JOURNAL OF SOFT COMPUTING AND DATA MINING
e-ISSN: 2716-621X

JSCDM

Vol. 5 No. 1 (2024) 142-151
https://publisher.uthm.edu.my/ojs/index.php/jscdm

Inventory Categorization Using Multiple Criteria Classification

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DOI: https://doi.org/10.30880/jscdm.2024.05.01.012

Article Info

Received: 1 December 2023
Accepted: 25 April 2024
Available online: 21 June 2024

Keywords

Inventory analysis, multiple criteria classification, fewer SKU, product, ageing, inventory life cycle, product life cycle, FSN, HML, FSN-HML, FSN-Fuzzy, decision tree, supply chain, machine learning, decision tree, support vector machine

Abstract

Inventory management holds paramount importance in modern business landscapes, where expert resource handling is essential for success. This study investigates the correlation between specific Stock Keeping Units (SKUs) and age categories of items, exploring factors influencing the speed of warehouse movement. Categorization based on product life cycle, pricing, and remaining stock is examined alongside savings levels. Employing multi-criteria classification algorithms, including traditional and machine learning techniques, the research illuminates inventory dynamics. This study compares bi-criteria, multi-criteria of traditional, and machine learning inventory classification methods, providing a comprehensive analysis of inventory categorization strategies. Machine Learning method achieved highest accuracy up to 99% by Decision Tree and 68% by Support Vector Machine. The accuracy score followed by the traditional method by using FSN-fuzzy method accuracy score up to 86.7%. The outcomes of the FSN analysis and fuzzy classification experiment will offer stakeholders valuable insights, potentially sparking innovative ideas for their business.

1. Introduction

Effective supply chain design is crucial for businesses to remain competitive by reducing costs and improving service levels. Over the years, companies have focused on standardizing processes and adapting to changing consumer demands to enhance product quality and efficiency. Inventory management is a key component of supply chain operations, involving the monitoring, control, and utilization of goods to ensure smooth production and meet customer needs [1]. In industries heavily reliant on inventory, such as retail and manufacturing, inventory management is critical for business success. However, determining when to replenish stock, what to produce, and how much to pay can be challenging decisions [2]. In this project, inventory classification is performed based on parameters such as fast-moving, slow-moving, and non-moving classes, aiding in effective inventory management.

Understanding the inventory life cycle (LCI) and product life cycle (PLC) is essential for effective inventory management. LCI system models are designed to facilitate decision-making, considering factors like market information and economic changes [3]. Additionally, the PLC complicates inventory management by requiring decisions across different time horizons. Recent frameworks propose comprehensive approaches to inventory control, focusing on product age quality and operational outcomes [4]. The need for inventory stems from ensuring smooth business operations, providing satisfactory service, minimizing losses, and optimizing cash flow. Various inventory classification strategies are available based on specific criteria and business objectives [5]. Overall, effective inventory management is essential for optimizing supply chain operations and ensuring business success in the competitive landscape today. Table 1 below shows four types of criteria classification strategies with machine learning classification strategies.

Table 1 *List of criteria and techniques*

No.	Type of Criteria	Technique
1	Single criteria	FSN, HML
2	Bi-Criteria	FSN-HML
3	Multi Criteria	FSN-Fuzzy
4	Machine Learning	Decision Tree

The inventory management process involves categorizing items based on their movement and value, which aids in efficient stock handling and decision-making. FSN analysis categorizes items into Fast-moving, Slow-moving, and Non-moving categories, utilizing turnover rates to determine their usage patterns. This classification helps prevent stock obsolescence and guides warehouse organization [6]. Meanwhile, HML analysis assists in pricing decisions and inventory control, with higher-value items subjected to stricter monitoring. Combining FSN and HML analyses into bi-criteria FSN & HML classification provides a comprehensive approach to inventory management, considering both usage rate and value. This enables organizations to prioritize inventory management efforts effectively, focusing on items crucial in terms of both movement and financial significance [6, 7].

Moreover, the multi-criteria FSN-Fuzzy classification technique integrates fuzzy logic principles with FSN analysis to offer a more nuanced inventory classification approach. Fuzzy logic allows for handling uncertainty in decision-making, particularly regarding vague concepts like fast or slow movement of items. This advanced method enhances inventory management by considering multiple criteria simultaneously, accommodating mixed or transitional movement patterns more effectively. In summary, these inventory classification methods contribute to streamlining inventory management processes, enabling organizations to make informed decisions and optimize their supply chain operations.

2. Related Work

This study explores inventory management techniques such as FSN and XYZ classifications, examining their application in warehouses with varying capacities. These classifications help allocate stock based on transaction frequency and order fulfillment costs, optimizing inventory handling. Additionally, the study discusses the company's utilization of traditional methods like ABC, FSN, and HML analyses for inventory categorization, emphasizing the importance of accurate classification in decision-making processes. It also introduces multi-criteria approaches such as ABC-HML to refine inventory policies based on multiple factors like usage value and urgency [8]. Furthermore, the study incorporates machine learning techniques like decision tree induction and support vector machine methods for classification tasks, showcasing their effectiveness in predicting inventory categories [9]. This holistic approach to inventory management underscores the significance of innovative methodologies like fuzzy classification and machine learning in optimizing business operations [10].

This study also highlights the evolving landscape of inventory management, considering advancements like multi-criteria ABC classification and fuzzy theory integration for data ambiguity handling [11]. By incorporating diverse methodologies such as fuzzy logic and neural fuzzy systems, the study seeks to address the complexities of inventory classification and decision-making effectively [12]. Moreover, the utilization of machine learning algorithms like support vector machines and self-attention-based learning methods underscores the importance of data-driven approaches in modern inventory analytics [13]. This study emphasizes the need for accurate inventory management to optimize business efficiency and customer satisfaction, advocating for a combination of traditional methods and innovative techniques to meet evolving supply chain demands [14, 15]. Overall, it provides a comprehensive overview of inventory management strategies, offering insights into future research directions and potential applications in real-world scenarios [16].

Furthermore, the study incorporates advanced methodologies like decision tree (DT) construction, which involves hierarchical partitioning of datasets to create tree structures resembling flowcharts [17]. DTs contain straightforward rules for sample categorization, with each node determining the next step for sample movement based on specific criteria. The DecisionTreeClassifier and Tree from SciKitLearn are utilized to build decision trees, with the former selecting an ideal split point at each node and the latter choosing a split point at random. This integration of traditional and innovative inventory management techniques underscores the importance of data-driven approaches in optimizing supply chain operations.

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3. Material and Method

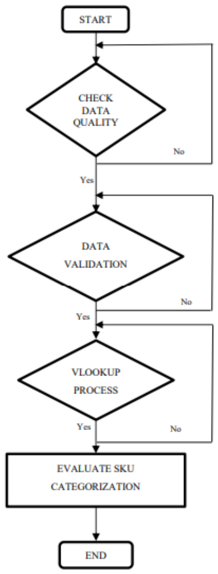
The method used in this study focuses on enhancing inventory data management, building upon previous research. The main objective is to improve classification accuracy in inventory management, addressing challenges associated with conventional and machine learning techniques. Specifically, the study explores the use of bi-criteria FSN-HML for item classification based on movement and sales, and multi-criteria FSN-Fuzzy for decision-making regarding rewards or tips for outlets. Decision Trees (DT) and Support Vector Machines (SVM) are recommended for classification evaluation. FSN-Fuzzy is introduced as a novel technique for inventory analysis in this project, alongside a comparison of traditional and machine learning methods. SVM and DT are well-established algorithms for classification tasks, each offering unique strengths and applications, with their selection depending on factors like problem complexity and data availability.

The initial phase involves a preliminary investigation or literature review to understand the setup of deep learning algorithms and establish the research objectives. This phase aims to detect and classify single, bi-criteria, and multi-criteria inventory classification methods, identifying research gaps and proposing suitable solutions. Following this, the second phase involves acquiring datasets, with data sourced from a private commercial database, the Sports Retailer dataset.

The third phase comprises conducting experiments to develop deep learning classifiers that minimize loss rates and achieve high accuracy for each inventory class. This phase includes utilizing various classification algorithms such as FSN, HML, FSN-HML, FSN-Fuzzy, and Decision Tree. The fourth phase focuses on evaluating the performance of the developed classifiers using machine learning techniques such as Support Vector Machine (SVM) and Decision Tree (DT).

The decision-making process of Decision Tree (DT) classifiers requires the division of data into increasingly smaller categories. This method is similar to a flowchart, where each phase finally leads to a conclusion. Support Vector Machine (SVM) classifiers, in contrast, identify the optimal approach to distinguish many groups of data points, similar to drawing a line between separate groups on a graph. Support Vector Machines (SVMs) are very proficient in identifying the most effective line or boundary that separates various groups in the data. On the other hand, Decision Trees (DTs) are more easily understandable as they operate in a manner similar to a decision-making tree. Both methods are used for categorizing tasks; however, the selection of which one to use depends on the specific data being handled and the desired interpretation of the results [18, 19].

The methodology further details the implementation process in JupyterLab for Python programming. It includes importing datasets, transforming data into usable formats, checking data quality, plotting data for visualization, adjusting data characteristics, balancing datasets, and creating training data using resampling techniques. The process is concluded once the machine learning process in JupyterLab is successfully completed, providing a comprehensive approach to inventory classification. Figure 1 below shows the flow charts of the traditional and machine learning models.

<table>
<tr><th colspan="2">Traditional</th><th>Machine Learning</th></tr>
<tr><td>Bi-criteria - FSN-HML (pg.43)</td><td>Multi-criteria - FSN-Fuzzy (pg. 45)</td><td>Supervised Machine Learning - SVM, DT (pg. 47)</td></tr>
<tr><td>


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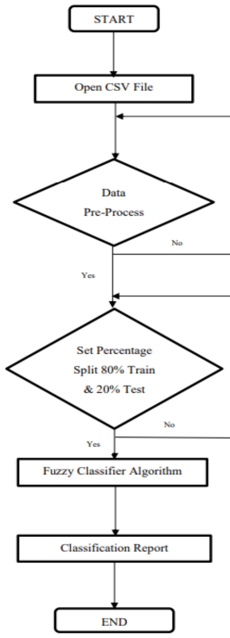

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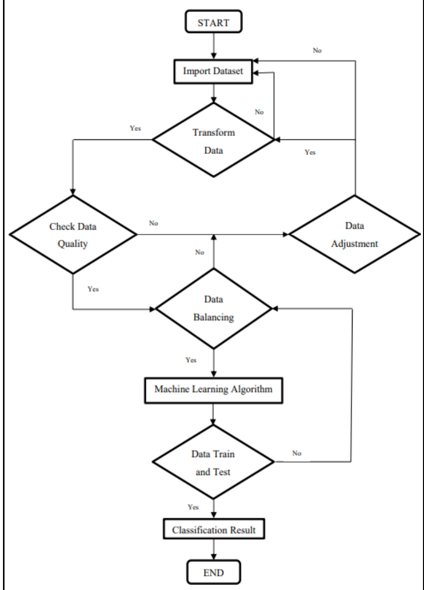

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Fig. 1 *Model flowchart*

3.1 Data Collection

The datasets were collected from the company, aiming to gather information from wholesalers, retailers, and the industry. Sports retailer dataset, a private commercial database, is the source of the dataset used in this paper. The raw data, spread across three Excel sheets, requires processing to make it usable for analysis. The dataset has 93396 rows and 12 columns after undergoing data cleaning. The dataset was divided into 3 sets of information, which are sales per-three months, product information and current balance in company inventory stock. The information of each variable is stated as shown in Table 2.

Table 2 *Dataset information details*

No.	Variables	Description
1	SKU_id	Unique identification number for each SKU.
2	Outlet_id	Unique identification number for each outlet in the closing stock inventory.
3	Age	Age of the product in terms of its life in the closing stock.
4	Bal_Qty	Quantity balance of a particular SKU in a specific outlet.
5	SalePrice	Price at which each SKU is sold during the closing stock inventory.
6	SKUerp	Unique identifier of SKU and may include product detail.
7	Outlet	Unique identifier of outlet.
8	Brand	Brand of the product associated with each SKU.
9	Division	Categorizes the products based on the division they belong to.

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10	Category	Categorizes the products based on their broader category or product type.
11	Subcategory	Refines the categorization of products into specific subcategories.
12	Product lifecycle	Provides information about the life cycle stage of each product.

The main focus of the inventory data assessment revolves around class-level classification, followed by evaluating the age level during data collection. Intermediate discussions address significant data maintenance and quality issues, while the final aspect pertains to providing tips or rewards to company staff based on outlets with higher sales of moving stock, contingent upon the age of the products. This underscores the overall high quality and utilization of the inventory data.

3.2 Research Design

This study aims at effective classification techniques for analyzing inventory in daily industrial operations. The workflow follows the plan illustrated in Figure 3. Initially, the primary problem and project requirements are defined. The next step involves understanding standard inventory analysis procedures and identifying potential research topics through literature review. Subsequently, data mining and preprocessing are performed. The project development is divided into two phases, focusing on traditional techniques like FSN and HML, FSN-Fuzzy, and supervised machine learning with decision trees (DT) and support vector machines (SVM). Finally, a unique dashboard is created to address the third objective. Both stages aim to meet project objectives 1, 2, and 3. Additionally, the research examines classification methods suitable for inventory analysis in daily industrial operations. After data preprocessing, exploratory data analysis (EDA) is conducted, followed by data visualization. Traditional and supervised machine learning methods are then applied, and the resulting data is presented on a visualization dashboard. The operational framework workflow is detailed in Figure 2.

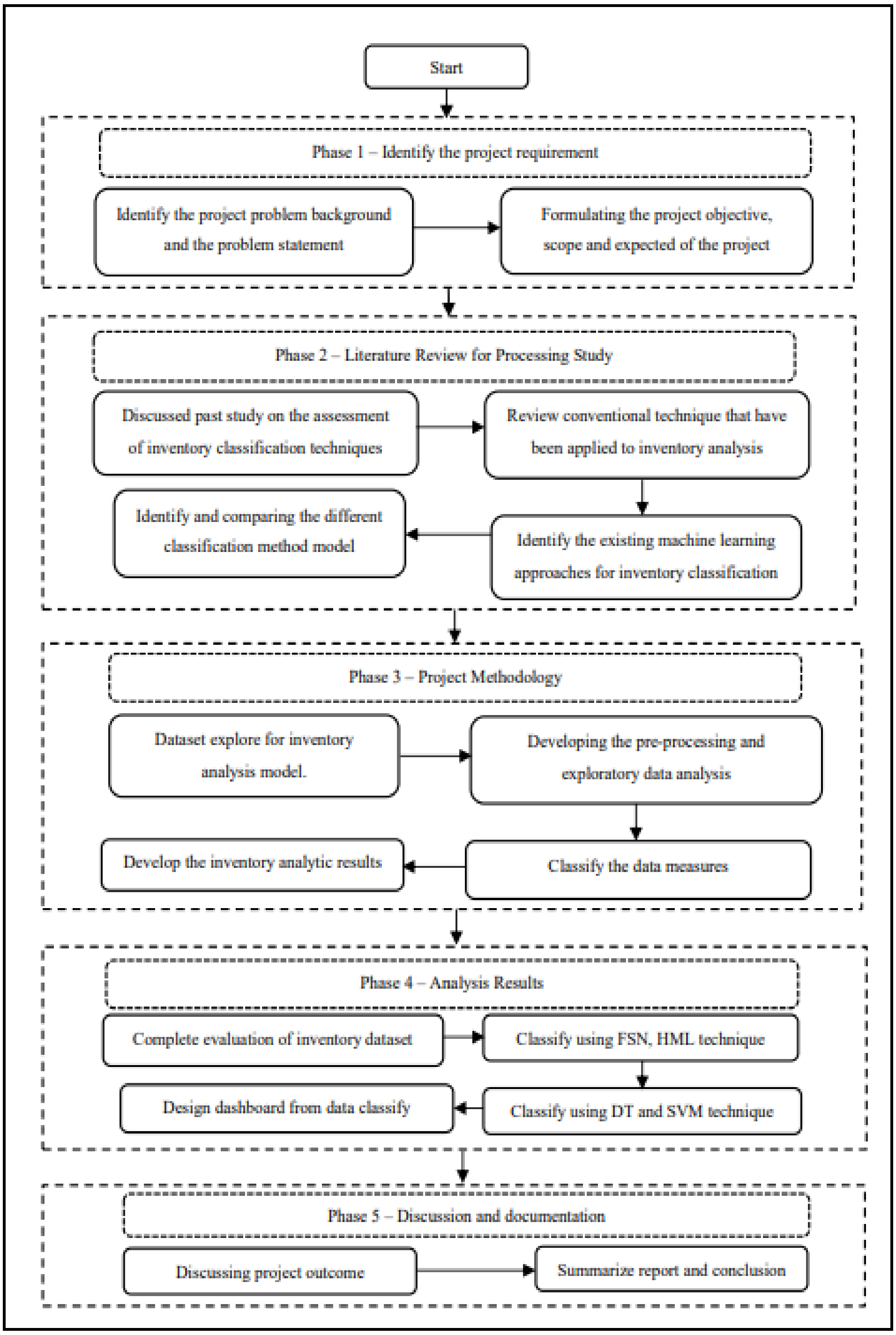

Fig. 2 *Operational flows description of study conceptual framework (pg. 28)*

3.3 Project Methodology

The datasets were collected by a company in the sport retailer industry and the methods that were used in this study are traditional and machine learning methods in order to categorize the inventory data. The processes of the research framework as stated earlier shows the phase of project methodology begins by the data exploration and data pre-processing by making data cleaning to the dataset. The process of data cleaning was carried out by using Microsoft Excel for the storage of dataset files and JupyterLab by Python language to clean the data. From the raw dataset, the invalid, null and duplicated data by SKU for each outlet was removed to prevent inaccuracies that may affect accuracy scores of the results. The process of data wrangling also took place in this study as it required to join and combine some of the data and rearrange it into orderly manners. Then, Exploratory Data Analysis (EDA) was conducted to examine the patterns, uncover insights, identify anomalies, relationships, and characteristics, and develop hypotheses of the data for further experimentation.

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4. Data Analysis

Exploratory Data Analysis (EDA) phase aids researchers in developing a thorough comprehension to facilitate informed decisions regarding modeling strategies. Additionally, it allows for the identification of any existing issues or challenges that must be resolved prior to advancing to subsequent analyses in this study. The analysis of this study is divided into five parts which are FSN, HML, FSN-HML combination, FSN-Fuzzy and Machine Learning analyses.

4.1 FSN Analysis

The FSN analysis sorts inventory items into Fast (F), Slow (S), and Non-Moving (N) categories using predetermined criteria. It involves combining attributes, computing sell-through rates, and applying specific guidelines to determine each class of SKU. The outcomes reveal how SKUs are distributed across these classes, providing valuable insights for evaluating inventory movement. Results of the FSN analysis are as follows in Table 3.

Table 3 *FSN analysis result*

No.	FSN Model	Sum of Balance Total
1	Fast moving	39503
2	Slow moving	63288
3	Non moving	217267

4.2 HML Analysis

The HML analysis classifies inventory items into High, Medium, and Low price tiers based on predefined rules considering item age and sales price. It establishes clear criteria for SKU classification, aiding in understanding price dynamics within the inventory and informing pricing strategies and inventory control. Results of the HML analysis are as follows in Table 4.

Table 4 *HML analysis result*

No.	HML Model	Total
1	High level	74889
2	Medium level	156939
3	Low level	88230

4.3 4.3 FSN-HML Analysis

Integrating FSN and HML results offers a comprehensive understanding of SKU classifications based on both movement and price considerations. This combined dataset facilitates visual representation and analysis, contributing to effective inventory management and pricing decision-making. Results of the FSN-HML analysis are as follows in Table 5.

Table 5 *FSN-HML analysis result*

Model	H	M	L	Grand Total
F	6,571	23,410	9,522	39,503
S	14,916	33,819	14,553	63,288
N	53,402	99,710	64,155	21,7267
Grand Total	74,889	156,939	88,230	302,058

4.4 FSN-Fuzzy Analysis

The FSN-Fuzzy classification method employs a fuzzy classifier to categorize inventory items, addressing imbalance through preprocessing and utilizing a multi-objective evolutionary fuzzy classifier. The results highlight accuracy and classification error rates of the model, shedding light on the effectiveness of inventory classification techniques. Results of the FSN-Fuzzy analysis are as follows in Table 6.

Run information	Detail							
Test mode	split 80.0% train, remainder test							
Accuracy	(80920) = **86.6539%**							
Classification error rate	(12463) = **13.3461%**							
TP Rate	**FP Rate**	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**	**PRC Area**	**Class**
0.999	0.003	0.999	0.999	0.999	0.996	0.998	0.998	N
0.991	0.157	0.562	0.991	0.717	0.683	0.917	0.558	F
0.102	0.003	0.874	0.102	0.182	0.271	0.55	0.22	S

Confusion Matrix

a	b	c	← classified as
63934	0	77	**a = N**
21	15598	123	**b = F**
73	12169	1388	**c = S**

Fig. 3 *FSN- Fuzzy analysis results*

Table 6 *FSN-Fuzzy analysis result*

Run Information				Detail				
Test Mode				Split 80% train, remainder test				
Accuracy				(80920) = **86.6539%**				
Classification error rate				(12463) = **13.3461%**				
TP rate	**FP rate**	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**	**PRC Area**	**Class**
0.999	0.003	0.999	0.999	0.999	0.996	0.998	0.998	N
0.991	0.157	0.562	0.991	0.717	0.683	0.917	0.558	F
0.102	0.003	0.874	0.102	0.182	0.271	0.55	0.22	S

Confusion Matrix

a	b	c	← classified as
63934	0	77	**a = N**
21	15598	123	**b = F**
73	12169	1388	**c = S**

Utilizing machine learning techniques such as Support Vector Machine (SVM) and Decision Tree (DT) classification, inventory items are categorized. Under-sampling is employed to tackle class imbalance, and performance metrics like accuracy, precision, recall, and F1-score are evaluated. These analyses assist in making informed decisions regarding inventory management strategies and pricing tactics.

The primary goal of this study is to determine how much research is done in the real world using both traditional and machine learning approaches to evaluate inventory models, analyse and classify important issues, and determine whether machine learning could be used to classify inventory analysis. The dataset is divided into two categories: a training dataset with 80% of the data and a testing dataset with 20% of the data. By feeding the classifier new datasets instead of the same dataset that has already been trained, the purpose of splitting the data is to make sure that learning generalisation has been accomplished. Results of the Machine Learning analysis are as follows in Table 7.

Table 7 *Machine learning analysis result*

No	Performance	Measurement	
		SVM	**DT**
1	Accuracy	0.68	0.99
2	Classification error rate	0.315	0.00883
3	Positive precision value (PPV)	0.68	1.0
4	Negative precision value (NPV)	0	0
5	Sensitivity / true positive recall (TPR)	1.0	1.0
6	Specificity / true negative recall (TNR)	0	0
7	Macro average	0.23	0.98
8	Weighted average	0.47	0.99

5. Conclusion

The main objective of this study is to offer a possible solution, a method by which firms can utilize inventory data to the maximum extent possible. The study's conclusions provide businesses with real-world pipeline implementation examples that they can quickly integrate into their current workflows to produce inventory from the company's stock and consumer input. This study has shown that by primarily using open source software, such an implementation may be carried out without imposing large financial expenses. This study acknowledges that certain corporate users, especially those aiming to use new technology, would not be able to access it due to financial limitations. Because the pipeline is entirely code-implemented, it is also incredibly repeatable, reused, re-able, and customizable. In summary, this study explored different methods to improve inventory management in businesses. By analyzing data and using techniques like FSN and HML analysis, fuzzy classification, and decision tree algorithms, we found ways to better understand inventory patterns and make smarter decisions. These findings highlight the importance of using data-driven approaches to optimize inventory and boost business efficiency. Moving forward, more research is needed to refine these methods and create even better inventory management systems that can help businesses thrive.

Acknowledgement

We extend our gratitude to Universiti Teknologi Malaysia for their invaluable support in providing the facilities and resources that were essential to this research.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

All authors have contributed significantly to the research and writing of this paper, each bringing their unique expertise and insights to ensure the quality and comprehensiveness of the final manuscript.

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