American Journal of Computer Architecture 2023, 10(2): 28-36
DOI: 10.5923/j.ajca.20231002.02

Artificial Intelligence Implementation in SAP

Anish Rege

MS-Management Information Systems, Texas Tech University, Lubbock, TX, USA

Abstract A major corporation with a complicated IT system like SAP ERP often receives hundreds of thousands of help desk inquiries annually. These requests may be made over the phone or online using Service Manager (SM) or Service Desk. "Enterprise resource planning" is a form of business process management software that automates technology, services, and human resources functions through a network of linked applications. This research study makes a recommendation for an intelligent system to provide user help for SAP ERP. It makes it possible for consumers to receive automatic responses to their support requests, which saves time for the investigation and resolution of issues while also boosting responsiveness to end users. The system uses machine learning algorithms to classify multiclass text for efficient question interpretation. The system uses a specialized framework to retrieve evidence, enabling the best response. The conversational AI capabilities allows the framework to create chatbots where groups of people can collaborate at the same time.

Keywords Artificial intelligence, Implementation, SAP, ERP, Service manager, Business, User support, System Application Product, Conversational AI, Chatbots

1. Introduction

The advancements in technology over the past few decades, powerful computers have been created that are both more compact and more affordable than ever before. As a result, advanced mathematical tools have become more accessible to businesses. The so-called "intelligent technologies" are the tools that enable companies to delve deeply into the data pools they already possess in order to gain analysis and business insight. Companies are able to supplement their currently manual business processes with automated and digital options if they make use of algorithms and automation [1]. "Digital transformation" refers to the transition from manual to digital processes in an organization. As one of the most prominent providers of software, SAP has been at the forefront of the industry in terms of incorporating "smart" and intelligent technologies into its product portfolio and functionalities. AI and machine learning embedded in corporate systems help clients automate repetitive operations and uncover new digital innovations. Instead of explicitly programming rules, data is used. AI is organically integrated into SAP applications, the cloud, and business networks, making digital information readily consumable throughout the whole enterprise. This may enhance customer service, company operations, employee job satisfaction, and more [2]. This software delivers an enterprise-ready cloud-based machine learning platform. It's straightforward to use and integrates seamlessly with SAP's corporate software and machine learning capabilities. Software developers may use a scalable and secure platform to add intelligence to corporate operations and apps.

* Corresponding author:
anish.rege@gmail.com (Anish Rege)
Received: Aug. 25, 2023; Accepted: Sep. 10, 2023; Published: Sep. 13, 2023
Published online at http://journal.sapub.org/ajca

2. Types of Intelligent Technologies

SAP intelligent technologies and solutions include a few critical technologies that don't rely on a specific operating system [3]. These have the potential to assist firms in developing higher efficiency while also reducing expenses. The following is an examination of each:

Artificial Intelligence: The term "artificial intelligence" (AI) refers to the processes that are used to give a computer the ability to mimic human behaviour. AI has been present for many decades in a variety of guises. Automated phone directories have replaced the traditional operator, who connected calls to the right department or person. Chatbots have been added to online assistance portals like Microsoft.com. These chatbots provide general problem-solving help and link to related publications [4]. Machine learning focuses on detecting and forming data relationships to help stakeholders make better decisions. Machine learning algorithms may be configured to seek for patterns and learn from data, improving their analytical skills. These techniques are used for big data sets with no obvious pattern.

Blockchain: The blockchain is a distributed ledger that increases the amount of transparency that is present throughout the whole transaction process. It does this by relying on a peer-to-peer network to conduct its operations. The decade of the 2010s witnessed a rise in the number of businesses that used this technology in an effort to improve their capabilities in the area of financial reporting [5]. The creators of Bitcoin were the first people to bring blockchain technology to the mainstream in the late 2000s. On a blockchain, transactions are grouped together into containers known as blocks, and each block is hashed to create a connection to its parent block and any child blocks it may have. Those who have access to the ledger are in a position to see the places where things were manufactured and the destinations to which they were sent since this provides a holistic view of all the transactions that took place throughout the whole of the ledger. People who are interested in buying food products that were produced or harvested in an environmentally friendly manner, for example, may choose to conduct business with companies that can show, through the use of blockchain, where their products originated in order to satisfy their desire to purchase such products.

Internet of Things: The "Internet of Things" refers to the network of linked electronic devices and physical assets that enable them to communicate with one another and collaborate [6]. Therefore, several benefits will accrue to the involved parties as a result of this. When it comes to providing services to others, those who build and utilize assets may tremendously benefit from the feedback mechanisms made accessible by the internet of things on things like user behavior, component wear, and other maintenance needs. Homeowners who have invested in Internet of Things-enabled technology may use their devices to streamline some aspects of their everyday routines. Smart thermostats, for instance, can acquire knowledge from the adjustments that you make to the temperature on a daily basis and start making those adjustments automatically, freeing you from the need to get out of bed and make those adjustments yourself [7].

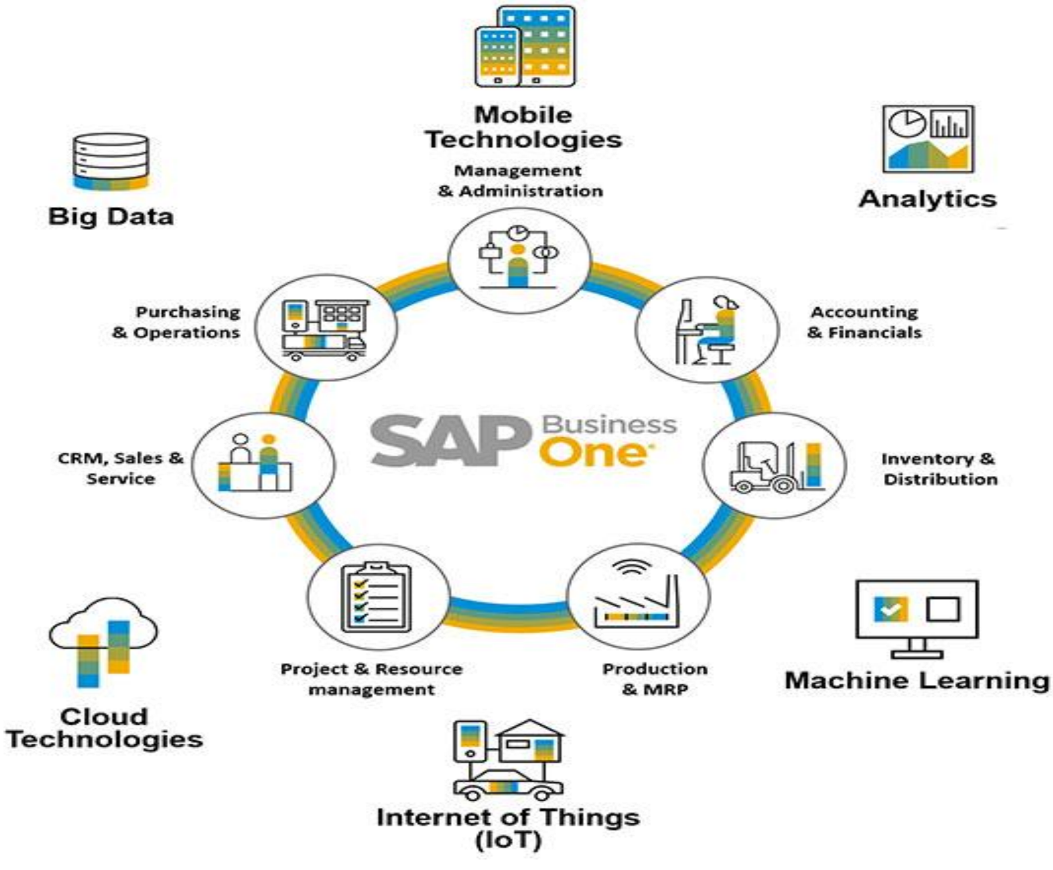

Figure 1. An intelligent user support system for SAP ERP

3. SAP Intelligent Technologies Products

Over the course of the last ten years, SAP has been steadily increasing the number of "smart" functionalities that are included in its product lineup. Customers have been able to gather historical data and make predictions about future outcomes as early as 2008 with the assistance of solutions such as SAP Predictive Analytics and the Intelligent Services tool made available by SAP Success Factors. The solutions achieved this result via the combination of SAP Success Factors and SAP Predictive Analytics. This is the nature of the remaining options accessible to us. The most recent release of SAP's business software is called SAP S/4HANA, and it has intelligent technologies as well. In 2017, machine learning capabilities were added, for instance, to automate the operations of invoice assignment and to make it simpler to reconcile receipts of goods and invoices. Time was avoided by doing this. In 2018, SAP S/4HANA Finance included the following predictive accounting function, as seen by the following text. The need for intelligent technologies skyrocketed in the middle of the 2010s, prompting SAP to develop the SAP Leonardo toolset in 2017 [8]. The services provided in this toolkit span a wide range of areas, including the Internet of Things (IoT), machine learning, analytics, blockchain, and big data. In 2019, SAP began the process of segmenting them into their own individual research and development departments. Each of those sectors would be responsible for funding and conducting its own R&D. These make up the majority of what SAP now provides as part of its selection of intelligent technology solutions, and they are supplied by the company.

3.1. SAP Conversational AI

This was once known as Recast.AI, and it is currently the AI bot platform for companies that enjoy the most popularity. SAP provides off-the-shelf customer care bots in addition to its world-class technology, an end-to-end bot platform, and other components in order to lead the revolution of customer relations throughout the globe and allow the intelligent organization [9]. SAP has the potential to give a technology that is on par with the best in the world thanks to its more than 30,000 developers and more than 60,000 bots. The SAP Conversational AI may be used to integrate with a variety of networks in order to deliver seamless social connectivity. Some examples of these platforms are Facebook, Twitter, and Slack. API integration is one method that may be used to achieve this goal.

This is the first stage in the development of a digital assistant, and it helps with day-to-day chores by providing suitable action alternatives depending on the consumer's position, the context, and the company environment. Specifically, it does this by analysing the consumer's position, the context, and the company environment. For instance, it enables the user to search for information relating to companies or to have a chat with industry specialists about business concerns in order to get aid in fixing an existing problem that has been encountered. A user may make artefacts such as notes, objects, messages, screenshots, and quick actions depending on the context of the screen they are now seeing [10]. These artefacts may then be collected, shared, and shared with others.

The following is a list of features that are included in SAP Conversational AI:

Digital assistant: Interactions in natural language are one example of a recent development.

Notes and screenshots: Inside of apps, you have the ability to take screenshots and make notes, and you can go back into the app at any time by clicking on the screenshot. Annotations can be added, and certain elements of the map can be hidden from view.

Recognizing business objects: It is possible to detect business items both inside the context of the currently active application and those that have been referenced in notes or conversations.

In-context chat: Communicate with other users while you are using your business application and

The Conversational AI framework will be the base where Chatbot can be developed. Some of the key features in Chatbot building are as follows:

Train: The natural language processing technology can be leveraged for creating intents and the language understanding of the chatbot.

Build: After the completion of fast training, a functioning bot can be build with a small dataset (with around 20 sentences in 1 intent). The bot memory can be leveraged to provide human-like conversations.

Connect: The bot can be connected to popular messaging channels like Amazon Alexa, Teams, Twitter, Slack. Also, a fallback channel can be built for the conversations to be transferred from the bot to a human agent if required. active application and those that have been referenced in notes or conversations.

Test: This is very helpful if you want to continuously improve your bot without disrupting the existing model.

Monitor: The log feed can be used to monitor the bot usage. The analytics will help evaluate the performance of the bot’s training dataset to improve the performance and ensure that the training dataset represents realty.

3.2. SAP Intelligent Technology-Based Solutions

Business Entity Recognition Service: The Business Entity Recognition Service is a machine-learning-based service that examines unstructured documents that have been submitted for processing extracts information that is pertinent to the documents, and then executes actions depending on the information that was extracted from the papers.

SAP AI Business Services: SAP AI Business Services is a platform that organizations may utilize to incorporate AI and machine learning capabilities into their business processes. Businesses may use this platform to streamline their operations. The cloud serves as the hosting location for this technology, making it available to businesses [11].

SAP Analytics Cloud: Data visualization, analytical tools, and strategic planning are all available to users of the SAP Analytics Cloud, a SaaS that provides these functions to its clientele. Users have access to this system courtesy of SAP.

SAP Block chain Business Services: It's possible that a wide variety of business actors would benefit from using the SAP Blockchain Business Services platform as a means of collaborating. It provides an open and objective architecture that gives everyone involved access to the same version of the truth in terms of business data. When combined with other information, this information can be used to make decisions and advance the economy. Both the SAP Blockchain service, which can be used to build blockchain-based applications, and the SAP HANA

Blockchain service, which can connect an SAP HANA database to an external blockchain, are made available. You can use either of these variants.

SAP Conversational AI: Chatbots are a type of digital assistant that can be fabricated with the assistance of SAP Conversational AI, which is a platform that can be utilised by software developers. Chatbots can engage in conversation with users. It was formerly known as SAP CoPilot, but it has since been updated to include the features that SAP obtained through the purchase of Recast.ai in 2018.

SAP Data Intelligence: SAP Data Intelligence is a cloud solution that brings together the IT and data science teams of an organisation in order to improve the utilisation of siloed data and make better use of artificial intelligence and machine learning. This is accomplished by bringing these teams together [12].

SAP Edge Services: By avoiding the need to transmit to a central repository before processing it, SAP Edge Services provides an expedited data processing solution at the network's periphery, which results in a reduction in the amount of time required for processing and the amount of storage space that is required.

4. Research Methodology

In this present study a closed-domain quality assurance problem would be an intelligent user assistance system. The purpose of this study is to provide a description of a quality assurance system that is based on machine learning techniques of text classification and has an application to a particular area of “SAP ERP user help”.

A high-level architecture of the proposed intelligent user support system includes the following components:

1. Content acquisition, which includes the generation, cleansing, and extension of a user request corpus.
2. An examination of the request, including the identification of the SAP module and a detailed request categorization.
3. The establishment of a knowledge database for the purpose of assigning distinct categories of inquiries to distinguishable classes of possible explanations.
4. The creation of a list of potential reasons for the specific kind of issue being experienced.
5. Collecting information from SAP in order to test hypotheses about the root causes of the issue.
6. In your response to the merging question, take into account the information that is available from the SAP “tables, the system log, and the user information”.
7. An expert has reviewed and approved the answer. If the answer is correct, it will be delivered to the user.

If the answer is incorrect, the request, in addition to the relevant class, will be included in R's training set. An algorithm that has been taught before and has since been improved.

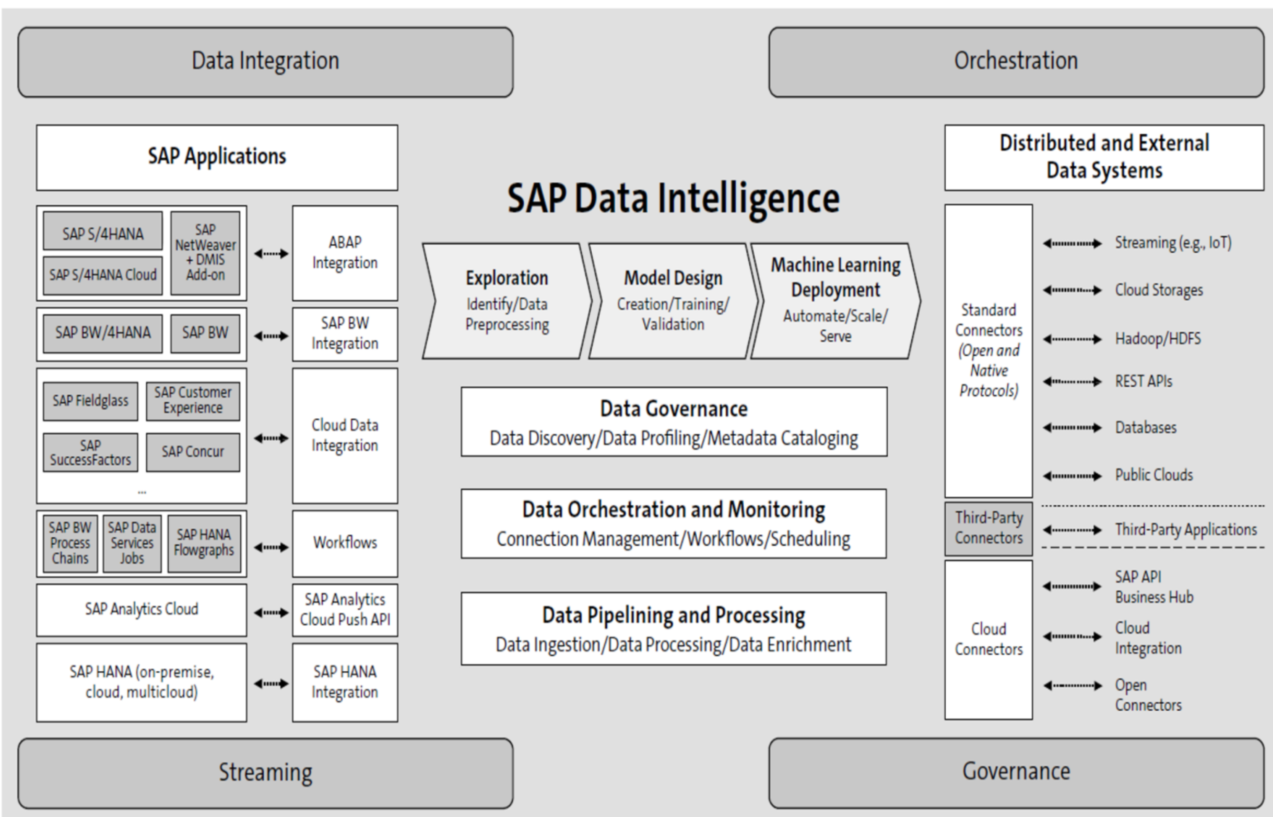

Figure 2. Architecture of SAP ERP data intelligence

4.1. Request Classification Algorithm

Text classification is a common job, and there are many different machine learning methods that can be used to complete it. One such job is the classification of requests, which provides multi-class classification. Although there were attempts made to construct more complicated algorithms for this task, such as recurrent convolutional neural networks, the gain in accuracy that resulted from these implementations was not appreciable. One of the most successful businesses in India provided the raw data, which was obtained from the SAP ERP support database. In line with the business processes that are actualized in the SAP ERP system, each and every request is first and foremost sorted into six primary categories, also known as modules. Human experts have assigned the requests that come out of each module to one of the classes that are included in the list of classes (C).

The following is a list of the primary categories, often known as modules:

- Purchasing and entering into agreements.
- Administration of possessions and materials.
- The planning and implementation of the budget.
- Construction and management of real estate properties.
- Expenses incurred for business travel and hospitality as well as payments.
- The management of user access.

An error message or other generic user request problem type is just one example of the types of issues that can be categorized under the umbrella term "class label" in SAP ERP. Labels for classes may include error messages or descriptions of common issues with user requests. Requests that are classified as belonging to the same class will have the same set of potential causes and the corresponding responses because of how the classes are built. This is so because identical requests assigned to the same class are constructed in the same way. Among the examples of class labels that can found in the Purchases and Agreements area are the following: "How to execute the request for supply," "Error: applicant is unavailable," "Specification not presented in agreement," "no resource identified when generating a request for supply," and so on. Users have the ability to articulate the same issue in a variety of ways, as shown by the following examples: Imagine a scenario in which a user is confronted with the issue "no resource discovered while generating a request for supply." The question might be phrased as follows: "while making Request for Supply, I am unable to choose the needed resource," or "when creating Request for Supply, the application is unable to locate the resource."

The following is the breakdown of the number of courses by category: $l1 = 81$, $l2 = 43$, $l3 = 26$, $l4 = 23$, $l5 = 34$, $l6 = 9$.

Total number of classes is $l = 216$.

Only one class may be linked to a given request at a time. The following is a list of how many requests were made in the sample that was labelled: $m1 = 4168$, $m2 = 2824$, $m3 = 1698$, $m4 = 868$, $m5 = 1609$, $m6 = 1388$.

The total number of requests contained in a sample that has been labelled $m = 12555$.

The process of constructing a TDM, or term-document matrix, in which each query is represented by a vector of numeric characteristics that correspond to tokens unearthed in queries. As the process progressed, it became clear that obliterating all stop words from the text would not be the greatest option. It became clear to us that the word "not" or "no" had significant weight within the context of the tasks we were given. It was also found that prepositions play a crucial role in the "User Access management" section of the software. Without them, your evaluation of the course would be severely flawed. Combining existing words into artificial terms is one way to increase classification precision while decreasing the total amount of words in a corpus. Words can be combined in a variety of ways, including acronym expansions like "RFS," which stands for "request for supply," Russian language synonyms like "storekeeper," and SAP-specific synonyms like "budget indicator red," which stands for "insufficient budget." A person made the decision to use these synonyms. Users may phrase the same issue in whatever manner they choose, which frequently results in quite strange terminology.

A sparse matrix, of which a TDM is an example, has a large number of entries that are all 0. This is because the vast majority of its components are all 0s. Eliminating all sparse words associated with each class helps minimize over fitting, improves class interpretability, and increases class generalization. One of the optimization targets is picking the right value for the sparsity threshold. This threshold value was selected for each category because it provides the highest possible average accuracy. All of our distinct types must meet 60% sparsity criteria. To further analyze the significance of keywords within requests, we employ a TF-IDF algorithm. However, this approach did not produce an adequate result for our problem; the specific phrases learned in the more private contexts were of great importance. We felt it necessary to implement the TF-SLF to address this disparity. This tactic is predicated on the idea that if a phrase is prevalent in the vast majority of documents that can be classified as belonging to a given category, then it must be an important phrase within that category. Applying this method will allow you to estimate how important various keywords are for various classes, while simultaneously decreasing the importance of terms that are critical for multiple classes.

The following algorithms are each taught using a training set, and then they are tested using a test set that is made up of random samples selected from each class in the proportion of 75% to 25%.

4.2. Naive Bayes Algorithm (NB)

One of the more straightforward approaches to multi-class analysis, Naive Bayes is based on the Bayesian Rule but it is also one of the most successful methods. The following equation (1) may be used to calculate the likelihood of document d belonging to class c given that equation:

$$p(c|d) = \frac{p(d|c).p(c)}{p(d)} \quad (1)$$

Therefore, the following two criteria are used to categories requests:

C'=argmaxc∈c (p(c|d))

= C'=argmaxc∈c (p(d|c).p(c))

= argmaxc∈c (x1,x2,……,xn|c).p(c)) (2)

Where $x1$, $x2$, … , xn – is what's known as a "bag of words" representation and it's a vector representation of d.

Making the premise that feature xi is conditionally independent, which is plainly false (the phrases "budget" and "control" are more typically used combined), but which permits joint probability analysis, $p(x1, x2, \dots, xn\,|c)$ to be modelled as the product of numerous different probability p(xi |c) being multiplied together. After that, the formula (2) is shown in its final form (3), which looks like this:

$$c_{NB} = \underset{c\in C}{\operatorname{argmax}}\, p(c_j) \prod_{x\in X} p\left(x|c\right) \quad (3)$$

In (3), the probabilities are changed to their frequency-based estimators, which are presented in the following format: P(cj) is an estimate that is derived from the ratio of inquiries that belong to class cj to the entire number of requests, and p(x|c) is a percentage that is derived from the number of times that term x occurs in the overall pool of words that are sought by class cj.

4.3. K Nearest Neighbors (KNN)

The K Nearest Neighbors method will yield the class that contains the training requests that are the most similar to the one that is now being classed. This class will be determined by comparing the training requests to the one that is being classified right now. The development of several subtypes of kNN is precipitated by the use of a wide range of similarity measures. To determine the distance, we make use of the Euclidean standard (4).

$$p\left(u, x_i\right) = \left(\sum_{j=1}^{n} \left|u^j - x_i^j\right|^2\right)^{1/2} \quad (4)$$

Where $x_i^j - i$ -th neighbor of the object u.

It is possible to arrange each u's neighbours from the training sample in ascending order with respect to. This can be done for each u. If $c_u^{(i)} -$ if this class is the class of object u's i-th neighbour, then the class of object u may be found using the equation (5):

$$c_{kNN} = \underset{c\in C}{\operatorname{argmax}} \sum_{i=1}^{m} \left[c_u^{(i)} = c\right] \bullet w\left(i, u\right) \quad (5)$$

By picking I u), one may build a wide variety of kNN algorithms, including, amongst many others, "exponentially weighted NN and Parzen window kNN". Modeling the number k of NN requires the use of cross-validation in conjunction with a leave-one-out approach.

4.4. Support Vector Machine (SVM)

V. Vapnik was the first person to introduce the non-probabilistic classification approach that is now commonly known as the Support Vector Machine. In this method, the empirical risk minimization technique is used to create a hyperplane in a feature space that has a high dimension. A method for classifying data into one of two categories is known as the Support Vector Machine (SVM). The standard method for conducting multiclass classification using SVM involves combining several binary "one-against-all" or "one-against-one" SVM classifiers. [Citation needed] [Citation needed] The "one-against-one" classification method is another application for this strategy that may be employed. We have k "one-against-all" optimization jobs, and the number is defined by the number of classes. These tasks are identical to the ones below:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + c \sum_{i=1}^{1} \xi_i \quad (6)$$

Where yi– class of

ϕ – kernel function.

C – Penalty parameter.

Therefore, the following constitutes a category of requests:

$$c_{SVM} = \underset{c\in C}{\operatorname{argmax}} \left(\left(w^c\right)^T \phi\left(x\right) + b^c\right) \quad (7)$$

Text should be categorized effectively using a support vector machine (SVM) with a linear kernel if the classes involved in the text classification problem can be linearly separated from one another.

4.5. Maximum Entropy (MaxEnt)

Logistic multinomial regression is a probabilistic log-linear classifier that maximizes the log-likelihood of a collection of weighted features produced from input data. It is also known as maximum entropy, which is a different name for this technique. After calculating the greatest likelihood, which is represented by the phrase (c|x), one may determine which class, c, the request x falls within.

$$p\left(c|x\right) = \frac{\exp\left(\sum_{i=1}^{N} w_i f_i\left(c, x\right)\right)}{\sum_{c'\in C} \exp\left(\sum_{i=1}^{N} w_i f_i\left(c', x\right)\right)} \quad (8)$$

Where (c, x) – ith binary quality that the x request has in relation to the c class, If a term is included in a request and the class is s, then the value of this feature is 1, but if it is not included, then the value is 0. This feature's value is zero if the term is not included.

5. Results and Discussion

Table 1 displays the findings with regard to its accuracy as well as its variation based on the results of local tests. The results for the parameters that demonstrated the highest level of performance on the test set are presented in the report.

Table 1. The mean and standard deviation of accuracy on local tests, expressed (%)

Support group (SAP element / procedure)	NB	kNN	SVM	MaxEnt
Purchases and agreements	76.5 (2.1)	85.3 (1.4)	**87.9 (1.9)**	87.2 (2.1)
Property and material management	76.7 (2.5)	86.5 (1.6)	89.4 (2.1)	**90.2 (1.5)**
Budget planning and execution	64.6 (3.4)	77.5 (3.5)	85.7 (1.5)	**87.3 (2.3)**
Real estate management and construction	88.8 (2.9)	91.2 (3.2)	**93.6 (2.9)**	92.5 (2.9)
Business trips and hospitality expenses and Payments	88.4 (1.9)	92.2 (2.1)	**94.5 (1.8)**	93.8 (1.4)
User Access management	82.2 (2.6)	91.8 (2.98)	**95.2 (2.6)**	56.4 (3.6)

It is clear from looking at table 1 that there is not just one option available for the classification algorithm type. The choices that have the most support are MaxEnt and SVM. To this point, we have finished all the steps that were necessary for the proposed system to be able to comprehend the nature of the issue that a user was attempting to describe in his request. This allows us to say that the proposed system is now capable of understanding the nature of the problem.

5.1. Answering the Request and Error Analysis

Following the definition of the issue class, the system will provide the subject matter expert with a response that has been pre-prepared for the problem class. Depending on the nature of the problem at hand, the solution to a query about class could be simple (as in the instance of "how to obtain the function of a material responsible person"), or it might involve a number of different ideas (as in the case of "no resource discovered while making a request for supply"). In the second possibility, it is vital to do more investigation and analysis. In this stage of the research, we will be putting theories to the test to determine which of the many possible causes are having an effect on the matter. When one is engaged in the process of putting hypotheses to the test, they are required to go through the motions of ticking off a list of stringent criteria that has been provided by an authority figure in order to reduce the number of potential explanations and replies. Following the retrieval of certain parameters from the SAP ERP system for each class of requests, a comparison must be made between those recovered parameters and the values that were supplied by the user request. In the case that the first request does not include all of the user parameters, the system will either look them up in a system log or it will ask the user to provide the information. If it cannot find the user parameters, the system will ask the user to provide them.

Following the accumulation of all of the data, a process of eliminating potentially contributing factors known as "pruning the trees" is carried out, and a conclusive answer is then offered (which may be a combination of multiple different explanations and suggestions). After that, the response is analyzed by a human professional, and if that specialist concludes that it is incorrect, another specialist will classify the answer.

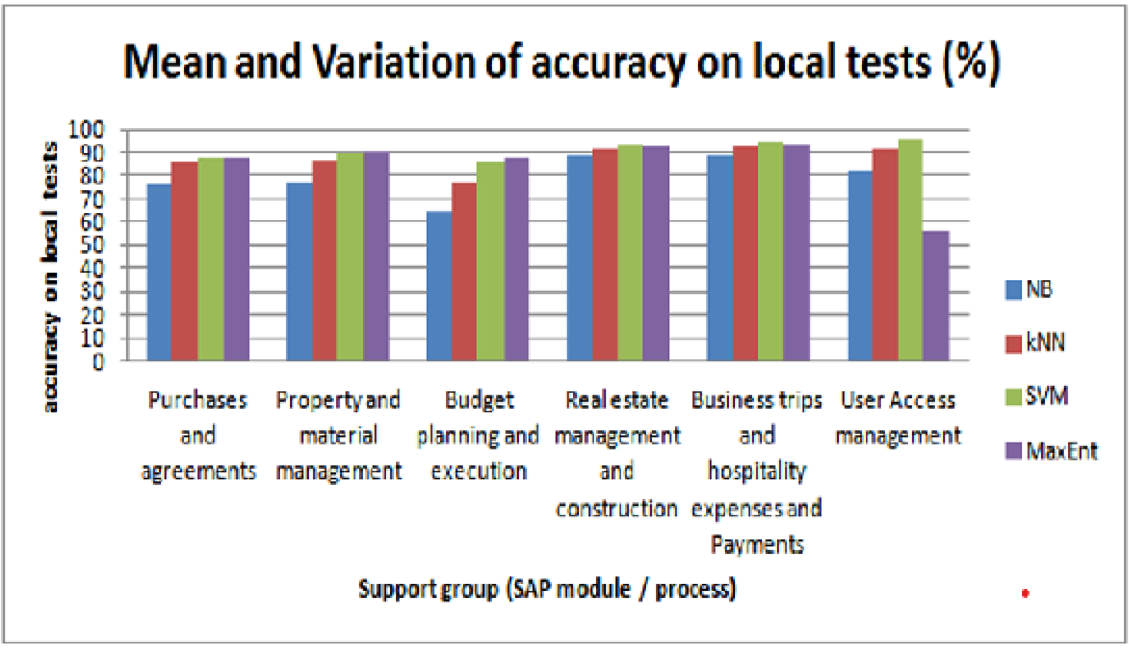

Figure 3. Mean and Variation of accuracy of tests

Taking into account all these factors, the process of developing a response might be conceptualized in the following way:

- Collecting information that is pertinent to the problem at hand in order to test hypotheses regarding its origin.
- Making a request to the SAP database to retrieve the required parameters that have been specified for each class.
- Confirmation that the criteria have been met.
- The elimination of hypotheses that are found to be incorrect.
- The construction of the conclusive answer.

5.2. Testing the Hypothesis

We will take a class from the "Purchases and agreements" module as an example since it indicates that "no resource was discovered while making a request for supply." This will allow us to demonstrate the point. For the purpose of putting the hypothesis to the test, the pieces of data that are necessary include the quantity of resources available as well as the number of requests for supplies. If the message does include these items of information, then we are able to proceed to the next stage of the process. If the system does not have the needed information, it will either send a request to the user asking for additional information or it will search it up in a system log. Both these options are available in the case that the system does not have the required information. The following phase, which comes after determining the total number of requests for different types of goods and resources, is to put the hypothesis to the test. Within the context of this discussion, there are a total of three of them.

- The date that the resource will expire must come before the date that the request for supply specifies as the date of consumption.
- The resource number you entered is invalid.
- You are not allowed to utilize a resource in the request for supply.

Each hypothesis has its own set of parameters, such as the resource's expiration date, the number of resources, and the request for supply ID, and if those parameters are met, the hypothesis is accepted as true. This hypothesis is rejected as untrue if it’s necessary criteria are not met. In the event that our hypothesis holds true, the user will receive a much more tailored response, such as "Good morning! Go with another tool out of the ones you have.

The appeals that claim a classification error occurred are reviewed. Both the training set and the classification algorithm used in the error analysis are regularly updated each week. The most common reasons for incorrect request categorization are as follows:

- The request made use of an uncommon synonym for the exact phrase that was being sought. In this particular instance, a synonym is included into the definition of a word.
- The presence of keywords belonging to several classes inside a single request In most cases, this issue is caused by lengthy inquiries, in which the user combines a number of queries into a single inquiry. These requests are evaluated on an individual basis by subject matter experts.

Implementation of these procedures using SAP AI techniques greatly helped Costa group which deployed computer vision-powered pollinators instead of bumblebees [13]. The usage of natural pollinators like bee was not allowed for indoor farming because of the struggles of native honeybee in environments which are not open. And for biological security reasons, Australia has banned the import of European bumblebees. As a result, the producer grower has resorted to the use of robotic pollinators which is powered by AI techniques on one-million tomato plants. The key takeaway for Costa group was, the use of agribot option as not only more efficient that manual pollination, it also reduces the spread of virus as there is no human contact involved with the plants.

6. Conclusions

One of the most difficult challenges in artificial intelligence is called "question answering," and it relates to the capacity to interpret questions presented by humans and offer appropriate responses. There is a discipline of computer science known as quality assurance (QA) that focuses on information retrieval and natural language processing. in contrast to the publicly accessible quality assurance systems. Presented below is a SAP ERP user support solution driven by automated means. It lays forth a clear architecture to provide the means for the system to evolve by detailing the primary phases involved in creating the corpus, identifying the issue, and deriving a solution. In order to achieve a high level of accuracy in understanding and responding to natural language requests, the system requires the collaborative efforts of human experts for data preparation, building a knowledge database, text mining techniques, and machine learning algorithms of multi-class classification, and is scalable on various problems of closed-domain question answering in different domains. In contrast, the system is scalable on a wide range of closed-domain question-answering challenges across domains. Nonetheless, the system is flexible enough to handle a wide variety of problems.

REFERENCES

[1] SAP penalty in Oracle suit is excessive, analyst says – Tomorrow Now, software, sap, oracle, IT industry, Government/Industries, government, applications. Tec world. Retrieved on 24 April 2011.

[2] SAP Challenges Oracle with $3.4 Billion Success Factors Purchase. 4 December 2011.

[3] SAP – HCL Technologies Announces Global Services Partnership With SAP to Deliver Joint Business Value Through 'Customer Centric Ecosystem'. Sap.com. Retrieved on 7 July 2011.

[4] Yusuf, Y., A. Gunasekaran, and M. Abthorpe, "Enterprise Information Systems Project Implementation: A Case Study of ERP in Rolls-Royce," International Journal of Production Economics, 87(3), February 2004.

[5] Fryling, Meg (2010). "Estimating the impact of enterprise resource planning project management decisions on post-implementation maintenance costs: a case study using simulation modelling". Enterprise Information Systems 4 (4): 391–421.

[6] SAP History: From Start-Up Software Vendor to Global Market Leader Retrieved 15 October 2007.

[7] Gargeya, V. & Brady, C. (2005). Success and failure factors of adopting sap in ERP system implementation. Business Process Management Journal, 11(5), 501-506.

[8] Greenbaum, J. (2009, January 14). Shane's blame game: management, not SAP retail, sinks jewelry company. Enterprise Matters, wordpress.com/2009/01/14/shanes-blame- game/.

[9] Jurka T P 2012 Maxent: An R Package for Low-memory Multinomial Logistic Regression with Support for Semi-automated Text Classification The R Journal 4(1) p 56–59.

[10] Jurafsky D and Martin J H 2009 Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics (2nd edition, Prentice-Hall).

[11] Lai S, Xu L, Liu K and Zhao J 2015 Recurrent Convolutional Neural Networks for Text Classification In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence 333 p 2267–2273.

[12] Logan D and Kenyon J 1992 HelpDesk: Using AI to Improve Customer Service In Proceedings AAAI-92 p 37–53.

[13] SAP AI in action: https://www.sap.com/uk/insights/viewpoints/eight-examples-of-artificial-intelligence-in-action.html Dec 2021.