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Sustainability Approach of SAP Application Management Service Solutions in the Field of Warehouse Management

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Organizations using SAP systems encounter the challenge of enhancing services while minimizing costs and response times. To achieve this, SAP offers a comprehensive range of sustainable cloud solutions in the field of Application Management Services (AMS), integrating machine learning, big data, and smart-machine technologies. This research endeavors to offer an alternative, sustainable approach, utilizing non-cloud-based machine learning to improve the efficiency of ticket classification in SAP AMS. This study presents an SAP Extended Warehouse Management (EWM) related case study in which various machine learning algorithms were applied to real-world SAP ticket data to automatically categorize incident tickets. As warehousing plays a major role in streamlining the supply chain, this approach aligns with the goals of sustainable supply chain process optimization. During the analysis, various classification algorithms were compared to achieve the best metrics. Our research did not just analyze the different algorithms for that specific business problem. The best model was integrated and deployed as well to accomplish a sustainable SAP AMS solution in the field of EWM.

1. Introduction

In today's digital era, information technology (IT) plays a vital role in the operations of many organizations. As businesses increasingly rely on IT systems, managing and maintaining complex infrastructures, such as SAP applications, becomes crucial. However, these systems' growing size, variety, and sophistication pose challenges in terms of cost, complexity, and sustainability (Bisong, 2019).

Sustainability is increasingly crucial in the business world, and SAP SE has taken a proactive approach to corporate sustainability by aiming to have a positive economic, social, and environmental impact. To achieve this, SAP offers a comprehensive range of sustainable cloud solutions. For instance, SAP offers a solution called Service Ticket Intelligence on the SAP Cloud BTP (Business Technology Platform), which employs machine learning for service ticket classification. However, many companies are not yet ready to adopt these cloud-based solutions.

This research paper focuses on the sustainability approach of SAP Application Management Service (AMS) solutions. AMS involves the strategic management of business application portfolios, including deployment, maintenance, support, and monitoring (Li et al., 2013). It aims to ensure high service quality and availability through regular service operations described in service-level agreements (SLAs) (Odun-Ayo et al., 2017).

The escalating technological advancements, such as cloud computing, artificial intelligence, blockchain, and augmented reality, introduce new complexities and maintenance issues to IT infrastructures. Organizations must align their IT strategies with business objectives while controlling costs and optimizing resources. However, managing SAP development and maintenance expenses requires specialized knowledge and expertise that may not be readily available within a company.

The paper aims to explore and propose a sustainable way to SAP AMS, considering the need for efficient resource management, cost control, and the adoption of cutting-edge technologies. By integrating sustainability principles, organizations can improve service quality, reduce costs, and enhance overall efficiency.

Additionally, the research addresses the challenges of ticket classification within AMS for SAP applications. The manual categorization of support tickets is time-consuming and prone to errors, affecting response times and customer satisfaction. The paper suggests the creation of an artificial intelligence-powered ticket classification

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engine to handle this. This engine would automate the ticket-handling process, significantly reducing manual labor and minimizing human errors while enhancing service quality and user satisfaction.
The objective is to minimize manual intervention, reduce categorization errors, and improve the overall process efficiency of warehousing, which is directly connected to supply chain management. By automating ticket categorization and assigning steps, the human resources of the IT help desk can be allocated to more valuable functions, thereby reducing Extended Warehouse Management (EWM) process breakdowns. With the improvement of warehouse management processes, supply chains can be more streamlined and can make them more sustainable.

2. Related Work

The automation of service desk ticket classification has been a focus of research in recent years, aiming to improve incident management teams' productivity, reduce ticket routing time, and minimize categorization errors. Several studies have explored different machine learning (ML) techniques and their applications in automating incident ticket classification.
This research path is based on text classification via Natural Language Processing (NLP), which plays a key role in the digitization of a wide range of modern industries. Uysal and Gunal (2014) highlighted that choosing the right combination of preprocessing functions instead of applying or avoiding them all significantly improves classification accuracy. Their research used frequently used preprocessing procedures, like eliminating stop words, lowercase conversion, stemming, and tokenization. Howard and Ruder (2018) emphasized the impact of fine-tuning and directionality on the behavior of a classifier, which can increase the model's performance by 0.5-0.7 times. Pranckevičius and Marcinkevičius (2017) – for basics and Shah et al. (2020) – advanced cases, compared several ML models such as Naive Bayes, Logistic Regression, Random Forest, Decision Tree, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), and provided their pros and cons for text classification purposes. Their findings indicate that for this application, the Logistic Regression multi-class classification achieved the highest accuracy.
Service ticket classification-related papers are focusing on incident content classification. Silva et al. (2018) developed a mechanism using support vector machines (SVM) and KNN algorithms to automatically classify incident tickets. SVM achieved an overall accuracy score of 89 %, while KNN achieved 82 % accuracy, showcasing the effectiveness of ML approaches in incident categorization. Paramesh and Shreedhara (2019) proposed an automated system for classifying service desk tickets, employing supervised ML techniques such as logistic regression, KNN, Multinomial Naive Bayes (MNB), and SVM. The study highlighted the superiority of SVM in achieving accurate classification results compared to other models.
Khramov (2018) conducted research comparing ML models, including SVM, Naive Bayes, and Random Forest, using grid search techniques to optimize hyperparameters. The SVM model, implemented with a Boolean vector representation, achieved an accuracy of 84.8 %. Altintas and Tantug (2014) suggested a two-phase categorization approach for incident tickets, utilizing Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction. Four algorithms, including KNN, SVM, decision trees, and Naive Bayes, were tested on a dataset of 10,000 problem tickets. SVM exhibited the highest accuracy of 86 % across various ML algorithms and datasets. Al-Hawari and Hala (2021) developed a technical support system employing an ML algorithm for efficient ticket classification. Utilizing ticket comments and descriptions during training improved model accuracy. Different ML models, including J48 (tree), Decision Table (rule), Naive Bayes, and SMO (SVM), were evaluated, with SMO achieving 81.4 % accuracy.
From a scientific perspective, these studies collectively indicate that machine learning techniques offer promising opportunities for automating ticket classification processes. However, it is important to consider the specific characteristics of the dataset, the preprocessing methods employed, and the choice of evaluation metrics when implementing these techniques.
Based on the literature review, we could not find a specific approach to classifying incident tickets for SAP Warehouse Management incident ticketing data. Furthermore, the reviewed studies only analyze the different metrics of the models and lack the deployment process of the models.

3. Methodology

To achieve the research goal, we applied the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework as the guiding methodology for this project. Each phase of the methodology is adapted and tailored to suit the specific requirements and challenges of automating ticket classification (Figure 1).

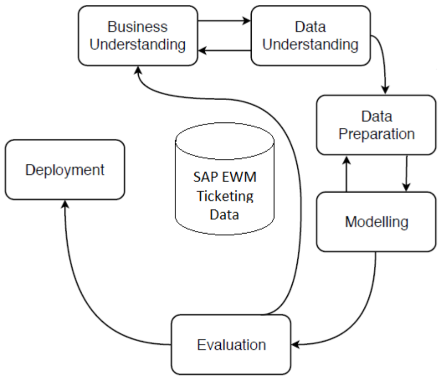

Figure 1: Flowchart of the methodology

It may be necessary to alternate between various phases because the phases' order is not strictly followed. The flowchart's arrows show the most significant and common dependencies between steps.

3.1 Phase 1: Business Understanding

The first task of the CRISP-DM methodology is the Business Understanding phase (Chapman et al., 2000). In this phase, a comprehensive understanding of the business problem and requirements for automating ticket classification in SAP AMS is developed. During this phase, extensive research was conducted in collaboration with a company that offers SAP support services and specializes in assisting clients with SAP EWM modules.
Through in-depth investigations and consultations with the company's personnel, it was discovered that they were facing a significant challenge in efficiently assigning the right tickets to the appropriate solution group. This inefficiency directly led to customer dissatisfaction as well as financial issues through breakdowns in warehouse processing. The existing manual ticket classification process proved to be time-consuming and error-prone, resulting in delayed resolutions and dissatisfied customers. The misallocated tickets often ended up in the hands of less qualified support staff, leading to suboptimal solutions and, in some cases, even escalations. The company's management emphasized the need for a robust and automated ticket classification system to streamline their operations, enhance customer satisfaction, and reduce financial losses resulting from misrouted or delayed tickets. By identifying these critical points and gathering insights from the company's operations, the foundation was laid for devising a suitable machine-learning solution that addresses the specific challenges in the realm of ticket classification for SAP AMS.

3.2 Phase 2: Data Understanding

The Data Understanding phase involves exploring and analyzing the dataset of support tickets in SAP AMS. The dataset consists of 1630 SAP EWM-related incidents, each with a unique key, creation date, requester, responsible person, and a title and description of the reported issue. The data has been modified to comply with GDPR regulations for privacy and security.
The incidents are managed through the Jira ticketing system used by the company. They are manually created and assigned to solution groups. The dataset was collected from the IT help desk professionals, providing insights into the specific support levels assigned to each complaint. During data preprocessing, irrelevant columns were removed, and the focus was given to the ticket description in English and the corresponding level of support. The distribution of tickets among these levels is as follows: Level 0 - 46.6 %, Level 1 - 22.9 %, and Level 2 - 30.7 %.

3.3 Phase 3: Data Preparation

After the necessary data cleaning tasks, concrete steps were involved in the pre-processing of the textual data. Regular expressions were used to strip the text of all URLs, cutting down on clutter and unnecessary details. Tokenization was used to divide the text into smaller chunks, and lemmatization was used to reduce each word to the smallest possible unit. The improved language comprehension allowed the machine learning models to perform better. Oversampling methods were used to correct the asymmetry in the data. The dataset was made even more by resampling the underrepresented groups until they had the same amount of samples as the dominant group. The TF-IDF method was used to quantify textual information. This method weights terms according to how often they appeared in a certain document and how uncommon they were overall (Qaiser and Ali, 2018). These procedures guaranteed a high-quality dataset and set the stage for model creation and testing to follow.

3.4 Phase 4: Modeling

During the modeling phase, the available data is utilized to develop a predictive model (Lamba and Madhusudhan, 2022). This phase involves selecting appropriate modeling approaches, experimenting with various algorithms, and comparing their outcomes using evaluation metrics and graphical representations (Raju et al., 2023). The objective is to identify the optimal model that can improve accuracy and effectively address the problem at hand.
In this phase, suitable modeling techniques are chosen based on the specific problem. This special case is a multi-class classification problem where the dataset consists of three distinct classes (L0, L1, and L2), and we utilized supervised machine learning techniques. These techniques consider the target feature as the decision to be predicted and the other features as input variables. In this study, the following modeling approaches and variants have been selected for comparison:

- Logistic Regression Model (L2 – Ridge regression)
- Decision Tree (CART – Classification and Regression Trees)
- Random Forest (Gini impurity)
- Support Vector Machine (C-SVC – C-Support Vector Classification)
- Neural Network (Multilayer Perceptron, one hidden layer, containing 100 hidden units)

These modeling techniques are widely used by data scientists for multi-class classification tasks (Pranckevičius and Marcinkevičius, 2017), and they provide a diverse range of algorithms to explore (Ejiyi et al., 2022).

3.5 Phase 5: Evaluation

After implementing the models, a comparative analysis is conducted to evaluate their performance. During the performance measurement, K-Fold Cross-validation was used with 5 folds to determine the averages of the metrics. The applied evaluation metrics provided an overview of each model's performance in terms of accuracy, F1 score, precision, and recall. These metrics help assess the models' ability to classify the tickets accurately.

3.6 Phase 6: Deployment

The final step in the data science process is deployment, where the trained model is put into production to integrate it into the decision-making process. In this phase, the model is applied to achieve the specified business goals of the company. During the deployment phase, the ticket classification process was automated by integrating the trained model with Jira. The trained model was serialized using the pickle module and saved as a file. This model file was then uploaded to the deployment script. A connection to Jira was established using the Jira API, and authentication was achieved using an email and API token.
To automate the ticket classification process, a script was developed, which retrieved new IT tickets from Jira using a JQL query and classified them using the trained model as in Figure 2. The script checked if a prediction comment already existed for a ticket and skipped it if present. For tickets without a prediction comment, the relevant ticket information was obtained, and the model was used to classify the ticket. Comments containing the predicted categorization were added to the ticket.

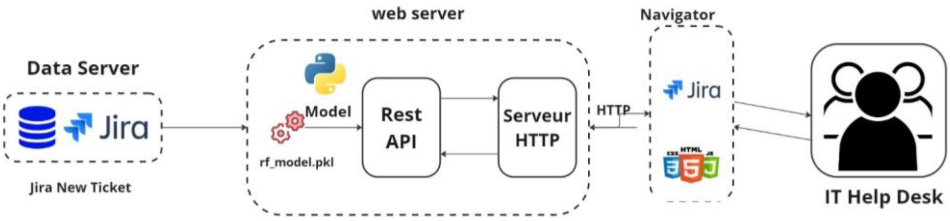

Figure 2: Automated EWM ticket classification workflow

The deployment architecture consisted of three tiers: the client tier, server tier, and data tier. The client tier presented the user interface and connected user requests to the server tier. The server tier, an HTTP web server, communicated with the Jira API and processed user requests by invoking the ML model. The data tier directly interacted with the Jira database.

4. Results

The comparative analysis pointed out the differences between the performance of the applied machine learning models. After the evaluation phase, the results are as follows.

Table 1: Comparing evaluation metrics

Model Name	Accuracy	F1-score	Precision	Recall
Logistic Regression	0.75	0.73	0.8	0.73
Decision Tree	0.80	0.83	0.83	0.84
Random Forest	0.83	0.82	0.83	0.83
SVM	0.79	0.79	0.80	0.77
Neural Network	0.79	0.81	0.82	0.82

The results indicate that the linear random forest classifier achieves the highest accuracy at over 83 %. This performance is comparable to the human operator-produced error rates of ticket classification. To assess the performance of the models further, the Receiver Operating Characteristic (ROC) curve was utilized. The ROC curve illustrates the trade-off between true positives and false positives in a binary classifier system (Gajjalavari and Rudravaram, 2022). Despite having a multiclass classification problem, each class was considered separately to evaluate the machine learning algorithms (Dingle et al., 2022).
The Area Under the Curve (AUC) of the ROC curve was compared for each model (Figure 3), serving as a synthetic performance index. Among the tested classification algorithms, the Random Forest exhibited the highest AUC of 0.96, indicating its superior performance compared to the other algorithms. The logistic regression, support vector machine (SVM), neural network, and decision tree algorithms achieved AUCs around 0.92, 0.95, 0.94, and 0.85, respectively.

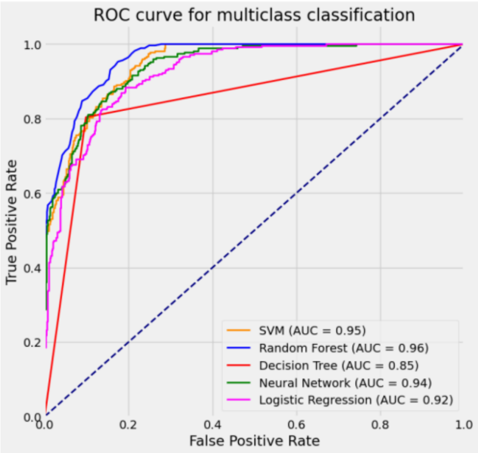

Figure 3: Comparing evaluation metrics

Based on the comparative study using evaluation metrics and ROC curves, it was observed that Random Forest and SVM reached the highest values. The SVM algorithm achieved an AUC of 0.95, showcasing its strong performance in the classification task. Considering the better evaluation metrics and higher AUC value achieved by the Random Forest algorithm, it was selected as the final predictive model.
However, it is essential to acknowledge that the performance of different machine learning algorithms can vary depending on the dataset and the specific field of application. The deployment phase successfully automated the EWM ticket classification process by integrating the trained Random Forest ML model with Jira. The script executed the classification of new tickets and added predicted categorizations as comments.
By streamlining the ticket routing process, the research results can enhance the operational efficiency of EWM processes. This generates a supply chain-related advancement in reduced delays and improved response times. Such operational efficiency improvements contribute to overall sustainability efforts by minimizing energy consumption and optimizing resource utilization.

5. Conclusions

In conclusion, this research has successfully contributed to the sustainability approach of SAP EWM Application Management Service through the development of a support prediction model based on ML techniques. As a novelty, this specific comparative analysis of Logistic Regression, Decision Tree, Random Forest, SVM, and Neural Network highlighted the variations in how well the used machine learning models performed in this SAP EWM ticketing dataset. The applied prediction model improved resource allocation by automating the ticket

classification and routing process. By efficiently assigning IT resources and support personnel, unnecessary workload and resource wastage are reduced, leading to improved resource efficiency and sustainability. Consequently, the utilization of machine learning techniques and the analysis of large volumes of data enable data-driven decision-making within SAP AMS. This approach supports sustainable practices by providing valuable insights for optimizing operations, resource allocation, and service delivery.
In summary, this research demonstrated the potential of machine learning algorithms to automate and optimize SAP EWM ticket classification processes in AMS, aligning with sustainability goals without relying on cloud solutions. By implementing these sustainable and efficient approaches, IT service organizations can enhance their services, reduce costs, and improve overall customer satisfaction. In future research, it is recommended to conduct a comprehensive analysis to quantify the specific environmental, social, and financial benefits achieved through the implementation of the support prediction model. This analysis will provide a deeper understanding of the sustainability impact of supply chain improvements and further strengthen the sustainability approach of AMS.

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