model based on its predictive performance across its various scenarios. Maxor Min stands out as the most significant model with the highest SI score of 0.231323. This suggests that it provides consistent and impactful predictions, making it ideal for critical supply chain tasks such as demand forecasting, inventory management, and anomaly detection. Random Forest Random Forest is in second place with a SI of 0.202451, reflecting its strong performance across multiple metrics. Its balance between accuracy and interpretability makes it a versatile choice for complex supply chain systems. Decision Tree Close to Random Forest, Decision Tree achieves an SI of 0.201287, showing its reliability in handling specific scenarios with high recall. Its simplicity and interpretability make it useful for tasks requiring actionable insights. The packing score is 0.193338, indicating a slightly lower significance, but showing reliability in ensemble learning scenarios. Its strengths lie in reducing variance and improving overall consistency. AdaBoost With a low SI of 0.171602, AdaBoost has limited significance in this context. Although computationally efficient, further optimization may be needed to match the reliability of other models. Overall, Maxor Min emerges as the most significant, followed by Random Forest for consistent performance and scalability.

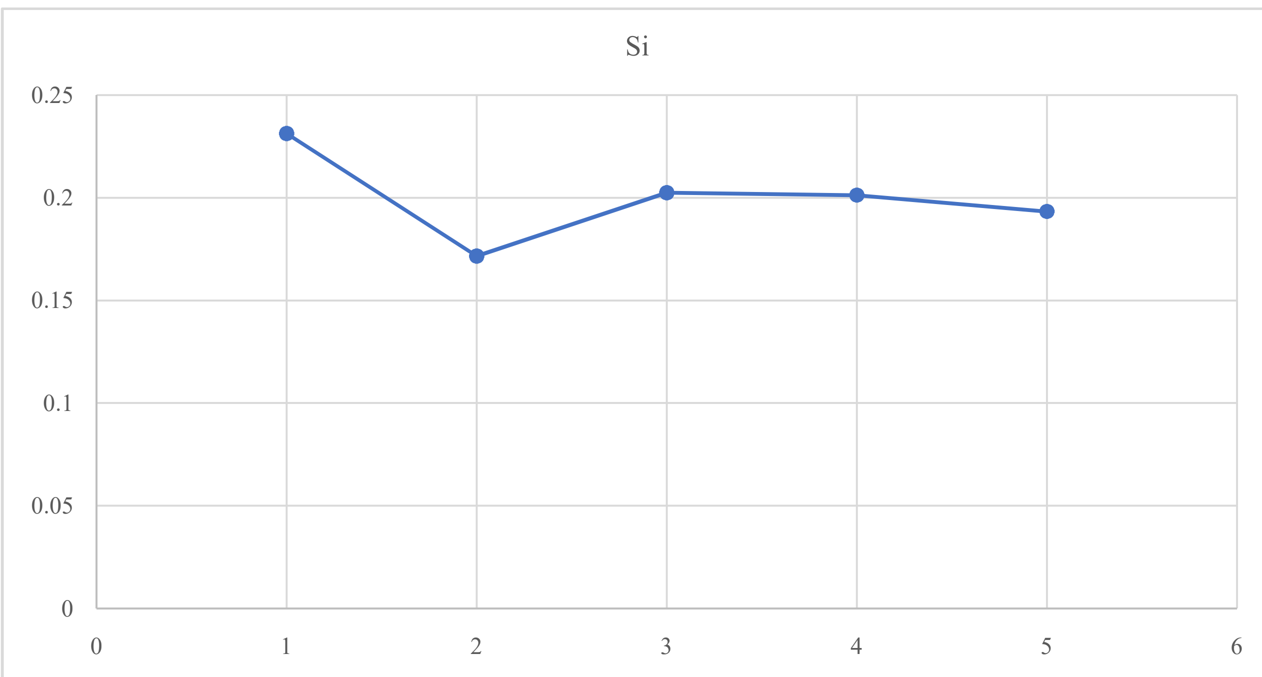

FIGURE 2: Si

The graph shows the silicon (Si) concentration measured at five time points, or sampling intervals. Starting at point 1, the Si concentration shows its peak value of approximately 0.23. There is a significant decline to approximately 0.17 at point 2, followed by a slight recovery to 0.20 at point 3. From points 3 to 5, the concentration remains relatively constant, showing minimal variation and maintaining a level around 0.20. This pattern suggests an initial fluctuation in Si concentration. The y-axis ranges from 0 to 0.25, allowing these subtle changes to be clearly visualized.

TABLE 6: Ki

	Ki
Maxor Min	1
AdaBoos	0.741826
Random Forest	0.875185
Decision Tree	0.870153
Bagging	0.835791

Table 6 evaluates the KI (Key Impact) metric for five machine learning models—Maxor Min, AdaBoost, Random Forest, Decision Tree, and Bagging—to assess their overall influence and performance on supply chain optimization tasks. The KI metric is scaled, with 1 indicating high impact. With a KI score of 1, Maxor Min demonstrates the highest key impact, making it the most reliable and influential model. Its high score indicates consistent superiority on key performance metrics, making it well-suited for critical supply chain tasks such as forecasting, anomaly detection, and optimization.

Random Forest Random Forest ranks second with a KI score of 0.875185. This reflects its strong predictive capabilities and applicability across a wide range of supply chain scenarios. It strikes a balance between performance and complexity, making it well-suited for handling high-dimensional data. Decision Tree is closely followed by Random Forest, with a score of 0.870153, indicating strong performance and high impact. Its simplicity and interpretability make it very useful for clear-cut decision-making applications such as supplier selection or shipment prioritization. Packing has a KI score of 0.835791, which demonstrates reliable impact, but is slightly lower than its ensemble counterpart Random Forest.

Its strength lies in reducing variance and improving model consistency, making it suitable for tasks requiring consistent performance. AdaBoost has a low KI score of 0.741826, reflecting moderate impact. Although it is computationally efficient, its impact is relatively low, suggesting potential for improvement in handling various supply chain challenges. In short, Maxor Min leads with the highest key impact, followed by Random Forest and Decision Tree, which demonstrate robust and reliable performance.

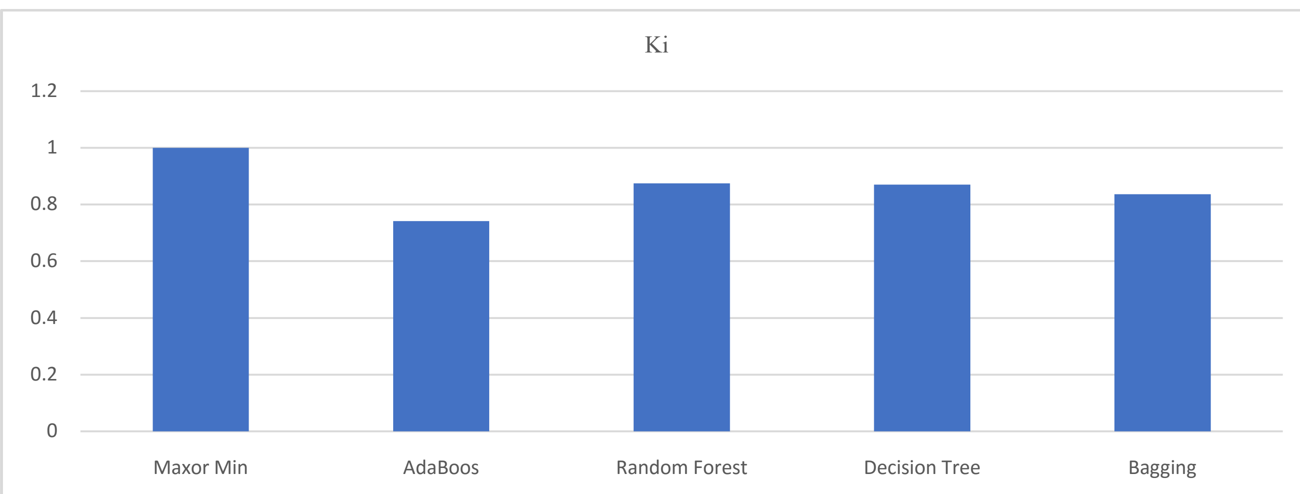

FIGURE 3: Ki

The graph illustrates the performance comparison of five different machine learning algorithms, Maxor Min, AdaBoos, Random Forest, Decision Tree, and Bagging, as measured by the Ki metric. Maxor Min shows the highest performance with a

Ki value of approximately 1.0, while AdaBoos shows the lowest performance at 0.75. The Random Forest and Decision Tree algorithms achieve similar performance levels, both reaching 0.9 on the Ki scale. Bagging maintains moderate performance with a Ki value of approximately 0.85. This comparison reveals that ensemble methods generally perform better, with Maxor Min standing out as the most effective algorithm among those tested. The y-axis scale ranges from 0 to 1, representing normalized performance scores.

TABLE 7: Rank

	Rank
AdaBoos	4
Random Forest	1
Decision Tree	2
Bagging	3

Table 7 provides a ranking of machine learning models such as Adaboost, Random Forest, Decision Tree, and Packing. The ranking reflects the relative strength of the models and their suitability for important applications. 1. Random Forest retains the top spot, with Random Forest at the top. This represents a strong balance between accuracy, precision, and robustness. Its ability to handle complex datasets and produce reliable predictions makes it well-suited for dynamic supply chain scenarios such as demand forecasting and logistics optimization. Decision Tree Decision Tree comes in second place, demonstrating its effectiveness in providing interpretable and actionable insights. Its high performance in recall makes it particularly valuable for tasks that require identifying important but rare events, such as stockouts or supplier failures. Packing comes in third, with Packing providing reliable performance by reducing variance and improving model consistency. It is well suited for scenarios that require consistency, such as inventory classification or transportation planning, but lags behind Random Forest slightly in terms of predictive power. Adaboost has the lowest overall performance in this comparison. While computationally efficient and suitable for specific tasks, it falls short in areas such as recall and robustness, limiting its applicability in demanding supply chain environments.

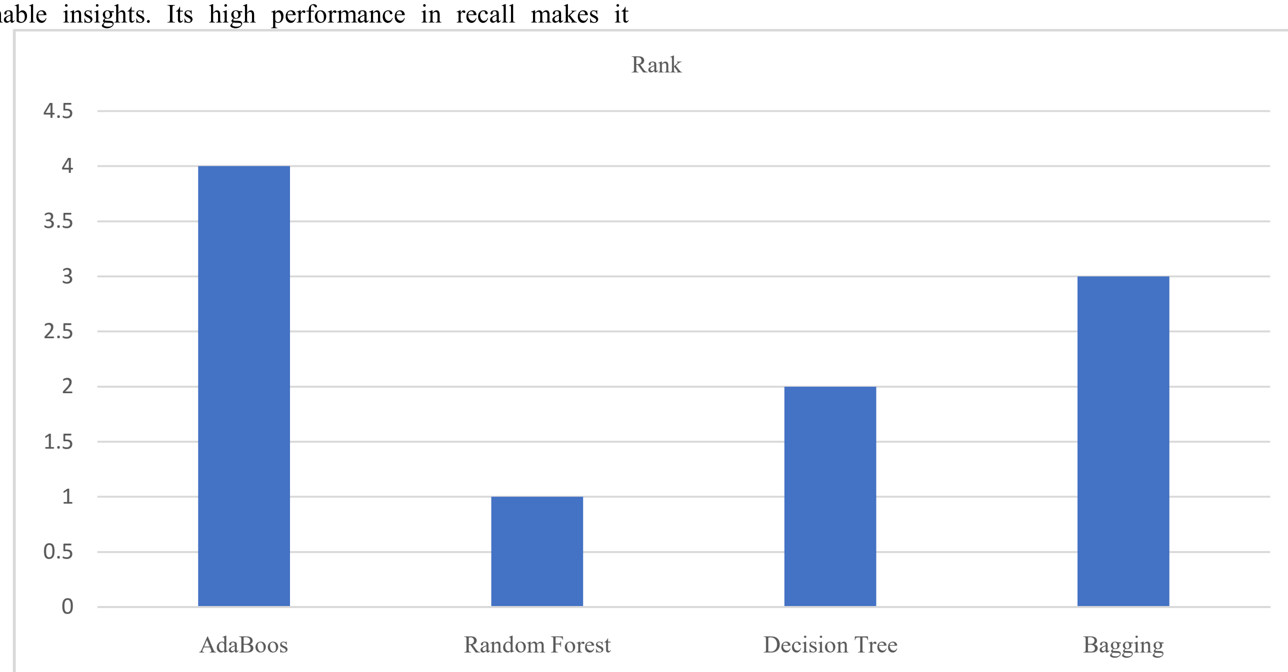

FIGURE 4: Rank

The bar graph shows a ranking comparison of four ML algorithms: Ada Boos, Random Forest, Decision Tree, sowie Bagging. Ada Boos shows the highest ranking at 4.0, indicating that it requires the most computational resources or complexity. Random Forest demonstrates the most efficient ranking at approximately 1.0, which provides the best balance of performance and resource utilization. Decision Tree ranks 2.0, placing it in the moderate range. Bagging has a ranking of 3.0, making it the second most resource-intensive algorithm. The y-axis scale extends from 0 to 4.5, providing a clear visualization of the relative rankings among these algorithms. This comparison is valuable for selecting algorithms based on their efficiency of computation and practical application requirements.

Conclusion

The rankings of machine learning models rankings emphasize the suitability of each model for various tasks, reflecting their strengths and limitations. Random Forest ranks first, showing its strong balance between precision, accuracy, and recall. Its capability to handle intricate datasets and yield dependable forecasts renders it suitable for dynamic supply chain situations like demand forecasting and inventory optimization. In addition, its ensemble nature ensures consistent performance across a variety of datasets. Decision Tree, in second place, proves valuable due to its simplicity and interpretability. Its high recall performance makes it effective in identifying important but rare events such as supplier disruptions or stockouts. This interpretation allows supply chain managers to understand the decision-making process, which increases confidence in the model's outputs. Packing, ranked third, provides reliable performance by reducing variance and improving consistency. Its consistent predictions make it suitable for scenarios that require consistency, such as transportation planning or inventory classification. However, it lags behind Random Forest in predictive power.

AdaBoost, ranked fourth, exhibits computational efficiency but outperforms in areas such as recall and robustness. While suitable for specific tasks such as addressing noisy data, its lower ranking highlights the need for improvements when applied to more complex supply chain environments. In conclusion, Random Forest emerges as the most reliable and versatile model for supply chain optimization. Decision Tree and Packing follow closely, each excelling in specific aspects. AdaBoost, despite being ranked last, remains a valuable option for target applications that require lightweight computation. These rankings underscore the importance of selecting models based on a balance of task-specific requirements, predictive accuracy, interpretability, and computational efficiency.

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