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THE FRAMEWORK OF INVENTORY PREDICTION MODEL USING ABC ANALYSIS FOR INVENTORY MANAGEMENT

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ABSTRACT

In the present day, there exist technologies that aid in forecasting the future. This is particularly beneficial in the business sector, where business intelligence technology is widely utilized for business development. Business analysis is a method that contributes to the advancement of business management. The aim of this study is to assist companies in managing inventory more systematically and effectively. The objective of this study is to propose a prediction model by applying business analysis and visualizing it in the form of a dashboard. Utilizing the CRISP-DM model as a framework, this study applies ABC analysis in the development of the prediction model. The choice of algorithm for this study will be based on selecting the best algorithm for model development proposal. Confusion Matrix is used in evaluating the model. The RapidMiner tool is used to develop the predictive model, while the dashboard is developed using the Power BI tool. The study will evaluate the dashboard by selecting three experts as assessors. Hopefully, this proposed model will enhance inventory management for the company even further.

Keywords: Business Intelligence, Business Analysis, Predictive Analysis, ABC Analysis, CRISP-DM

Introduction

Over the past decade, there has been a notable shift in how businesses handle their operations, particularly regarding the adoption of technology for sales forecasting and inventory management. Business Intelligence (BI) has emerged as a key tool for conducting analytical processes. Initially conceived by Howard Dressner, an analyst at Gartner Group, in the early 1990s, BI has evolved into a strategic initiative recognized by business leaders for its role in enhancing efficiency and fostering innovation.

Business Intelligence (BI) primarily involves technology-driven methods for analyzing and presenting business data to facilitate decision-making, focusing on historical and current data to provide descriptive insights into past or ongoing activities. Complementing BI is Business Analytics (BA), which delves deeper into analysis, often utilizing predictive or prescriptive modeling to interpret, analyze, and visualize data for informing business strategies, streamlining processes, and improving performance. Both BI and BA serve information access, data analysis, and reporting purposes, empowering employees and managers across organizational levels with timely and relevant information, ultimately enhancing decision-making processes.

Prediction analysis, a critical technique within business analytics, utilizes historical sales data, market trends, and relevant information to forecast future product demand. The objective is to predict the quantity of specific items or products a business should stock to meet customer demand while minimizing surplus inventory or stockouts. By analyzing past sales patterns, seasonal fluctuations, and other variables, businesses can optimize supply chain management, reduce carrying costs, and enhance overall operational efficiency.

Many companies encounter challenges in managing their inventory, particularly within warehouse operations. One prevalent issue is persistent overstocking, where staff consistently order more products than can be sold within a reasonable timeframe. This overstocking ties up physical space and can hamper warehouse efficiency. Another problem arises from insufficient stock for high-demand products, often due to inaccurate demand forecasting. If a company struggles to predict which products will be in high demand, it may end up with inadequate stocks when actual demand exceeds projections, resulting in lost sales opportunities. Additionally, stock shortages can strain the company's supply chain as it attempts to meet demand.

Furthermore, some companies lack information about the demand for their stock, indicating a failure to understand the factors influencing stock market demand. This information gap may stem from communication issues with suppliers, as the company may not prioritize transparent communication. Without regular updates on financial performance and prospects, suppliers may struggle to make well-informed decisions about the company's stock, leading to further complications.

Therefore, this study focuses on businesses offering a diverse range of products to meet consumer demand across various categories. By encompassing multiple brands, it highlights the breadth of product offerings available in the market, enabling consumers to choose based on preferences and requirements. Specifically, the study aims to utilize business intelligence to analyze and forecast stock trends for a company. Through data analysis, the company can gain deeper insights into stock movements, navigate industry challenges effectively, and make informed decisions regarding inventory management. Predictive modeling may be employed to anticipate inventory demand, optimizing inventory levels and directing attention to high-demand products.

This study proposes a model to assist companies in forecasting future inventory needs. The objectives of this study are as follows:

i. Proposing an inventory prediction model for a company using ABC analysis.
ii. Developing a dashboard to visualize the results of inventory management predictions.

The next section will begin by examining related works in the field of business analysis trends. Subsequently, the study will present the methodology framework and finally, the paper will conclude with a summary of the study.

Related Work

To forecast the future of businesses effectively, it's optimal to merge business management, business modeling procedures, and information technology. Leveraging big data proficiently through predictive analytics can be highly advantageous for businesses. Companies that exhibit proactive, forward-thinking approaches and can anticipate patterns or behaviors stand to benefit significantly from this technology.

Predictive analytics encompasses several steps through which a data analyst can forecast future outcomes based on present data. The process of predictive analytics is depicted in Figure 1 below:

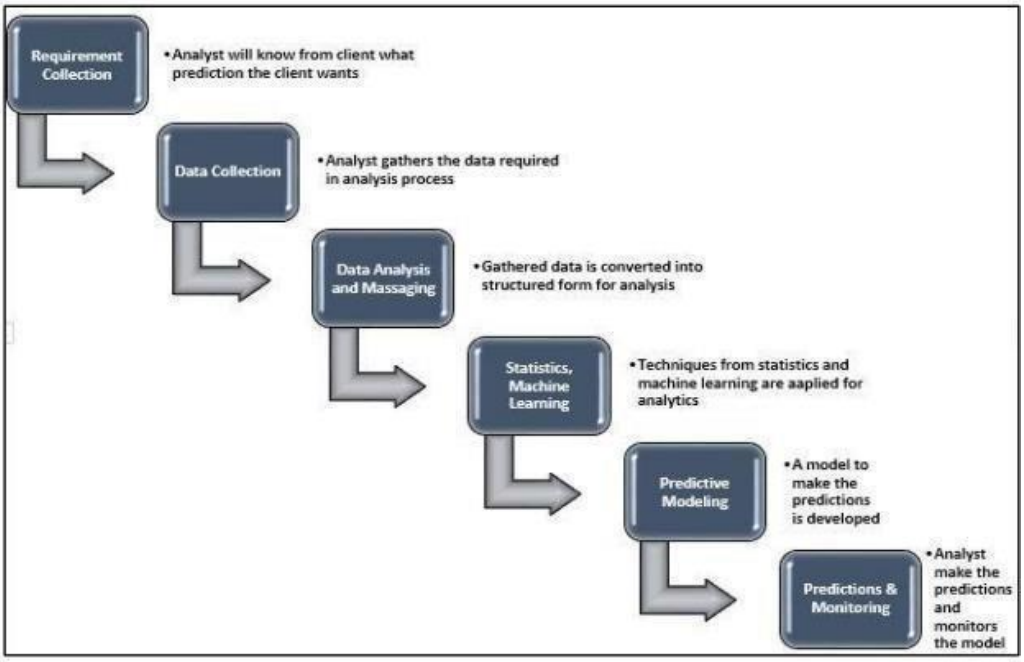

Figure 1: Predictive Analytics Process

Choosing the right prediction modeling strategy is crucial as it drives the predictive analytics process. Predictive analytics involves using statistical algorithms and machine learning techniques to analyze historical data and predict future events or trends. It identifies patterns, correlations, and relationships in data to create models that forecast outcomes, enabling informed decision-making for businesses and organizations. Techniques include linear regression, decision trees, neural networks, and time series analysis. By leveraging predictive analytics, entities can gain insights into future scenarios, optimize processes, manage risks, and make proactive decisions for competitive advantage. Table 1 illustrates a previous study implementing predictive analytics techniques.

Table 1: The Techniques Of Predictive Analytics

Technique	Purpose	Evaluation	Article Citation
Decision Tree	Classification model but it can be sed in regression as well. It is a tree-like model which relates the decisions and them. possible consequences.	An illustration of an upside-down tree; it features a hierarchical tree structure with leaf, internal, branch, and root nodes.	(Kaminski et.al, 2018)
Regression Model	The relationship between a dependent variable and one or more independent variables and analyzes how the value of the dependent variable changes on changing the values	Once one or more explanatory variables change, a regression model can show whether changes in the dependent variable's value are related to those changes.	(Arnstrong et.al, 2012)
Time series analysis	Statistical technique that uses time series data that is collected over sometime at a particular interval. It combines traditional data mining technique sand prediction.	Use techniques. like cross- validation and visual inspection of prediction versus actual values are commonly used for assessment	(Lin, 2003)
Ensemble Learning	These models are created by merging the prediction. outcomes of multiple models of a similar sort that have been trained. The model's accuracy is increased in this way.	Evaluate by bagging and boosting, aiming to improve overall model. performance and combining predictions from multiple models.	(Polikar, 2006)
Classification	The task of categorizing data into predefined classes or labels based on its features.	The classification model draws an interpretation based on the initial training values that were entered. It will predict the fresh data's class categories.	(Eckerson,2009)
Clustering	Machine learning task that involves grouping similar data points together based on their inherent patterns or features, without predefined labels.	One method of classifying objects in various groups that have the foreach comparable group at a wide scale is clustering.	(Charles et al,2022)

Methodology Framework

For the methodology framework, we're using The CRoss Industry Standard Process for Data Mining (CRISP-DM) Model. It's a structured way to develop projects, widely recognized for discovering knowledge in different projects. CRISP-DM helps us by breaking down the project into clear steps, making sure we don't miss anything important. It's like a cycle, so we can keep improving and making changes as needed. This method is reliable for getting valuable insights to help with decision-making. Our adapted CRISP-DM framework includes seven stages: Project Planning, Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Each stage is explained in Table 2 below, based on Saltz's work from 2021.

Table 2: Methodology Framework

Phase	Activity	Deliverable
Project planning	Propose potential project. Prepare interview questionnaire	Proposed work. Questionnaire.
Business understanding	Conduct interview. Determine business objectives. Access situation. Determine project goals. Produce project plan.	Interviewed result. Business objective. Current process. Project goals.
Data understanding	Collect data. Describe data. Explore data. Verify data quality.	Sales data. Inventory data.
Data preparation	Select data. Clean data. Construct data. Integrate data. Format data.	Determined data sets. Cleaned dataset. Selected attributes. Combined data set. Formatted data.
Modelling	Select modelling technique. Generate test design. Build model. Access model.	ABC analysis, Decision Tree Accuracy.
Evaluation	Evaluate results. Review process. Determine next step.	Confusion matrix
Deployment	Deploy model.	Dashboard Development Expert Evaluation.

Model Development

In this study, we will employ the ABC analysis, which is widely recognized as one of the most effective methods for inventory classification. The ABC analysis is based on the Pareto Principle, which suggests that roughly 20% of causes lead to 80% of effects. This method categorizes items based on their importance or their contribution to specific goals, such as sales, profit, or project success.

The project adopts the ABC analysis technique after recognizing the need for a systematic approach to prioritize and manage various tasks and components effectively. ABC Analysis, being strategic in nature, categorizes items or activities into three categories based on their importance, influence, or contribution towards achieving a specific goal or aim. Each category signifies a different level of significance or contribution to the overall objective. These categories are labeled as Class A, Class B, and Class C, with a depiction of the model shown in Figure 2.

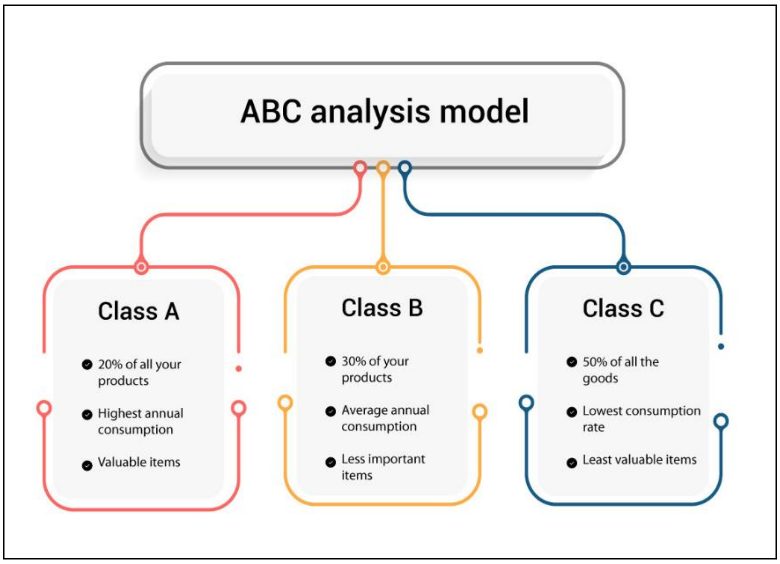

Figure2 : Description of ABC analysis

Class A, also known as High Impact, comprises items that are of utmost importance and consequence. These components are critical to a project or process, though they may be few in number, their impact is significant. For example, high-value products with substantial sales volume would fall under Class A. Class B, referred to as Moderate Impact, lies between the highly impactful Class A and the less crucial Class C. Items in Class B are of intermediate relevance. While they contribute to achieving the main goal, they may not hold as much importance as those in Class A. An example could be a product in inventory management with consistent sales and a reasonable profit margin. Class C, also known as Low Impact, includes products with minimal significance or effect. Although these items are important, they do not have a substantial impact on the overall goal. Products in Class C in inventory management might have lower profit margins or sales volumes compared to those in Class A and B.

Model Validation

Ensuring the accuracy and reliability of categorization in ABC analysis involves validating the outcomes after assigning products to categories. Before evaluation, a predictive model was constructed using RapidMiner, a tool that seamlessly integrates various machine learning algorithms such as decision trees, support vector machines, and more. The chosen algorithm for this project is a decision tree.

A decision tree is a tree-like model used in machine learning and data mining to make decisions. It consists of nodes representing decisions based on specific features or attributes, branches representing outcomes, and leaf nodes representing final decisions or predicted outputs. Decision trees are commonly used for classification and regression tasks.

Following the modeling process, the predictive model will be evaluated, and the categorization results will be validated. This involves assessing the coherence of the categorization with past data and market patterns. During validation, any significant changes in product performance or market conditions should be considered. After validating the results of product categorization, a dashboard will be created to display the outcomes. Table 3 provides a summary of the modeling and validation results.

Table 3 Summary of modelling and validate results.

Activities	Description
Predictive Model	Using RapidMiner
Modelling technique	Construct model using predictive algorithm
Validate	Validate predictive model and results.

Dashboard Development dan Expert Evaluation.

The final step is the dashboard board development. Creating a dashboard to display the outcomes of an ABC analysis is a strategic step that enhances the understandability and accessibility of the information. As Sarikaya et al. (2018) suggest, dashboards visualize data and are most effective when they support users in achieving their goals. Unfortunately, many dashboards are not designed with usability in mind; instead, they prioritize visualizing as much data as possible to showcase graphical capabilities.

This study utilizes Power BI to develop the dashboard. Power BI is a business analytics service offered by Microsoft, enabling users to visualize data and share insights. It seamlessly converts data from various sources to create interactive dashboards and Business Intelligence reports. Utilizing Power BI simplifies dashboard development due to its user-friendly features and ease of use.

Conclusion

The study's expected outcomes include the development of a prediction model for inventory management, presented in a well-designed dashboard. This tool aims to significantly enhance management strategy by leveraging historical data and relevant analytical insights, thereby improving inventory prediction accuracy. The dashboard offers a visual representation of essential inventory metrics and classification parameters, allowing users to quickly grasp product distribution across different categories. This facilitates easy visualization of product categorization, distinguishing between items with low and high customer demand. Essentially, it provides staff with a clear overview of product popularity and demand levels.

Moreover, the dashboard enables staff to plan and organize inventory effectively by monitoring stock levels and anticipating potential shortages or overstock situations. Its visual nature simplifies the prioritization of stock orders based on current needs and market trends, leading to more informed and efficient decision-making in inventory management. Overall, the dashboard serves as a powerful tool for streamlining planning processes and optimizing stock orders with greater accuracy, empowering staff to make data-driven decisions and enhance overall inventory management efficiency.

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