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Enhancing Spare Parts Inventory Management through Machine Learning Based Classification

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Abstract

Efficient inventory management in various industries relies on effective spare parts classification. In this study, the Support Vector Machine (SVM) algorithm is employed as a machine learning classification method to categorize spare parts inventory. The objective of the study is to enhance the understanding of spare parts classification and provide practitioners with valuable insights for informed inventory management decisions. By applying the SVM algorithm to a dataset of 500 spare parts and conducting a thorough analysis, this study provides insights into the potential applications and limitations of the method. The findings highlight the SVM classifier model's notable predictive accuracy.

Keywords
Machine Learning, Support Vector Machine (SVM), Spare parts classification, MCDM, and Inventory management.

1. Introduction
Effective spare parts classification plays a crucial role in achieving efficient inventory management across various industries, as it ensures that the right parts are readily accessible when needed. Industries like food production heavily rely on their spare parts inventory to ensure uninterrupted flow of operations by maintaining the availability of necessary components and equipment for timely repairs and maintenance. Efficient spare parts management directly enhances production efficiency and overall operational effectiveness. Conversely, inefficient spare parts management can lead to challenges such as an overabundance of spare parts, increased inventory costs, and suboptimal warehouse space utilization. To address these issues, it is essential to establish effective spare parts management practices that ensure the prompt, accurate, and cost-effective availability of spare parts while optimizing warehouse operations.

The ABC classification method is widely used to categorize items based on their relative importance and cost. This method enables organizations to prioritize inventory items by focusing on high-value items that contribute significantly to overall costs. An alternative advanced classification method is Support Vector Machines (SVM), a popular machine-learning algorithm recognized for its accurate data classification capabilities. By utilizing SVM, organizations can train models to classify spare parts based on their various attributes and characteristics.

In this study, the firm's warehouse faces challenges stemming from poor inventory management. The primary issue lies in the absence of a spare parts classification system. Currently, the warehouse operates without a classification system, resulting in a significant accumulation of non-moving and obsolete spare parts that occupy valuable space. These challenges not only impede the efficiency of the supply chain but also hinder the warehouse's ability to provide spare parts in a timely manner. To address these issues, the study utilizes the ABC and SVM classification methods within the context of inventory classification to categorize spare parts effectively. The implementation of an efficient spare parts classification system is expected to enhance operational efficiency, reduce search time, and ensure the timely availability of spare parts. Ultimately, these improvements will contribute to overall performance enhancement and increased customer satisfaction.

1.1 Objectives

The objective of the study is to contribute to the existing body of knowledge on spare parts classification and assist practitioners in making informed decisions regarding inventory management. The study can guide organizations in evaluating and determining the most suitable approach for their specific spare parts classification needs. The outcomes of the study are expected to empower organizations to enhance their spare parts management practices, leading to improved operational efficiency, reduced downtime, and increased overall productivity and profitability.

2. Literature Review

This literature review aims to provide a comprehensive overview of the existing research in the field of spare parts classification, with a specific emphasis on two key topics: ABC classification and the application of the Support Vector Machine (SVM) classifier. The review will highlight the practical applications of these methods and their potential to address real-world challenges encountered in spare parts management.

ABC analysis categorizes inventory items into A, B, and C groups, with A representing critical parts, B representing medium-value items, and C representing low-value and noncritical items. This approach, also known as Pareto analysis or the 80/20 rule, originated from Vilfredo Pareto's observation that 20% of the population holds 80% of the wealth. The ABC analysis is widely used in inventory management, focusing 80% of attention on 20% of items. Combining ABC analysis with other methods enhances its effectiveness in various domains. For instance, Eric et al. (2016) demonstrated the benefits of integrating ABC and GA methods in optimizing line production processes, resulting in significant cost reductions across multiple production lines. This highlights the potential of combining different approaches to enhance efficiency. In the field of inventory management, Flores and Whybark (1986) conducted a study that showed how implementing ABC classification improved resource allocation and decision-making. They emphasized the use of a joint criteria matrix to enhance the ABC analysis framework, providing valuable insights for inventory management practices. Furthermore, ABC analysis has proven valuable in the healthcare sector, specifically in controlling pharmaceutical expenditure in Greek National Health Service hospitals (Kastanioti et al. 2016). By identifying drugs requiring stringent control, ABC analysis enables prudent allocation of funds and offers insights for interventions and reforms in pharmaceutical procurement and health policies.

Overall, ABC Analysis offers advantages in inventory management by categorizing items based on value and usage, preventing stock shortages or excesses. It enables efficient resource allocation and informed decision-making. However, it has limitations, relying on historical data and overlooking interdependencies among items. It assumes consistent demand and may not account for fluctuations or supply disruptions. Complementary techniques are needed for effective inventory management. Additionally, it lacks specific guidance on handling methods and may overlook variations in costs and holding costs. Frequent reassessment is necessary due to its time-sensitive nature.

The support vector machine (SVM) is a powerful machine learning algorithm initially proposed by Vladimir Vapnik and Alexey Chervonenkis in 1963. However, it gained widespread attention and recognition in the 1990s (Awad and Khanna 2015). SVM aims to find a hyperplane that effectively separates data points belonging to different classes in high-dimensional spaces. It has demonstrated excellent performance in various contexts and is particularly effective for classification problems, handling multi-class, binary, and linear classification. Support vectors, critical data points, play a crucial role in determining the optimal hyperplane. By striking a balance between minimizing errors and maximizing the margin between classes, SVM achieves optimal separation. This algorithm has found successful applications in image recognition, text classification, bioinformatics, and various industries, including food and manufacturing (Amarappa and Sathyanarayana 2014).

In a study by Nashat et al. (2011), SVM was used to classify biscuits in real-time based on color inspection on moving conveyor belts. The study demonstrated the effectiveness of the SVM classifier in this task, outperforming discriminant analysis methods for both direct and Wilk's λ classifications. The SVM achieved the highest correct classification rate of 96.5% among the tested classifiers. Baly and Hajj (2012) introduced a new method for monitoring tool conditions in the manufacturing sector using SVM. The research focused on multi-classifying tool states, including transitions from sharp to worn and potential breaking. The results of the study have significant implications for enhancing operational efficiency, reducing production losses, and improving cutting processes. In the food industry, rapid methods have been developed to ensure appropriate and safe conditions and monitor the microbiological quality of products like meat (Papadopoulou et al. 2013). A study in this domain examined the deterioration monitoring of aerobically packaged beef fillet at various storage temperatures. By utilizing kernel-based SVM classification models, the study accurately predicted the sensory class of meat samples, achieving prediction accuracies ranging from 89.3% to 92.8%. SVM has also demonstrated success in the manufacturing industry beyond tool condition monitoring. For example, SVM has been applied to classify spare parts for weapon equipment with an accuracy of 91% in distinguishing between 123 different spare parts (Hu et al. 2017). Additionally, a study by Sabanci et al. (2022) focused on classifying pepper seeds using deep features with SVM. The classification was performed using all features and selected features, resulting in accuracies of 98.05% and 97.07%, respectively. SVM offers advantages such as flexibility and efficiency in high-dimensional spaces, making it suitable for large, complex datasets. It utilizes a subset of training points for the decision function, leading to memory efficiency. However, SVM has certain limitations, including the lack of direct probability estimates in its outputs and potential performance degradation when the number of features greatly exceeds the number of samples.

In today's data-driven world, machine learning has become a powerful tool for classification, revolutionizing various fields and transforming decision-making processes. Machine learning algorithms analyze large amounts of data and make accurate predictions, making them highly valuable. Classification, a fundamental problem in machine learning, involves assigning labels or classes to inputs based on their features. Algorithms such as decision trees, support vector machines (SVM), and neural networks have gained attention for their ability to handle complex and large-scale datasets efficiently (Liu et al. 2020). These algorithms learn patterns and relationships between input features and labels from training data, enabling them to make accurate predictions on new data. Compared to traditional rule-based or heuristic approaches, machine learning algorithms have demonstrated superior accuracy in classification tasks. They can learn complex patterns and relationships from data, leading to precise and reliable predictions. For example, a recent study achieved skin cancer classification accuracy comparable to expert dermatologists, showcasing the potential of machine learning in accurate classification (Khera et al. 2018). Machine learning techniques excel in handling large and high-dimensional datasets, extracting relevant features, and learning from intricate data structures. In the field of natural language processing, machine learning algorithms have successfully performed sentiment analysis, classifying text into positive, negative, or neutral categories. The Sentiment140 dataset, which consists of millions of labelled tweets, has been widely used to train machine learning models for sentiment classification (Go et al. 2009). Feature extraction and selection are critical steps in machine learning algorithms. These steps automatically extract relevant features from raw data and select the most informative ones for classification tasks. This eliminates the need for manual feature engineering, saving time and reducing subjectivity. In a study published in the Journal of the American Medical Informatics Association, machine learning models outperformed traditional methods in feature selection when classifying breast cancer subtypes based on gene expression data. This demonstrates the potential of machine learning algorithms to improve the accuracy and efficiency of classification tasks (Basavanhally et al. 2009). Another significant advantage of machine learning algorithms is their scalability and efficiency in processing and classifying large volumes of data. Traditional methods may struggle to handle the computational demands of analyzing vast datasets, especially with the rise of big data. Machine learning algorithms can leverage parallel computing architectures and distributed systems, enabling them to efficiently process and classify big datasets. For example, TensorFlow, Google's deep learning framework, can train complex neural networks on large-scale datasets across multiple GPUs or distributed systems (Abadi et al. 2016). In summary, machine learning algorithms have revolutionized the field of classification, offering improved accuracy, efficient handling of complex and large-scale datasets, automated feature extraction and selection, and scalability. The evidence from studies across various domains and the successes of industry applications demonstrate the promising support for machine learning in classification.

As advancements in machine learning continue to unfold, we can expect further enhancements and broader applications of these algorithms in the realm of classification.

In conclusion, this literature review highlights the practical applications and potential of ABC analysis and SVM algorithm in various industries. These approaches have proven effective in improving spare parts inventory management and classification accuracy, addressing real-world challenges, and enhancing operational efficiency.

3. Methods

This study focuses on the classification of spare parts inventory, employing two methods: ABC analysis and the SVM classifier algorithm. The following sections provide a complete explanation of the steps involved in each method.

3.1 ABC classification

The application of ABC analysis for spare parts classification is based on the Pareto principle, which asserts that a significant portion of outcomes (80%) is determined by a smaller portion of inputs (20%). To implement ABC analysis, it is necessary to have records of the cost per item and the annual quantity of products. The annual consumption value can be calculated by multiplying the annual quantity of products by the cost per item. Based on the annual consumption value, items are categorized into three groups:

1. Category A: This category comprises a smaller number of items but represents a substantial portion (60%-80%) of the total annual consumption value. However, these items constitute only a fraction (10%-20%) of the overall inventory.
2. Category B: This category includes a greater number of items, accounting for 20%-30% of the annual consumption value and making up around 20%-30% of the total inventory.
3. Category C: This is the largest category, encompassing numerous items. Although these items contribute to 5%-15% of the annual consumption value, they constitute a significant portion (50%-70%) of the total inventory.

By utilizing ABC classification, organizations can prioritize the management of category A items over those in categories B and C, in line with the Pareto principle. This approach ensures that the most valuable items receive appropriate attention.

3.2 Support Vector Machine

The SVM algorithm is a type of supervised learning algorithm used in machine learning to solve classification problems by finding the optimal hyperplane that differentiates between the classes. This algorithm requires pre-defined labels to perform the classification. In this study, the A, B, and C labels will be used for the SVM. The following steps were taken to classify the spare parts:

1. Data Preprocessing: The original dataset provides information on spare parts, including the quantity on hand, the average unit cost per item, and the inventory value cost. It is not uncommon for large datasets to have missing values. In this particular dataset, 22 missing data points were identified. To handle this issue, missing values were estimated by calculating the average value of each respective column.
2. Class Label: The spare parts are classified into three categories, namely 'A', 'B', and 'C', based on the ABC analysis performed using the ABC classification method described in Section 3.1.
3. Data Splitting and Standardization: The dataset is divided into two sets: a training set and a testing set. The training set comprises 80% of the data, while the remaining 20% is allocated to the test set. In order to ensure consistent scaling across variables, the features in the dataset are standardized.
4. Hyperparameters: A grid search is conducted to identify the optimal hyperparameter values for the SVM model. The hyperparameters considered in the grid search include the gamma value (kernel coefficient) with options of 0.001, 0.01, 0.1, and 1, the regularization parameter C with options of 0.1, 1, 10, 100, and 1000, and the choice of kernel function. After performing the grid search, the selected hyperparameter values are gamma = 1, C = 1000, and the kernel function as the Radial Basis Function (RBF).
5. Model Evaluation: The trained SVM model is evaluated on testing data using several performance measures, including recall, precision, accuracy, and F1-score. Additionally, a confusion matrix is generated to provide insights into the SVM classifier's performance, specifically regarding true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The following equations are employed to calculate these performance measures.

$$Recall = \frac{\sum TP}{\sum(TP + FN)}$$

$$Precision = \frac{\sum TP}{\sum(TP + FP)}$$

$$Accuracy = \frac{\sum(TN + TP)}{Total\ Number\ of\ Data\ Instances}$$

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

4. Data Collection

The inventory currently comprises 12,878 distinct types of spare parts, each associated with crucial information such as organization code, item number, item description, category segment, locator, available quantity, and cost per item. In order to gain valuable insights, a preliminary analysis was performed on a random and representative sample of 500 spare parts. This analysis involved the utilization of both ABC analysis and SVM classification techniques.

5. Results and Discussion

The ABC analysis and SVM algorithm are both valuable methods for spare part classification, each with its own distinct characteristics. In this section, we will apply these methods to the 500 spare parts dataset to gain insights into their classification.

First, we conducted the ABC analysis and categorized the spare parts accordingly. Out of the 500 parts, 93 were classified as class A items, 122 as class B items, and 285 as class C items, as presented in Table 1 below. The classification of parts into these categories is based on their respective values and importance. The class A items, comprising 93 parts, hold a significant proportion of the total cost. This highlights the criticality of effective management and procurement strategies to ensure their availability whenever required. These parts play a crucial role in overall operational efficiency, and therefore, their proper management becomes of utmost importance. Moving on, the analysis identified 122 parts as class B items, representing moderate value and importance compared to class A parts. While they may not carry the same level of criticality, it is vital to manage these parts appropriately to prevent any disruptions to operations. Neglecting their management could lead to operational inefficiencies and potential delays in maintenance or repairs. Finally, the analysis classified 285 parts as class C items, indicating their relatively lower value and importance. While these parts may be considered less critical, they still have an impact on inventory costs and require proper management. Failing to adequately manage these parts could result in unnecessary expenses and potential inventory imbalances (Table 1).

Table 1. Classification results for the ABC analysis

Category	Number of parts	Annual Consumption Value	% of total cost	% on hand value
A	93	2193.25	79.78	14.78
B	122	412.33	15.00	27.20
C	285	143.45	5.22	58.03
Total	500	2749.03	100	100

On the contrary, the SVM algorithm was employed to categorize spare parts into classes A, B, and C, utilizing the labels generated by the ABC analysis. The outcomes of the SVM classification demonstrate positive results, indicating the model's proficiency in recognizing and categorizing spare parts accurately. With an overall accuracy of 87%, the model achieved a high level of correctness in its classifications. This accuracy percentage serves as an encouraging indicator of the model's reliability and suggests that it has a strong ability to predict the appropriate category for each spare part.

In addition to the overall accuracy of the SVM model, precision, recall, and F1-score measurements offer a more detailed evaluation of its effectiveness within each category. These metrics provide insights into the model's performance in terms of correctly classifying spare parts and capturing relevant instances within each category. Across categories A, B, and C, the precision, recall, and F1-score metrics consistently exceed the 70% threshold, reaching an exemplary performance level of 95% in some cases, indicating a reliable performance of the SVM model within each category. This implies that the model demonstrates a strong ability to accurately identify and classify spare parts in all three classes. Table 2 provides a comprehensive summary of the classification results obtained from the SVM model.

Table 2. Classification results for the SVM model

Category	**Precision**	**Recall**	**F1-score**	**Support**
A	0.94	0.71	0.81	21
B	0.75	0.82	0.78	22
C	0.90	0.95	0.92	57
Macro average	0.86	0.83	0.84	100
Weighted average	0.87	0.87	0.87	100

In relation to Class A, the SVM model exhibits a minimum recall performance measure of 71%. This value indicates that out of 21 parts that should be categorized as Class A, the SVM mistakenly classifies 6 parts as Class B or C. However, on a positive note, the F1 score for Class A reaches 81%, which is generally considered acceptable in practical applications. Practitioners often regard an F1 score of 0.7 or higher as indicative of good performance. Regarding Class B, the precision metric records a minimum percentage of 75%. This suggests that out of 24 parts that should not be classified as Class B, the SVM erroneously categorizes 6 parts as Class B. Nevertheless, the F1 score for Class B remains at 78%, which is considered good. For Class C, all metrics surpass the 90% threshold across the testing data, which consists of 57 parts. This indicates strong performance by the SVM model in accurately classifying parts in Class C. To visually represent the prediction summary, Figure 1 presents a confusion matrix that displays the numbers of correctly and incorrectly classified instances for each class.

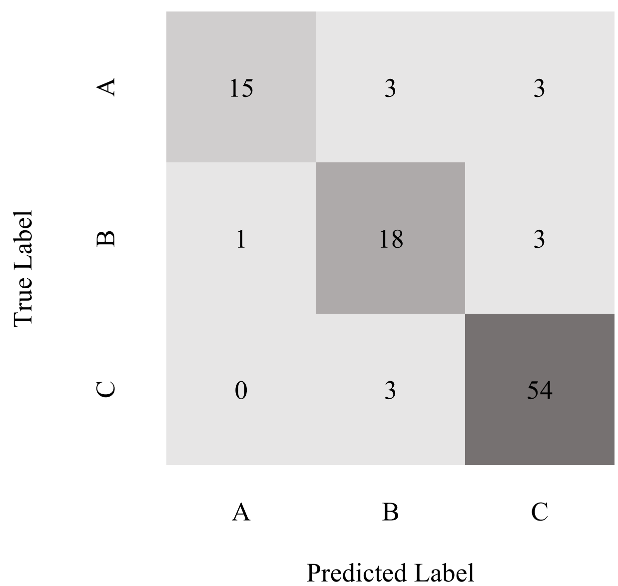

Figure 1: Confusion matrix of the SVM model

As mentioned earlier, the ABC analysis offers valuable insights into the value and significance of spare parts, serving as a guiding framework for efficient inventory management strategies. Moreover, the SVM approach leverages specific features to accurately classify spare parts, resulting in a notable level of accuracy and exhibiting precision in identifying high-priority parts.

To enhance the accuracy of spare parts classification, several suggested improvements warrant consideration. Firstly, a comparative analysis of various machine learning classification methods could be undertaken to identify the most accurate algorithm. Future research endeavors may focus on determining the optimal set of features for improved classification outcomes. Moreover, considering the diverse inventory characteristics across different industry sectors, it is essential to investigate the performance of machine learning algorithms specific to each sector, taking into account factors such as perishability and diversity.

6. Conclusion

Due to the significant volume of inventories held by many companies, considerable attention is devoted to inventory classification, and diverse management tools are employed for different classes. The ABC classification, which applies the Pareto principle, is a widely utilized analytical method for categorizing inventory into three classes: A, B, and C. However, inventory classification should be viewed as a multi-criteria problem, as the traditional ABC method relies on a single criterion.

To address this limitation, this study utilizes Support Vector Machine (SVM) to consider multiple criteria in inventory classification. The SVM algorithm achieves an impressive 87% accuracy in classifying inventory. While this study represents an initial exploration of machine learning accuracy in inventory classification, it is recommended to replace traditional classification methods that overlook critical data features and rely on a single criterion. Advanced methods like SVM and other classification approaches that utilize various data features should be adopted. This is particularly crucial in the era of Big Data to enhance the effectiveness and efficiency of inventory management.

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