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Smart Inventory Optimization using Machine Learning Algorithms

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***Abstract*— Industries increasingly rely on efficient inventory management, logistics, and supply chain operations, and ML-based intelligence frameworks have emerged as indispensable tools. In this study, ML algorithms are tailored for intelligent inventory management. This research centers around the application of ML techniques within the framework of the ABC Inventory Classification methodology. To assess the effectiveness of these algorithms, a comprehensive training and testing was conducted, followed by model classification. The five ML algorithms examined in this study include Decision Tree Algorithm, Support Vector Machines (SVM), Random Forest Classifier, Naïve Bayes Classifier and K-nearest neighbors (KNN). The goal is to shed light on how these ML algorithms perform in comparison to one another when used for inventory management. Through analysis using inventory dataset, the inference made was that Random Forest Classifiers provides the highest accuracy at 93%. Improving the effectiveness, precision, and financial performance of inventory management practices across various industries and supply chain segments by leveraging the power of ML is an important step of this research. This research study makes significant progress towards integrating intelligent ML-driven solutions into the intricate world of supply chain operations.**

Keywords*— *Machine Learning, algorithms, ABC Inventory Classification, K-nearest neighbors (KNN), Bayes, Random Forest, Inventory, SVM, Smart Inventory, Inventory Management, Smart Inventory Optimization, Inventory ML model

I. Introduction

During the global health crisis that occurred, many businesses experienced significant impacts on their systems for managing the flow of goods. Disruptions in transportation and manufacturing delays were prevalent, making it challenging for companies worldwide to adapt to these unprecedented circumstances. The pandemic caused a notable transformation in consumer preferences, resulting in an increased demand for items such as sanitizers and disinfectants, while non-essential goods experienced a decline in demand. This sudden surge in demand led to the premature depletion of stocks and outstanding orders, while the unexpected decrease in demand raised the costs associated with holding inventory. AlDhanhani et al.[1] have given a detailed study of how Business Intelligence solutions were to be made during the COVID-19 pandemic. The pandemic has increased the need to process large amounts of data quickly. This affects businesses' supply chains and inventory management systems and it has been a subject of concern and analysis during this global health crisis.

In this study, the proposal made is of implementing a classification model based on ABC (Always Better Control) Classification. ABC Classification is further based upon various features like high expenses, high priority, and high perishability which gives a generalized viewpoint to understanding the method of controlling the stock of products in the inventory. This technique has hence proved to be efficient in managing materials and it better controls high-priority goods. [2].

This study focuses on the development of a predictive decision-making model aimed at addressing the increasingly volatile demands for a more efficient multi-criteria ABC classification of stock-keeping units (SKUs) in a warehouse setting. To achieve this, the proposed model leverages machine learning (ML) classifier algorithms to accurately predict and categorize items within the inventory. Specifically, five ML classifier algorithms, namely Support Vector Machine (SVM), Decision Tree Algorithm, Random Forest Classifier, K-nearest neighbors (KNN) and Naïve Bayes Algorithm are employed to classify stock goods and items based on multiple attributes. The trained ML model is subsequently applied in real-time SKU classification to facilitate efficient inventory management, particularly during unforeseen pandemic circumstances where demand and supply exhibited high levels of dynamism.

The study is structured into several sections. Section II consolidates data from relevant prior studies. Section III presents the proposed methodology in detail. Section IV outlines the results and analysis of the experiments conducted and provides a comparative analysis. Section V presents a comprehensive conclusion based on the findings presented throughout the study. Finally, Section VI includes all the references.

II. Related Work

Krishnakumar.S et al. [3] have proposed a thorough analysis of the most recent research trends in medistock inventory control systems. The study focuses on and examines key points regarding the significance of inventory control in healthcare. They have used Economic Order Quantity (EOQ), Just-In-Time (JIT) and Min/Max Inventory control algorithms as their fundamental study.

A. Mishra et al. [4] have proposed an IoT and machine learning based system for effective inventory management. For the predictive analysis of SKUs in the inventory management, they have used three machine learning algorithms: Support Vector Machines (SVM), K-nearest neighbors (KNN), and Bayes.

Srinivas Kedarisetty et al. [5] have proposed that managing inventory entails monitoring the movement of goods across the supply chain starting from their purchase until they are sold. Microsoft Excel can function as a tool, for inventory management. Specifically learning techniques such as neural networks and convolutional neural networks are employed in their study to improve accuracy and determine the most effective algorithms, for efficient inventory management.

Bhamidipati Raviteja et al. [6] have put forth the Support Vector Machine (SVM) algorithm and the Decision Tree for Supply Chain Management (SCM) to forecast the success of the supply and how well it can be managed. The supervised learning algorithms search for patterns and connections between inputs and outputs when a new dataset is available without labels. Based on the connections they find, they map the inputs to the corresponding outputs to achieve this.

III. Proposed Methodology

To evaluate and compare various ML algorithms for inventory optimization, a comprehensive analysis using inventory data was conducted. The performance of various algorithms, including random forest classifiers, was evaluated using the metrics of accuracy, precision, F-score, and support.

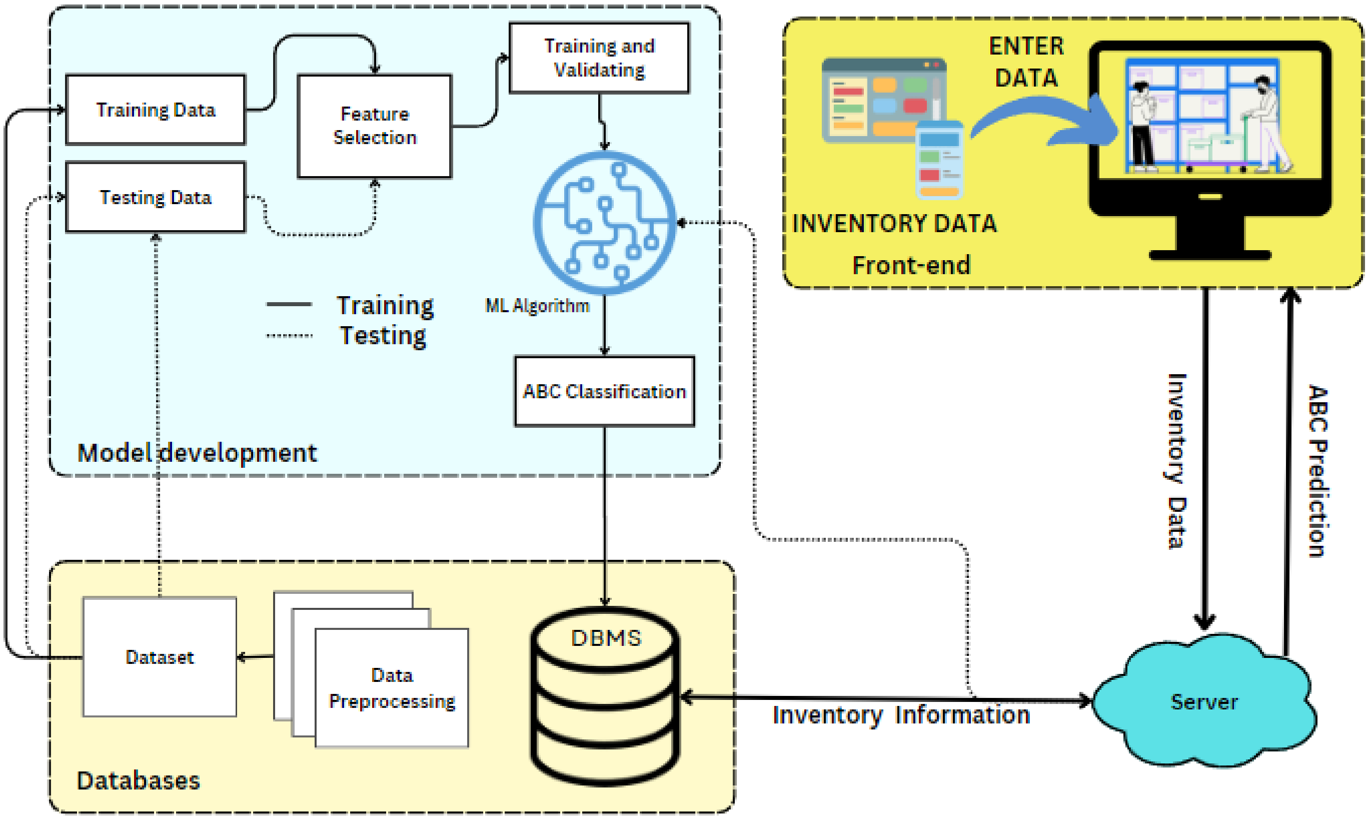

Fig. 1. Block diagram of the proposed real-time tracking of inventory using ML algorithms and DBMS for data analytics

A. System Implementation

This section revolves around the description of how Smart Inventory Management and Optimization system into action can be put up. This system relies on Machine Learning (ML) algorithms to manage and optimize inventory based on the ABC classification framework. Fig. 1 shows the process of implementing the system involving data preparation, selection of features, training and validating models managing the database and seamlessly integrating everything into a user-friendly front-end interface.

i) Data Preparation & Feature Selection

Careful execution of data preprocessing tasks preceded the implementation process. To ensure optimal generalization of the model, the dataset was partitioned into training and testing sets. Emphasis was placed on the crucial stage of feature selection, where meticulous identification of attributes from the dataset took place. The selected features served as the foundation for input variables in the machine learning algorithms, contributing to enhanced accuracy and efficiency.

ii) ML Algorithm Implementation

The system's core comprises machine learning algorithms designed specifically for utilization within the ABC classification framework. Under this framework, inventory items are divided into three distinct classes—A, B, and C each representing a different level of significance and requiring unique management approaches. [9] The machine learning models are skilled at identifying and responding to these categorizations, offering specific recommendations and actions.

iii) Database Management System

The implementation plan depends on the incorporation of a well-structured Database Management System (DBMS) that serves as the backbone of the system. This DBMS acts as a storage, for all data related to inventory ensuring management, storage and retrieval. The smooth integration of this database with machine learning algorithms allows for access, to information enabling informed decision making.

iv) Front-End Interface

The system's user interaction component was carefully developed using Flask to guarantee a simple user experience. A user-friendly front-end interface allows users to easily enter data, including sales records and item details. Following the completion of data entry, the system seamlessly activates ML algorithms to intelligently optimize inventory in accordance with the ABC classification. Users can make well-informed decisions about inventory management thanks to the front-end interface's actionable insights and recommendations.

In conclusion, Smart Inventory Management and Optimization solution's system implementation is the result of meticulous data processing, thorough research, and sophisticated algorithmic modelling. Through this multifaceted strategy, businesses can be facilitated with the tools they need to improve operational efficiency, lower operational costs, and streamline inventory operations. This system is both a promising answer to the current inventory management problems and a testament to the transformative potential of machine learning in the field of supply chain management.

B. Working & Machine Learning Algorithms

The Machine Learning classifier models, as proposed during the system implementation phase, flag off and pave the way for ABC Classification. 600 samples were used in our dataset for the ML Classifier Algorithm (equally divided between the train and test datasets). The Pareto's 80/20 rule, which states that 20% of inventory items represent 80% of the total cost, is the foundation for the ABC Classification.
Because it acknowledges that not all of the individual items that make up the entire inventory are of equal relative importance, Pareto's Principle is significant. This implies that resources such as time, money, and other resources should be distributed among the items in an inventory in proportion to their relative importance. [7]

The five algorithms used for classification are – Naïve Bayes, Decision Tree Algorithm, Support Vector Machines (SVM), Random Forest Classifier and K-nearest neighbors (KNN).

a. Naïve Bayes Algorithm

The Naïve Bayes algorithm calculates the conditional probability of an event given the occurrence of another event.

Naïve Bayes Theorem is mathematically represented as,

$$\boldsymbol{P(A|B) = \frac{P(A) \,.\, P(B|A)}{P(B)}} \tag{1}$$

As provided in eq (1),

P(A) = probability of event A

P(B) = probability of event B

P(A/B) = probability of event A given event B has occurred.

P(B/A) = probability of event B given event A has occurred.

Naive Bayes technique known as the Gaussian Classifier was used in implementing, which uses the Gaussian normal distribution. To create a predictive ML Model, we imported the Gaussian NB Classifier from the Sklearn library.

b. Support Vector Machines (SVM)

The main goal of integrating SVM into our inventory management framework is to create a decision boundary, also known as a hyperplane within the dimensional space of inventory data. This hyperplane plays a role, in categorizing inventory items into groups based on factors like demand patterns, seasonality and supply chain dynamics. This allows us to make data driven decisions regarding stock levels, reorder points and resource allocation.

In this approach, SVM is utilized to identify support vectors that represent pivotal data points in our inventory dataset. These support vectors play a role in our optimization strategy as they help to identify items with characteristics or facing unique challenges. By harnessing the power of SVM and support vector identification the proposed methodology empowers inventory management systems to make decisions. This leads to accuracy in demand forecasting reduced carrying costs minimized stockouts and ultimately enhances inventory performance. Through this research endeavor the aim is to contribute towards advancing inventory management solutions that leverage state of the art machine learning techniques, for agile and responsive supply chain operations.

SVM equations are given as follows:

$$y_i(w^T x_i + b) \geq +1 \qquad (2)$$

$$y_i(w^T x_i + b) \geq +1 \qquad (3)$$

for $i = 1,2,\ldots m$

Combined equations (2) and (3):

$$y_i(w^T x_i + b) \geq \pm 1 \qquad (4)$$

Equation (4) is the final SVM equation after combination. The kernel function can be calculated using Langrage multipliers and the above equation can be used to find the minimum and maximum. SVM's detailed analysis is available. [8]

c. K-nearest neighbors (KNN)

The KNN algorithm makes predictions by comparing how closely it resembles the data points in the training dataset. The data point that is closest, to the test point is considered to belong in the class.[11] To measure the distance, between data points KNN utilizes a Euclidean Distance formula as mentioned in eq. (5), which can be mathematically expressed as follows;

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad (5)$$

Where, n = number of dimensions

With ABC class labels as the target variables, the KNN model was trained using the chosen features. The effectiveness of the model was evaluated using a validation dataset. To improve the precision of inventory optimization, experiments were conducted to identify the ideal KNN hyperparameters, including the number of neighbors (k) and distance metrics. The efficiency of the KNN-based inventory optimization within each ABC class was evaluated using industry-standard classification evaluation metrics like accuracy, precision, recall, and F1-score. We have imported the K-Neighbors Classifier from sklearn to develop the KNN ML Model.

d. Decision Tree Classifiers

Decision tree classifiers are powerful machine learning tools that can automatically identify optimal thresholds for item classification based on multiple attributes. The ABC analysis can be combined with decision trees to produce a more flexible and data-driven inventory classification system. The decision tree classification is used due to its ability to adapt which enables businesses to create unique inventory plans for each class of goods. For instance, aggressive replenishment strategies, such as higher safety stock levels and more frequent reorder points, may be required for Class A items, which represent high-value and high-importance products. Class C items, on the other hand, which are less crucial, might profit from more efficient inventory management.[10] The decision tree-driven ABC analysis facilitates the customization of inventory policies to meet the specific requirements of each item category.

e. Random Forest Classifiers

Through ABC analysis, Random Forests adds robustness and adaptability to inventory optimization. Random Forests improve classification accuracy by combining multiple decision trees, ensuring that objects are assigned to the most appropriate ABC categories. This flexibility is essential in dynamic business environments because it enables the model to independently adapt to changing circumstances. Additionally, Random Forests lessen the need for manual intervention, freeing up time for strategic decision-making. They allow for the customization of inventory plans for each category of goods, optimizing resource use and enhancing financial effectiveness. Inventory management is elevated to a data-driven and agile practice through the integration of Random Forests into ABC analysis, leading to improved performance and responsiveness.

IV. Result And Analysis

Table 1 below portrays the sample inventory dataset with 5 entries (SKU0001, SKU0002, SKU0003, SKU0004, SKU0005) and parameters (Item_Cost, Item_Count, Total_Cost, Lead_Time, Shelf_Life, EOQ, Lead_Time_Var, Seasonality, WarehouseLoc, Customer_Reviews, Historical_Sales_Data, Demand_Fluct & ABC_Classification) wherein most of them hold core significance in structuring and training our ML models. [12...15]

Table I. Sample List of Inventory Dataset (14 Col.)

SKU_ID	Item_Cost	Item_Count	Total_Cost	Lead_Time
SKU0001	10.5	150	1575	5
SKU0002	5.25	300	1575	7
SKU0003	15.75	100	1575	3
SKU0004	8	200	1600	4
SKU0005	3	500	1500	6

Table I(a) COL. 1 – 5

Shelf_Life	EOQ	Lead_Time_Var	Seasonality	WarehouseLoc
180	175	low	none	A1

365	210	medium	seasonal	B2
90	90	high	none	C3
120	140	medium	none	A1
240	320	high	seasonal	B2

Table I(b) COL. 6 - 10

Customer_Reviews	Hist_Sales_Data	Demand_Fluct	ABC_Classification
4.5	250	Increasing	A
4	350	Stable	B
3.8	120	Decreasing	C
4.7	180	Increasing	A
4.2	400	stable	B

Table I(c) COL. 11 - 14

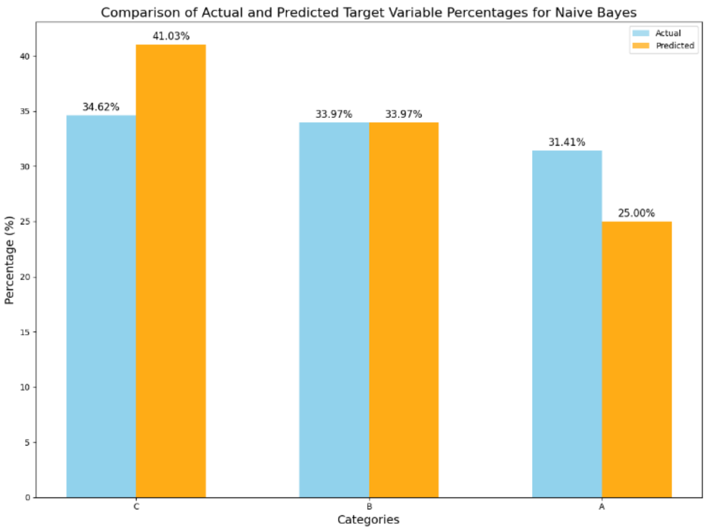

Fig. 2. Predicted Vs Actual (Naïve Bayes)

Fig. 2, Fig.3, Fig. 4, Fig. 5, Fig. 6 provides the comparative analysis of actual versus predicted target variable basis A, B, C classification of SKUs using the Naïve Bayes Algorithm, Support Vector Machine (SVM), K-nearest neighbors (KNN), Decision Tree Classifiers and Random Forest Classifiers respectively. As we deep dive into the analysis, it can be inferred that actual proportion of A, B and C in the dataset was 31.41%, 33.97% and 34.62% respectively. But the prediction which predicted by the algorithms was slightly different from the actual one.

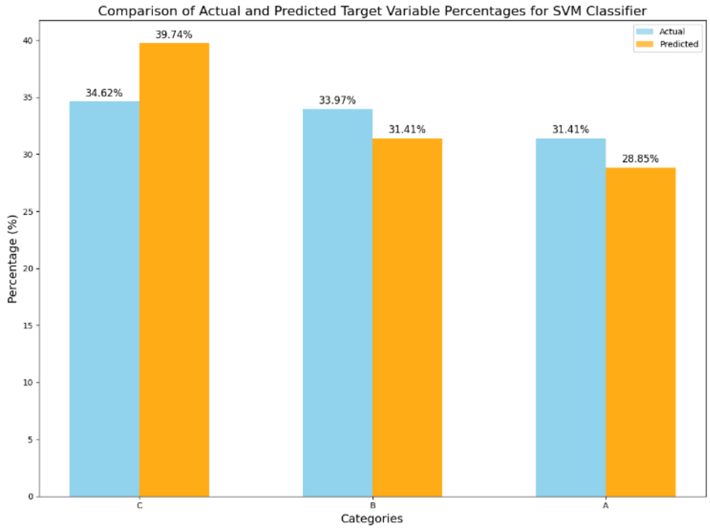

Fig. 3. Predicted Vs Actual (SVM)

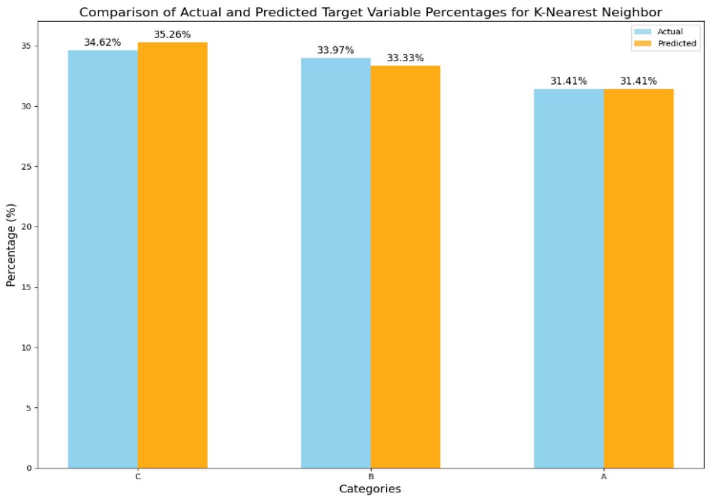

Fig. 4. Predicted Vs Actual (KNN)

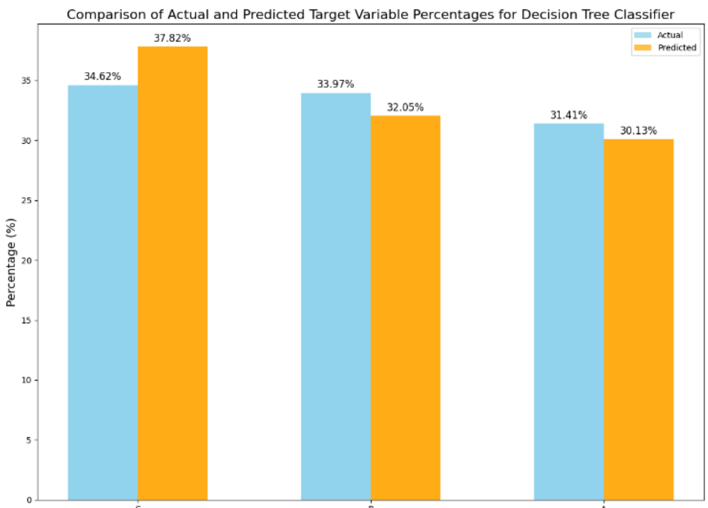

Fig. 5. Predicted Vs Actual (Decision Tree)

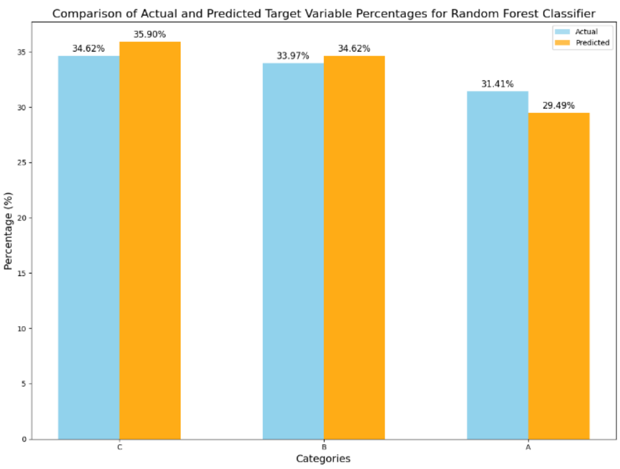

Fig. 6. Predicted Vs Actual (Random Forest)

Table II. Performance Analysis of Various ML Algorithms in ABC Classification

Table

ML algorithm	Class	Precision	Recall	F1 Score	Support	Accuracy
Random Forest Classifier	A	0.94	0.90	0.92	49	0.93
	B	0.93	0.98	0.95	53	
	C	0.92	0.91	0.92	54	
	Summary	0.93	0.93	0.93	156	
Decision Tree Classifier	A	0.87	0.84	0.85	49	0.87
	B	0.89	0.96	0.93	53	
	C	0.85	0.81	0.83	54	
	Summary	0.87	0.87	0.87	156	
SVM	A	0.00	0.00	0.00	49	0.40
	B	0.67	0.19	0.29	53	
	C	0.38	0.98	0.54	54	
	Summary	0.35	0.39	0.27	156	
KNN	A	0.46	0.49	0.48	49	0.54
	B	0.64	0.66	0.65	53	
	C	0.53	0.48	0.50	54	
	Summary	0.54	0.54	0.54	156	
Naïve Bayes	A	0.69	0.90	0.78	49	0.74
	B	0.75	0.75	0.75	53	
	C	0.79	0.57	0.67	54	
	Summary	0.74	0.74	0.73	156	

II. shows the Precision, Recall, F1 score, Support and Accuracy parameters to analyze the five algorithms/ models used. Each model is sub-divided into three sections: A, B & C with each having it's own values of precision, recall, f1-score and support. Random Forest Classifiers produce highest accuracy at 93% followed by Decision Tree Classifiers, Naïve Bayes, KNN, SVM poised at 87%, 74%, 54% and 40% respectively.

V. Conclusion

The COVID-19 pandemic has underscored the critical role of strong inventory management systems in addressing supply chain disruptions. This research study has presented an innovative solution through a predictive decision-making model based on ABC Classification principles, empowered by various machine learning classifier algorithms. By leveraging the capabilities of these algorithms, companies can effectively navigate volatile demand scenarios and enhance their inventory management practices. The fusion of data-driven insights and machine learning will continue to shape the future of inventory management, providing companies with the flexibility and competitive advantage to thrive amidst uncertainty. As discussed, it is evident that technology and ingenuity will redefine inventory management, making it a strategic asset for companies in an ever-evolving business landscape.

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