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Performance Analysis of Machine Learning Algorithms in SAP Extended Warehouse Management Using ARAS Methodology

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ABSTRACT

This research explores a standardized approach to improve ticket classification performance in SAP Application Management Services (AMS) using cloud-based Machine learning, especially emphasis SAP Extended Warehouse Management. The study investigates a number of machine learning methods, such as support vector machines, random forests, logistic regression, decision trees, and neural networks. Automatic classification of event tickets. While SAP offers solutions such as Service Ticket Intelligence in SAP Cloud BTP, many organizations face challenges in adopting these cloud-based solutions. This research emphasizes integration modern technologies with warehouse management systems, highlighting the critical role of data processing and analytics in improving supply chain operations. The study also incorporates the ARAS (Associative Ratio Assessment) methodology with multi-criteria decision-making approaches to assess system performance and improve operational efficiency. The investigation includes material flow systems, accuracy metrics, and F1-scores to assess how well different machine learning models perform.

This methodology combines theoretical framework analysis with practical implementation strategies, addressing the technical and organizational aspects of SAP ERP implementation. The research examines the challenges of digital transformation in business process management, including the automation of workflows and the adaptation of organizational structures. Special attention is paid to integrating enterprise resource planning systems with strategic enterprise management across production units. The findings highlight the importance of balancing technical capabilities with organizational and human factors in successful system implementation. While acknowledging the challenges of system integration and data management, this study contributes to understanding how machine learning technologies can improve warehouse management performance. The research provides valuable insights for organizations looking to improve their warehouse management processes with advanced technology solutions while maintaining operational efficiency and customer satisfaction.

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Introduction

SAP provides a robust suite of standardized cloud solutions that seamlessly integrate machine learning, big data, and intelligent automation within its application management services. This study investigates an alternative standardized approach that utilizes cloud-based machine learning to enhance ticket classification performance in SAP AMS. The Service Ticket Intelligence feature of SAP Cloud BTP (Business Technology Platform), which use machine learning to categorize service tickets, is one noteworthy example. However, a lot of companies are currently unprepared to employ these cloud-based solutions [1].Students are exposed to a variety of business scenarios through this simulation, which helps them use SAP Business Warehouse software to make well-informed decisions. These scenarios provide a comprehensive training experience by serving as simplified simulations of actual business activities. Students will take part in strategic decision-making aimed at maintaining a business's cash flow and profitability. Students engage with PC4YOU, a SAP virtual business created for instructional and demonstration purposes, during the process. In the end, they use SAP's reporting capabilities to assess the system's advantages and improve their strategic plans. Many companies now use enterprise resource planning software for management their various divisions, improving operational efficiency, effectiveness, and customer focus, ultimately increasing shareholder value.

The implementation of ERP systems has provided these companies with a vast amount of data to support strategic management. However, translating strategic decisions into tangible operational objectives remains a constant challenge in modern business. To maximize the benefits of ERP software, many companies have integrated strategic enterprise management (SEM) as a coordinating function across all product units [2]. Many organizations are moving to HANA as the main database for SAP and non-SAP applications, serving as an alternative to traditional databases such as Oracle and SQL Server. This transition is driven by HANA's in-memory computing features allow for real-time processing. It offers significantly faster data retrieval, performing 3,600 times faster than conventional databases and scanning HANA, a multi-model database, can process 3.5 billion records per second per core while storing data in memory rather than on disk. It uses a columnar storage mechanism to organize data into tables. The memory in a The SAP HANA database consists of two components: table data and working memory, with SAP recommending a 1:1 ratio between them.

As tabular data grows, the working memory requirement also increases. SAP HANA can be deployed on-premises or in the cloud on certified hardware. Memory configurations typically range from 256GB Up to 12TB within a scalable architecture, connected to the appropriate CPU configuration [3]. Modern decision-making relies on a growing amount of statistics and factual data. Visualizing business statistics is becoming essential because it allows for rapid data scanning and understanding. Geographic Information System technology improves business reporting by integrating maps, providing Unique advantages in visualization and geographic analysis that clarify data relationships. However, for interactive GIS analysis, Business data in the data warehouse should be seamlessly integrated with geographic maps.

SAP Business Warehouse offers analytical application suites that provide comprehensive solutions for business analysis and reporting across a variety of domains. These tools evaluate business performance and aid in both tactical and strategic decision-making to enhance profitability, reduce costs, and boost competitiveness. In SAP, hybrid, or non-SAP systems, SAP BW also provides interfaces that allow it to be used as an e-business intelligence platform. A relational OLAP engine, a warehouse management tool, automatic data extraction and staging capabilities, a pre-configured metadata repository, and a front-end system (Business Explorer) with sophisticated reporting and analytics tools are all included. Organizations have implemented enterprise systems to overcome traditional system challenges, address Y2K concerns, improve competitive advantage, expand globally, and establish a unified technology platform. As the demand for greater supply chain integration increases, these systems offer a promising solution. Current technological advances are expanding existing enterprise system capabilities, and future developments aim for seamless integration across organizations. However, the reality is more complex than it appears. A review of the enterprise system (ES) literature highlights significant implementation challenges. Beyond the technical issues, a deeper issue emerges – the struggle to achieve effective enterprise integration. Research indicates that up to 60% of ES implementations result in dissatisfaction, primarily due to insufficient consideration of organizational and human factors.

To maximize the return on ES investments, organizations must give equal priority to these factors along with the technical aspects [5]. The volume of data flowing within and between organizations, originating from a variety of sources and locations, is rapidly expanding. Efficient data processing is critical to business success. To harness this vast data flow, many organizations have implemented data warehousing systems. An business data warehousing solution that is both reliable and effective is SAP Business Warehouse. It provides reports, pre-configured information models, and automated data loading and extraction techniques, guaranteeing a shared view of company data for easy analysis and interpretation. SAP BW organizes and analyzes enormous volumes of operational and historical data using online analytical processing (OLAP) to produce insightful information. We discussed the main implementation issues and offered methods for planning and modeling the integration of temporal data in a data warehouse. addressing issues such managing various time zones, accounting for daylight saving time, portraying holidays and fiscal periods, integrating the time dimension into commercial data warehouses, and seasons [6]. Modern trends in the international transport market highlight the increasing reliance on integrated information systems among trading partners. The use of isolated systems across different transport modes and border terminals, with redundant functions, complicates operations and extends cargo handling and transit times.

There are two methods for accessing the public information area. The first involves the use of Internet technology and a web interface, while the second requires the installation of remote sites and connection to databases. Both methods utilize publicly available information and seamlessly integrate with the existing information systems of regional logistics companies. In cases where functionalities overlap, users can opt for the most convenient solutions and refine their decisions to select the best-fit product. The shared information platform provides a diverse range of technical solutions and a flexible framework for managing transport and logistics systems, allowing users to incorporate their unique information systems into it. For effective implementation, the common information area can use various technical capabilities available in existing operational information systems [7].

The availability of information technology improves the communication and control necessary to maintain competitiveness in global logistics. As the world becomes more interconnected, the strategic importance of management information systems has grown. Organizations are increasingly exploring MIS as a strategic tool driven by globalization and increasing competitive pressures.A warehouse management system has been developed to improve and optimize efficiency all aspects of warehouse operations, providing a structured approach to performance management. Barcode data collection solutions within a WMS provide a robust and flexible automated identification system that seamlessly integrates warehouse operations with enterprise software. By integrating advanced radio frequency and barcode technologies into central warehouse operations, WMS enables comprehensive management of fulfillment centers and warehouses, encompassing tasks such as receiving, storage, picking, and other related operations. A best-in-class solution uses cutting-edge technology to improve operational efficiency, ensuring that the warehouse can focus on fulfilling customer orders accurately and promptly [8].

The core of SAP's sophisticated data management technology is the SAP HANA database. Delivering a cohesive and potent system that can handle transactional and analytical workloads inside a single data model is its primary objective. It operates in a highly scalable environment, supporting a wide range of query scenarios. The main characteristics that distinguish SAP HANA from conventional relational database engines are examined in this study report. It starts by describing SAP HANA's general architecture and design tenets. It also disproves the notion that columnar storage is best suited for analytical tasks rather than transactional operations. The concept of record lifecycle management is presented in this work. It makes use of several storage formats at different points in a record's lifecycle. In addition to outlining the basic idea, it explores how records might be efficiently moved through their lifecycle, maximizing database entries from write-optimized to read-optimized storage formats [9]. Beyond the scientific field, transformative learning can provide valuable support in many practical areas, including business process management. Many companies are currently facing the challenge of digital transformation.

Digitalization affects not only production, but also processes, management strategies and the entire organizational structure. These changes demand a high degree of automation and flexibility in adapting models and workflows. Building business process models from scratch usually requires significant resources and incurs considerable costs. Organizations sometimes struggle with a lack of expertise, making it difficult to model workflows to the required standard. Case-based reasoning can help in this process by applying the principle that similar problems often have similar solutions. Existing business process models serve as a source of empirical knowledge and, with necessary adaptations, can be reused to create new workflow models [10]. To achieve both objectives of the thesis, the theoretical section should first present key concepts related to SAP ERP implementation projects, ensuring a thorough understanding. This includes an overview of project management principles, along with the specific aspects of IS/IT implementation projects. Additionally, the thesis outlines essential concepts for understanding the SAP ERP implementation process. It then provides a detailed examination of this process, followed by an analysis of critical success factors based on insights from books and academic literature. After presenting and explaining these key concepts, the research section is introduced, incorporating both qualitative and quantitative components. The qualitative research includes two in-depth interviews with experts in SAP ERP implementation projects, aiming to validate the theoretical findings and offer practical perspectives on the critical success factors of SAP ERP implementation [11]. We live in an era of rapid technological progress, presenting new challenges and opportunities. Augmented Reality, as an enhanced view of the environment, is one such innovation.

It enriches our worldview, creating added value for society. Currently, overlaying reality with digital objects is a growing trend. This article aims to explore the use of AR in warehouses as a tool to streamline employee tasks and improve human-warehouse interactions. By using AR, a mobile display unit can present 3D models and related information, with devices such as smart phones, tablets, and smart glasses acting as display units. Marker-based augmented reality is a widely used method for real-time object tracking. This approach can be based on characters, images, or physical objects designed to store digital information. The technology detects a marker to determine the position, orientation, or other spatial properties of an object, and then, using specialized software, the marker is transformed into a digital object within the AR environment. Markers have evolved to the point where any image, including elements of the physical world, can act as a marker. Barcodes and later, QR codes are among the earliest examples of this technology [12]. The ability to provide accurate and reliable information is becoming increasingly valuable to organizations. Developing an information system requires careful consideration of local characteristics, available technology, and the business environment. Considering the different types of organizations and their activities, case studies are a useful way to explore best practices in this field. European trends highlight the growing importance of medium-sized enterprises, especially in small, open economies like Hungary.

As part of our study, a Hungarian company in the Szeged region was selected to demonstrate the implementation of a new barcode-based warehouse management system designed to streamline daily operations. Enterprise Resource Planning systems are advanced management technologies that effectively integrate and streamline an organization's internal operations. They serve as the foundation for business intelligence development while improving decision-making by providing comprehensive information support [13]. Additionally, the thesis outlines essential concepts for understanding the SAP ERP implementation process. It then provides a detailed examination of this process, followed by an analysis of critical success factors based on insights from books and academic literature. After presenting and explaining these key concepts, the research section is introduced, incorporating both qualitative and quantitative components. The qualitative research includes two in-depth interviews with experts in SAP ERP implementation projects, aiming to validate the theoretical findings and offer practical perspectives on the critical success factors of SAP ERP implementation [11].This shift allows a company to evolve from a manufacturing organization to a purchasing organization, leveraging the value creation models of outsourced partners. Four key reasons for outsourcing include cost reduction, access to unavailable internal IT resources, business process improvement, and freeing up internal resources to focus on customers and time management. In addition, third-party logistics providers have evolved from mere asset providers to strategic partners in supply chain decision-making. As a result, establishing effective trust-building models has made choosing the right 3PL a critical strategic decision for leading companies, vendors, and prime contractors in supply chains [14]. Implementing an ERP application is a process of improving organizational restructuring and modernizing management. Understanding the ERP system's features and operational procedures is crucial for the logistics management module's successful integration.

The SAP logistics module, which covers purchasing, spare parts, and logistics, connects Jiasuo Wan Fang's three main departments: the marketing department, the material distribution center, and the equipment maintenance center. The material distribution center noticeably excludes "spare parts" since the equipment repair center has a separate storage for spare components. All facets of planning, purchasing, inventory control, warehouse operations, and other business procedures are covered by these three domains. Users from various system modules can communicate and exchange real-time business data depending on their access permissions thanks to the Logistics Management module's complete integration with finance, quality control, and other features. The total comprehensiveness of the system and managerial efficiency are both improved by this smooth integration. Key supply chain operations including purchasing, inventory control, warehouse management, and material requirements planning are all included in the Logistics Management module, which is meant to support the SAP ERP supply chain [15].

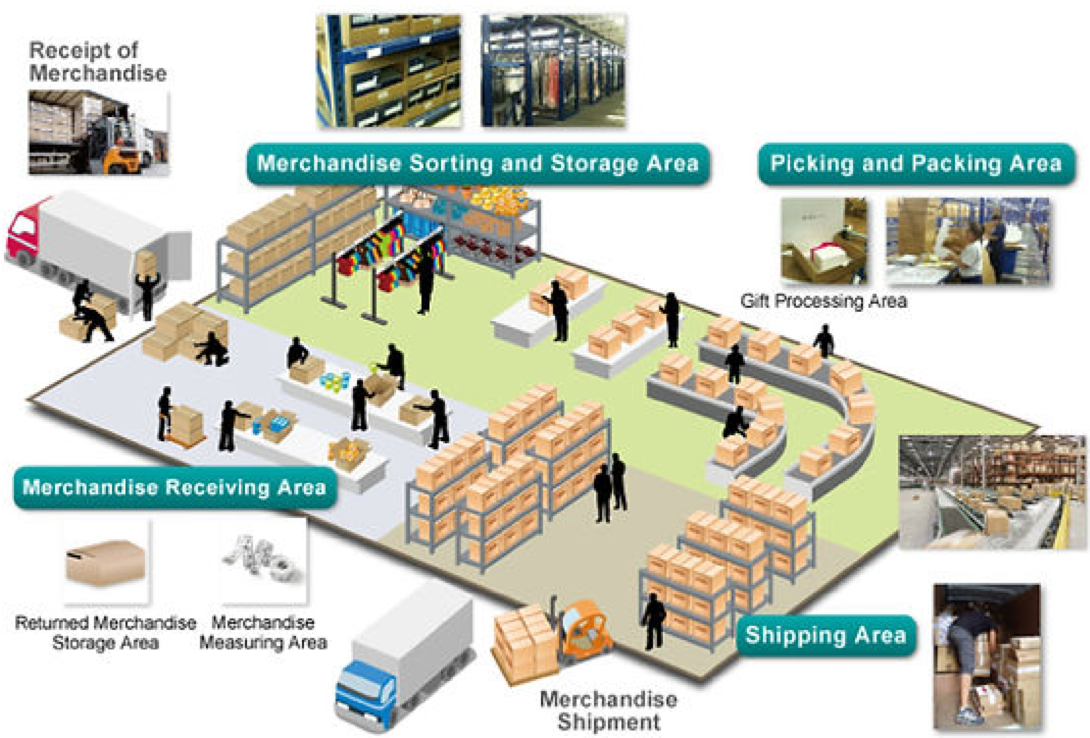

Figure 1. SAP S/4 HANA Extended Warehouse Management

MATERIALS AND METHOD

Logistic regression: Logistic regression is intended for binary or multinomial outcomes, as opposed to linear regression, which predicts continuous values. It estimates the likelihood that an input falls into a particular category using the logistic function. This method is frequently applied to classification jobs like identifying spam emails or forecasting a customer's propensity to make a purchase. The model determines the likelihood of a particular event and applies a logarithmic transformation to establish a linear relationship between the predictors and the log-odds, ensuring that the projected probabilities remain within the permissible range of 0 to 1.

Decision tree: A graphical tool that aids in decision-making by outlining possible outcomes depending on various options is called a decision tree. The original decision is represented by the root node at the beginning, which branches into internal nodes for options and then continues to terminal nodes with final outcomes. Through the visual representation of potential outcomes and paths, this methodical technique aids in the evaluation of complex problems. In business, healthcare, finance, and other analytical fields, decision trees improve clarity and facilitate well-informed decision-making.

Random forest: Regression employs averaged results, whereas majority voting is used for classification predictions. This method minimizes variance, decreases overfitting, and improves accuracy. Key predictive factors can be identified with the help of random forests, which can handle both numerical and categorical data, are robust to noise, and provide insights on feature relevance.

Support vector machine: A Support Vector Machine (SVM) is a robust supervised learning algorithm designed for classification and regression tasks. It determines the optimal hyperplane that maximizes the margin between different classes in a high-dimensional space, ensuring effective data separation. The data points closest to this boundary, known as support vectors, play a crucial role in defining the hyper plane's position and orientation. SVMs can handle both linear and nonlinear data by applying kernel functions, which transform input data into higher dimensions for improved class separation. This adaptability makes SVMs particularly useful in complex classification problems across various domains. The data points closest to this boundary, known as support vectors, play a crucial role in defining its position and orientation. SVMs are highly effective in handling both linear and nonlinear data by employing kernel functions that transform input data into higher dimensions, improving class separability. This makes SVMs particularly useful in complex datasets, such as image classification, text analysis, and medical diagnostics.

Neural network: These networks process data through weighted connections and activation functions, allowing them to learn complex patterns and relationships. Due to their strong pattern recognition capabilities, neural networks are widely used in applications such as speech recognition, image processing, natural language processing, and predictive analytics. By adapting to both linear and nonlinear data, they excel in solving intricate problems, making them valuable in fields like healthcare, finance, and autonomous systems.

Accuracy: Since accuracy might be misleading for unbalanced datasets, metrics such as precision, recall, and F1 score are essential for a more comprehensive evaluation. These metrics help assess the balance between correctly identifying affirmative cases and ensuring their relevance.

F1-score: The F1 score is a vital machine learning metric that balances precision and recall for accurate model assessment. It ranges from 0 to 1, with 1 indicating perfect performance. Particularly useful for imbalanced datasets, it considers false positives and false negatives, providing a comprehensive evaluation of model effectiveness.

Material flow system: The smooth flow of components, final goods, and raw materials along the supply chain is controlled by a material flow system. It includes both external logistics that connect suppliers to clients as well as internal procedures like packing, storage, and transportation. Optimized material flow improves overall operations by preventing bottlenecks, minimizing waste, and guaranteeing efficient production. By guaranteeing timely material availability and real-time inventory visibility, the process is further streamlined by utilizing lean approaches and cutting-edge technology like digital tracking and conveyor systems.

Recall: Recall, also known as sensitivity, is a metric used in machine learning that assesses a model's capacity to locate all pertinent positive cases in a dataset. In applications like fraud detection and medical diagnosis, where missing positive cases can have major repercussions, a high recall score shows that the model successfully captures the truest positives. But concentrating only on recall could result in a higher proportion of false positives. Recall is frequently examined alongside precision in order to provide a balanced assessment, guaranteeing a more thorough evaluation of model performance.

ARAS Method

MCDM techniques are widely used to evaluate and rank the optimal machine state in various machine operations. Among these methods, the ARAS approach stands out, combining quantitative metrics with utility theory to evaluate alternatives and determine the best option [20]. Manufacturing companies rely primarily on human labor and machinery as their main resources. Underdeveloped companies rely heavily on skilled labor with minimal mechanical assistance. In contrast, technologically advanced companies engaged in mass production prioritize machinery, with human resources mainly supervising mechanical operations. The type of machinery used varies based on the application, from simple mechanical hand presses to highly advanced robotic systems [21]. Teachers often choose the lecture method because of its simplicity and minimal equipment requirements. This approach primarily involves explaining concepts to effectively present learning content. A major advantage is the ability to cover the subject within a specific time frame, making it a preferred choice among educators. However, a major disadvantage is that students' understanding is limited by the teacher's level of expertise, making their learning highly dependent on the instructor. Furthermore, teachers with poor communication skills may struggle to engage students, which can lead to boredom and prevent them from achieving learning objectives [22]. The ARAS methodology is used to assess the relative performance of several choices based on predetermined criteria, whereas the AHP method is applied in this study. The decision-making process is more effective when these two tactics are combined. Items like a two-door closet, a bookcase, a dining table and chairs, and a food cabinet are prioritized for sale or donation based on the results of this comprehensive strategy.

Strong validity and reliability are demonstrated by the study's methodologies, which successfully aid in decision-making consistent with the "Spark Joy" notion [23]. To gain a thorough grasp of the background, design, and uses of the HF-AHP and ARAS techniques, this study performs an extensive literature review. It also looks at how they contribute to decision-making.A case study will be carried out at a wastewater treatment plant to demonstrate the selection of the best supplier alternative across five distinct projects, focusing on maximizing facility benefits. Lastly, conclusions and recommendations will be provided to offer meaningful insights for future research in this domain.During road construction, asphalt release agents (ARAs) are applied to surfaces including truck beds, pavements, coatings, tools, and other objects (typically metal, but occasionally plastic) that come into contact with asphalt mixtures. Through interactions between the bitumen, the ARA, and the treated surface, these agents reduce bitumen adherence. ARAs, in contrast to bitumen removers (BRs), prevent bitumen residue from building up on asphalt manufacturing equipment and on-site, rather than dissolving bitumen [24]. Studies on conventional controllers such as PID controllers and intelligent controllers such as fuzzy logic controllers emphasize their extensive application in industrial control systems due to their simplicity and ease of implementation.

As a conventional control method, PID controllers regulate temperature by adjusting proportional, integral, and derivative parameters to achieve optimal system performance and accurate control in self-tuning processes. A new approach using particle swarm optimization for PID parameter tuning is proposed, which improves efficiency and effectiveness [25]. In evaluating suppliers for a textile industry company, alternatives were evaluated based on criteria that positively affect GSS. The ARAS method, a reliable MCDM approach, was used to rank the decision alternatives by their utility function values, considering multiple criteria. In addition, the fuzzy ARAS technique was used to handle the uncertainty and complexity commonly found in real-world situations.Quality control, which focuses on preventing defective products from reaching customers, is a key aspect of manufacturing. Traditionally, visual inspection has relied on human inspectors. However, advances in high-speed specialized equipment have enabled the use of image processing algorithms, improving the efficiency of industrial inspection processes [26].

ANALYSIS AND DISCUSSION

TABLE 1. SAP Extended Warehouse Management

	Accuracy	F1-score	Material flow system	Recall
Logistic regression	0.75	0.73	0.8	0.73
Decision tree	0.8	0.83	0.83	0.84
Random forest	0.83	0.82	0.83	0.83
Support vector machine	0.79	0.79	0.8	0.77
Neural network	0.79	0.81	0.82	0.82

Table 1, which evaluates machine learning models for SAP Extended Warehouse Management (EWM) using the ARAS method, shows that various classifiers demonstrate distinct performance metrics. With a recovery of 0.8, logistic regression attains an accuracy of 0.75 and an F1-score of 0.73. With an accuracy of 0.8, an F1-score of 0.83, and a recovery of 0.84, decision trees do better than it. With a recovery of 0.83 and an F1-score of 0.82, random forests exhibit superior accuracy. The accuracy and F1-score of support vector machines are 0.79 and 0.77, respectively. The accuracy and F1-score of neural networks are 0.79, 0.81, and 0.82, respectively. These metrics indicate that decision trees and random forests are particularly useful in optimizing warehouse operations within SAP EWM. Integrating machine learning into SAP EWM can improve demand forecasting, route optimization, and quality control, leading to improved efficiency and decision-making in warehouse management.

$$X_{max} = \text{Max}\,(X_1 \ldots\ldots X_n) \quad (1)$$

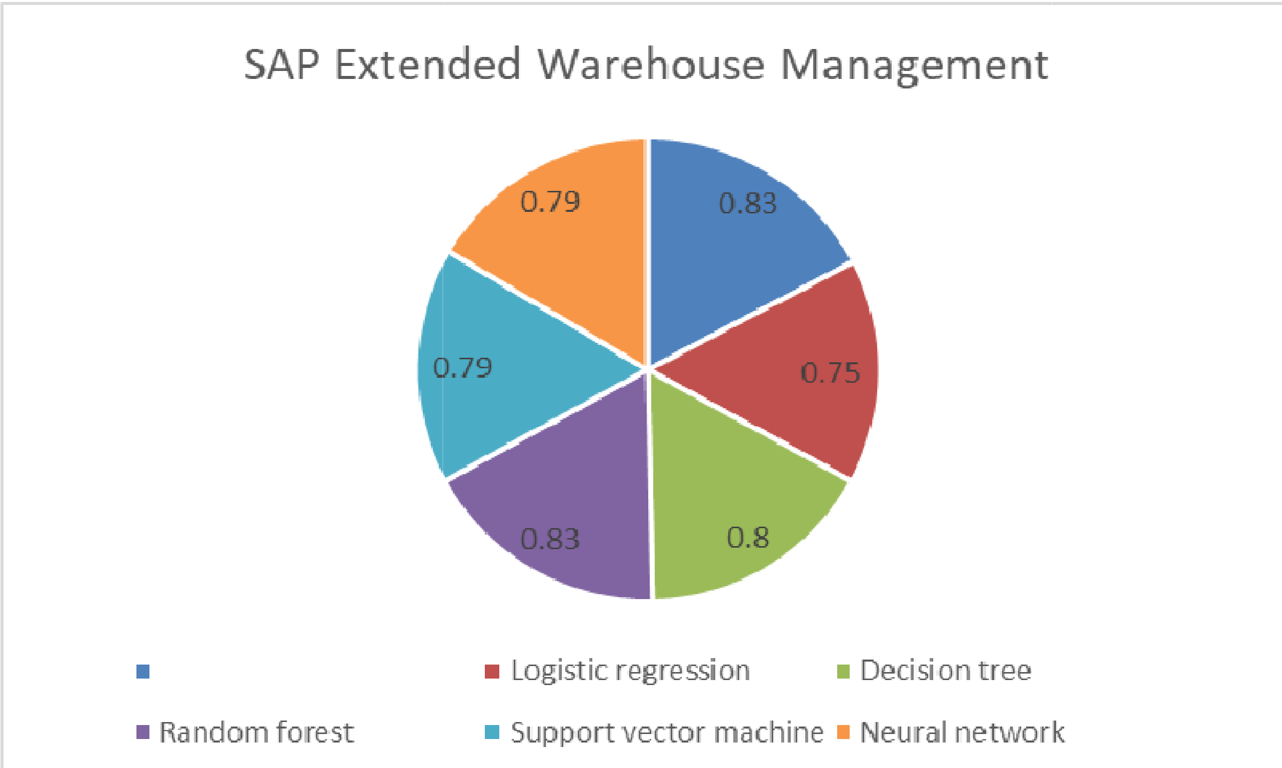

FIGURE 1. SAP Extended Warehouse Management

Figure 1 presents the performance evaluation of SAP Extended Warehouse Management using various machine learning models across four key metrics: Accuracy, F1-score, Material Flow System, and Recall. Among the models, Random Forest achieved the highest accuracy (0.83), while the Decision Tree demonstrated the best F1-score (0.83) and recall (0.84), indicating strong classification performance. Logistic Regression recorded the lowest performance across all metrics. Support Vector Machine and Neural Network models performed moderately well, with balanced scores across the evaluated parameters. These results highlight the effectiveness of different machine learning techniques in optimizing warehouse management processes and improving operational efficiency.

TABLE 2. Calculation of maximum value

	Accuracy	F1-score	Material flow system	Recall
Max	0.83	0.83	0.83	0.84
Logistic regression	0.75	0.73	0.8	0.73
Decision tree	0.8	0.83	0.83	0.84

Random forest	0.83	0.82	0.83	0.83
Support vector machine	0.79	0.79	0.8	0.77
Neural network	0.79	0.81	0.82	0.82

Table 2 presents the calculation of maximum values for different machine learning models based on four evaluation metrics: Accuracy, F1-score, Material Flow System, and Recall. The maximum values recorded across all models are 0.83 for Accuracy and F1-score, 0.83 for the Material Flow System, and 0.84 for Recall. Among the models, logistic regression achieved the lowest scores, particularly in F1-score (0.73) and Recall (0.73). The decision tree model attained the highest Recall (0.84) and matched the maximum Material Flow System value (0.83). Similarly, the random forest model reached the highest Accuracy (0.83) and performed consistently across other metrics. The support vector machine showed balanced performance, though slightly lower in Recall (0.77). Meanwhile, the neural network demonstrated competitive results, particularly in F1-score (0.81) and Recall (0.82), making it a strong contender for classification tasks.

$$X_{1no} = \frac{X_1}{\sum(X_1 + X_2 \ldots X_n)} \quad (2)$$

TABLE 3. Normalized Matrix

	Accuracy	F1-score	Material flow system	Recall
	0.173278	0.172557	0.169043	0.173913
Logistic regression	0.156576	0.151767	0.162933	0.151139
Decision tree	0.167015	0.172557	0.169043	0.173913
Random forest	0.173278	0.170478	0.169043	0.171843
Support vector machine	0.164927	0.164241	0.162933	0.15942
Neural network	0.164927	0.168399	0.167006	0.169772

Table 3 shows the normalized matrix in the ARAS method, which standardizes performance metrics to facilitate model comparison. This table provides normalized values for precision, F1-score, item flow structure, and recall across different models, ensuring a fair evaluation. The highest values indicate the best performing model for each metric. For example, decision tree and random forest models show strong performance across multiple parameters. By normalizing the data, ARAS allows for interoperability between different models, which helps in selecting the most balanced approach. This systematic evaluation ensures that the results are based on comprehensive performance rather than isolated metrics.

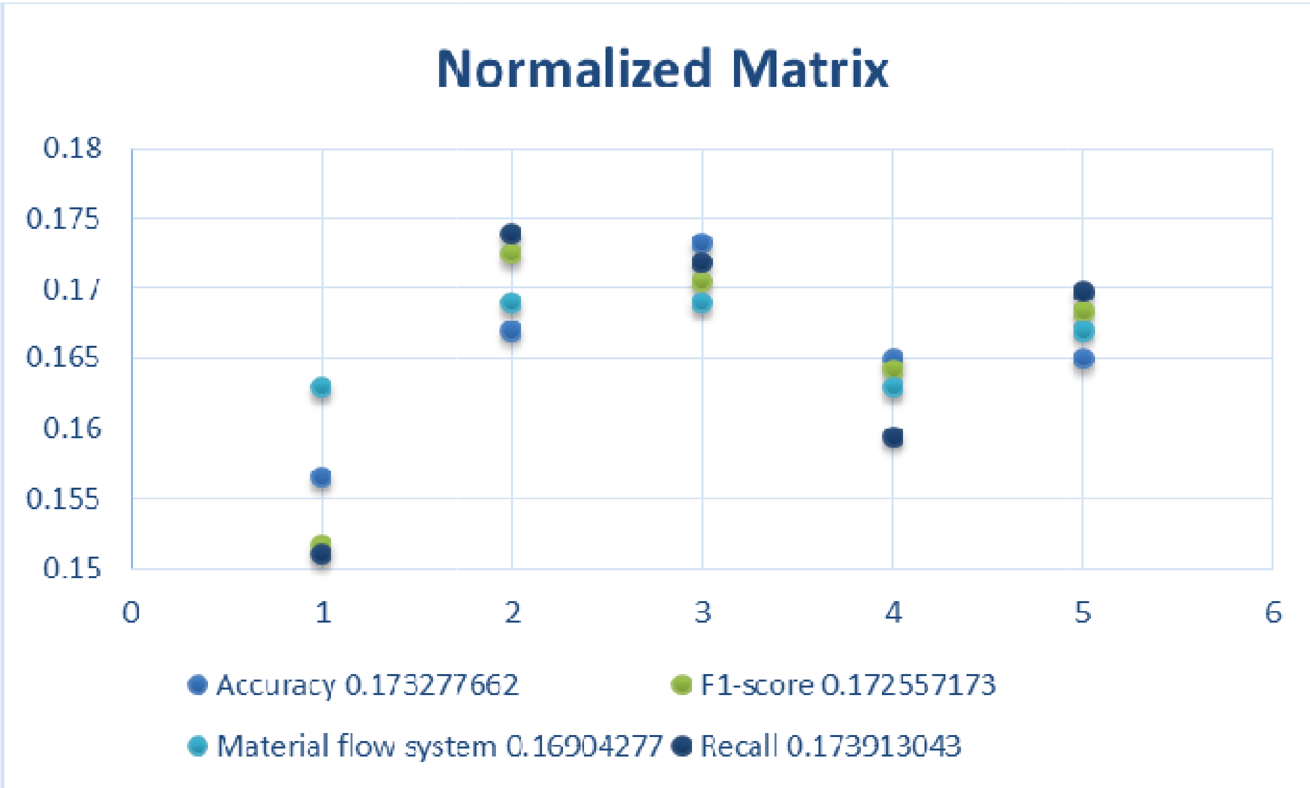

FIGURE 2. Normalized matrix

Figure 2 presents a normalized matrix using the ARAS method, which enables standardized comparison of machine learning models. The values for precision, F1-score, item flow structure, and recall highlight the relative performance of each model. The random forest and decision tree models exhibit strong consistency, ensuring balanced evaluation across multiple criteria for optimal model selection.

$$X_{wnormal1} = X_{n1} \times w_1 \quad (3)$$

TABLE 4. Weighted Normalized Matrix

	Accuracy	F1-score	Material flow system	Recall
	0.043319	0.043139	0.042261	0.043478
Logistic regression	0.039144	0.037942	0.040733	0.037785
Decision tree	0.041754	0.043139	0.042261	0.043478
Random forest	0.043319	0.04262	0.042261	0.042961
Support vector machine	0.041232	0.04106	0.040733	0.039855
Neural network	0.041232	0.0421	0.041752	0.042443

Table 4 The weighted normalized matrix in the ARAS method refines the model evaluation by incorporating weighting factors, ensuring a more balanced evaluation across precision, F1-score, item flow structure, and recall. This table highlights the adjusted performance of various models, where higher values indicate better fit. The random forest and decision tree models demonstrate competitive performance across multiple metrics, making them strong candidates. By using weight normalization, ARAS improves the interoperability of different models, allowing for a more objective and data-driven selection process. This systematic evaluation ensures that the results are based on comprehensive, weighted criteria rather than isolated performance metrics.

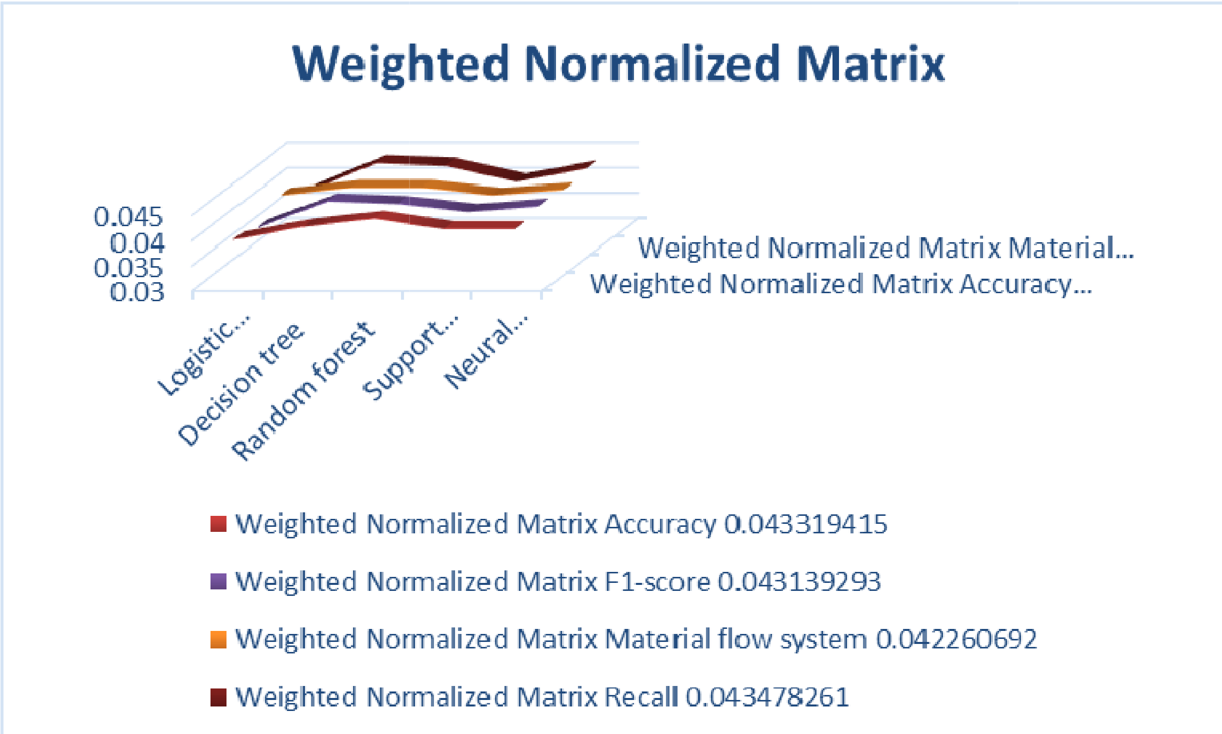

FIGURE 3. Weighted Normalized Matrix

Figure 3 presents the weighted normalized matrix using the ARAS method, which includes weighting factors for symmetric model estimation. The random forest and decision tree models show strong performance in terms of precision, F1-score, object flow structure, and recall.

This weighting approach ensures an objective comparison, which aids in selecting the most effective machine learning model.

$$Si = \sum(X_1 + Y_1 \ldots\ldots Z_n) \ (4)$$

$$Ki = \frac{X_{wnor}}{\sum(X_{wnor1} + X_{wnor} \ \ldots X_{wnorn})} \ (5)$$

TABLE 5. Final Result

	Si	Ki	Rank
	0.172198	1	
Logistic regression	0.155604	0.903634	5
Decision tree	0.170632	0.990907	2
Random forest	0.17116	0.993976	1
Support vector machine	0.16288	0.945891	4
Neural network	0.167526	0.972871	3

Table 5 presents the final results of the ARAS method, ranking machine learning models based on their performance scores. Si values indicate overall performance, while Ki values indicate comparative performance. Random forest achieves the highest ranking with Ki = 0.993976, followed by decision tree. Neural networks take third place, while logistic regression is ranked lowest. This ranking structure improves model interoperability by providing a structured comparison. By analysing these final results, decision makers can select the most effective model based on a comprehensive evaluation rather than isolated metrics, ensuring optimal performance in real-world applications.

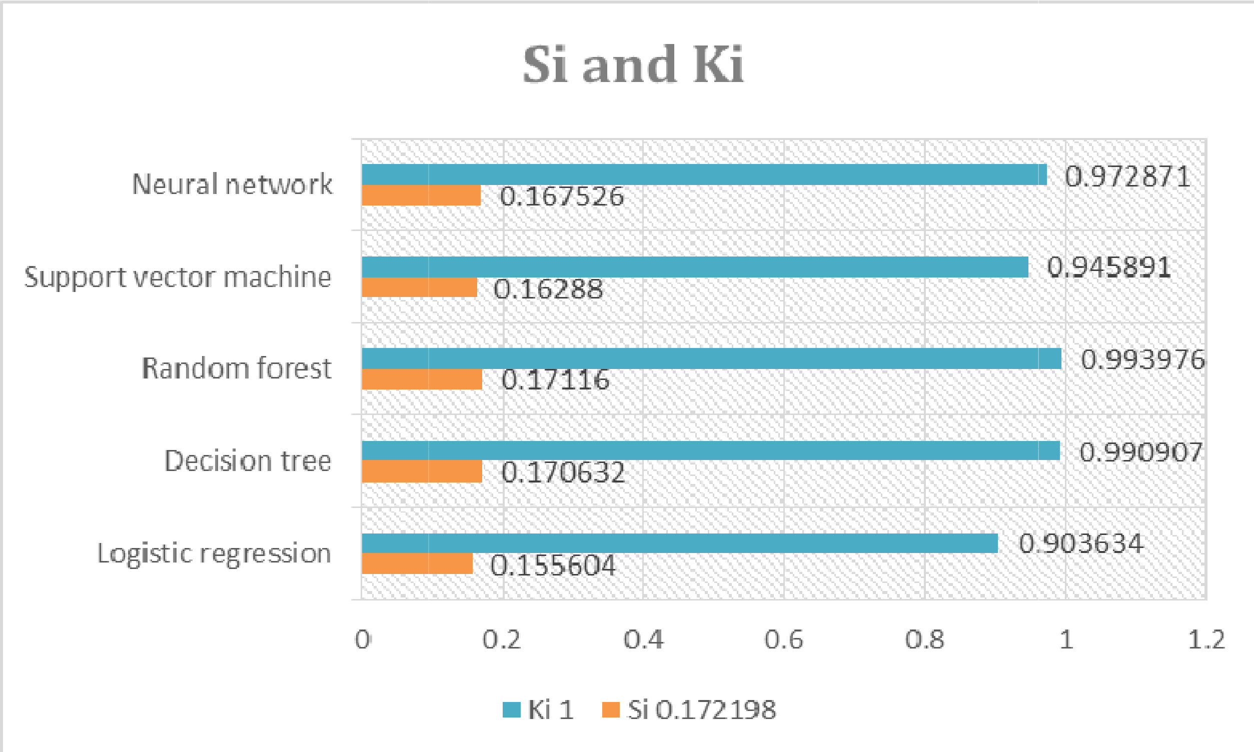

FIGURE 4. Si and Ki

Figure 4 presents the Si and Ki values using the ARAS method, which indicate model performance and relative performance. The random forest and decision tree models demonstrate the highest Ki values, making them the most effective. The logistic regression ranks lowest, highlighting its relatively weak performance. This analysis ensures objective model selection.

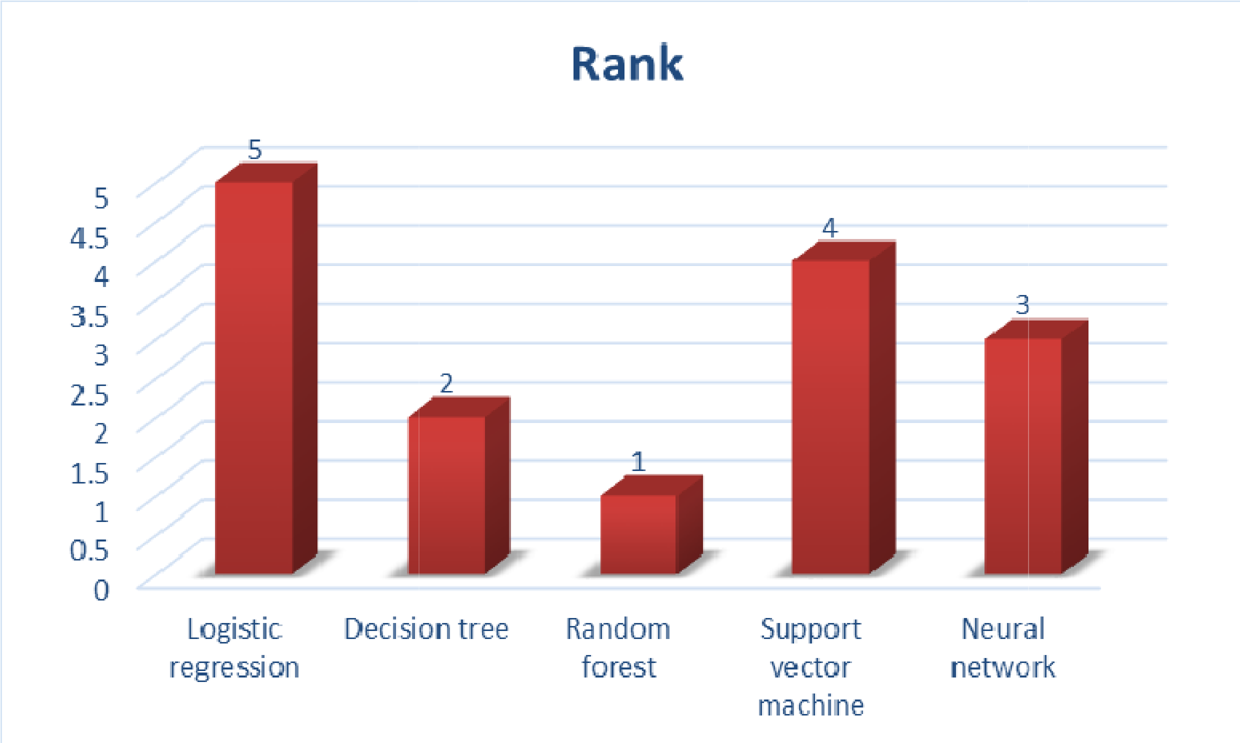

FIGURE 5. Shows the Rank

Figure 5 illustrates the ranking of machine learning models using the ARAS method. Random forest achieves the highest ranking, followed by decision tree and neural network. Support vector machine and logistic regression have lower rankings. This ranking provides a clear comparison, ensuring the selection of the most efficient model for optimal performance.

CONCLUSION

Analysis of machine learning models for SAP Extended Warehouse Management using the ARAS method has revealed significant insights into the performance of various classification approaches. A comprehensive evaluation of five machine learning models logistic regression, decision tree, random forest, support vector machine and neural network shows varying levels of performance across multiple metrics including precision, F1-score, material flow structure and recall.Random Forest emerged as the best performing model, receiving the highest ranking with a Ki value of 0.993976 and showing excellent performance across multiple metrics (precision: 0.83, F1-score: 0.82, material flow structure: 0.83, recall: 0.83). This consistent performance across all metrics indicates that Random Forest is particularly well suited for warehouse management applications within SAP EWM. The decision tree model came in second place with a Ki value of 0.990907, showing particularly strong performance in recall (0.84) and F1-score (0.83), making it a viable alternative for implementation.Neural networks came in third place, while support vector machines and logistic regression came in fourth and fifth place, respectively. The logistic regression model, with the lowest Ki value of 0.903634, showed relatively weak performance across all metrics, suggesting that it may be less suitable for complex warehouse management tasks.

The ARAS method proved to be a useful approach for evaluating and ranking these machine learning models, providing a balanced assessment that considers multiple performance criteria simultaneously. This comprehensive evaluation framework ensures that the selection of machine learning models for warehouse management systems is based on a holistic view of their capabilities rather than individual metrics in isolation.These findings have important implications for organizations implementing SAP EWM systems. The superior performance of ensemble methods, especially random forest, suggests that these approaches should be prioritized when developing machine learning solutions for warehouse management. The results indicate that such implementations can lead to improved demand forecasting, route optimization, and quality control within warehouse operations.Future research could investigate the performance of these models under different warehouse conditions and with varying data complexity. Additionally, exploring the integration of these models with other SAP modules could provide valuable insights into enterprise-wide optimization opportunities. The findings of this study contribute to the growing body of knowledge on the use of machine learning in enterprise resource planning systems and provide practical guidance for organizations looking to improve their warehouse management capabilities through advanced analytics.

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