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lIntegration of NLP and NLU in the Implementation of Chatbot in Asset Management System

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Abstract: PT XYZ, a startup in the Information Technology sector, developed an asset management application to digitalize the asset management process for its clients. However, as new features were added, the application became more complex, causing difficulties for new users. PT XYZ responded by introducing a customer service system to assist new users in exploring the company's services and application features. To improve service efficiency while maintaining quality, the company opted to implement a chatbot. The chatbot was designed to provide automatic and responsive assistance, reducing the load on the customer service team and increasing user satisfaction. The author integrated NLP and NLU in designing the chatbot for PT XYZ using the open-source RASA framework. This framework was chosen for its strong capabilities in natural language processing and understanding conversational context. The NLP and NLU models are used to create a customer service engine in the form of text messages that answer questions specifically related to the use of the asset management application. By leveraging this technology, the chatbot can provide relevant and accurate responses, even when faced with variations in language and complex questions. Based on black box testing, the chatbot successfully recognized the intent behind user queries. The testing was conducted to evaluate how well the chatbot understood and responded to user questions. The results, using a confusion matrix, showed that precision, recall, accuracy, and f1-score all achieved a perfect score of 1.0.

Keyword: Chatbot, NLP, NLU, Artificial intelligence, Asset management.

INTRODUCTION

In recent years, the development of artificial intelligence (AI) has become one of the fastest growing technologies, in the world. [1]. AI is the ability of a system to interpret external data accurately, learn from that data, and use that learning to achieve specific goals and tasks through flexible adaptation. [2]. The advent of AI is not just a trend, but has become a reality that brings significant impact across different walks of life. The general public is increasingly adopting AI in their daily lives, from smartphone apps that use voice recognition technology to e-commerce platforms that optimize the shopping experience thanks to predictive algorithms such as product recommendations, availability predictions, and many more. The implementation of AI is not only limited to certain sectors, but has penetrated into various fields of life. In healthcare, AI is used to analyze complex medical data and support more accurate diagnoses [3]. In the manufacturing sector, AI-powered intelligent robotics enable more efficient production. The education sector is exploring the potential of AI to personalize learning and provide adaptive solutions according to each student's needs.

One noteworthy concrete implementation of AI is the chatbot. A chatbot is a computer program created to simulate a conversation between humans [4]. Chatbots have become an effective solution in providing instant and interactive customer service [5]. In an era where digital communication is increasingly dominant, chatbots are becoming an efficient intermediary between humans and technology, providing responsive services and enabling more intuitive interactions. Thus, AI, specifically through the implementation of chatbots, not only embodies technological development, but also changes the way we interact with the world around us.

PT XYZ, a startup company in the Information Technology (IT) sector, is actively developing an asset management application to support the company's digital transformation. These assets vary widely, including land that serves as the location of the company's factory, buildings used as warehouses or offices, production machinery needed to manufacture products, and vehicles used to transport the company's products. This application is specifically planned to digitize the management of these assets in the client company through the implementation of functions such as asset recording, location tracking, maintenance, replacement planning, asset state monitoring, asset performance analysis, and real-time inventory updates.

However, as the features in the application increase, their complexity also increases, creating barriers for ordinary users who experience difficulties when interacting with asset management services through the application. PT XYZ responded to this challenge by providing customer service to support users in overcoming their difficulties. Although customer service has been implemented, the growth of incoming user queries has exceeded the current service time. This results in many user queries going unanswered, especially outside of company business hours, as customer service is not available for 24 hours. This situation can ultimately lead to a decrease in service quality and service efficiency. In addition, problems arise in the form of repetition of answers and the same frequently asked questions, which causes an ineffective workload for the customer service team. Each new member of the team needs time to understand the scope of the application users' problems before they can provide satisfactory answers.

Judging from the problems experienced, a chatbot feature is designed to be integrated into the asset management application, as a service supported by rules and artificial intelligence (AI), providing a chat interface in the form of text messages to interact with users. This chatbot will be built using NLP and NLU models. Natural Language Processing (NLP) is a branch of computer science, artificial intelligence, and linguistics that focuses on the interaction between computers and natural human language. Natural language includes information that humans understand, either in the form of voice or text, with the aim of conveying information between users [6][7]. Natural Language Understanding (NLU) is a branch of artificial intelligence that allows computers to analyze, understand, and interpret human language like humans. NLU processes text or speech to capture the user's meaning, context, and communicative intent [8][9].

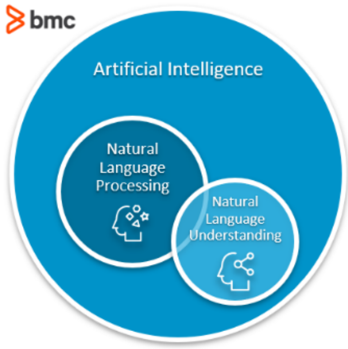


Figure 1. NLP & NLU Relationship. Adapted from [9]

Related research that has been done before in [10] using an NLP approach with the Dialog Flow framework, resulted in 92.5% accuracy from 40 question and answer data, with 37 correct and 3 incorrect answers. Research in [11] aims to design an automated chatbot to facilitate Customer Service Toko Cahaya Fajar Terang in answering questions related to payment registration and stock items. Using the NLP approach with TF-IDF and Cosine Similarity methods, the chatbot achieved 90% accuracy in question and answer. Research in [12] developed a customer service chatbot for 24-hour academic information services at AMIKOM University, using NLP and Fuzzy String Matching to facilitate keyword searches.

Research in [13] aims to help farmers access important information related to agriculture based on time relevance. This research uses the concept of NLP, with the results of 86.12% of applications can parse sentences, 70% answer according to time relevance, and 73.33% display answers according to user requests. The research in [6] focused on developing a chatbot that can assist users in accessing information about the Information Technology Program at the Department of Informatics Engineering, University of Surabaya. By utilizing the NLP approach and applying the cross validation and user validation methods, this research succeeded in achieving an accuracy of 83.33% through cross validation and 76% through user validation, involving 10 users. Research in [14] aims to create a chatbot for consulting prayer procedures. This research uses qualitative methods and LSTM deep learning models with the RASA NLU framework. As a result, the chatbot is able to recognize questions and provide responses in the form of text and images with 96% accuracy. Research in [15] aims to create a chatbot service to answer student questions related to administrative information. NLU modeling is done with the RASA NLU framework. The evaluation results show the accuracy of the NLU model is 0.995 for precision, recall, and F1-Score, and the accuracy of the dialog model is 0.70 with precision 0.72 and F1-Score 0.70.

Previous research was also conducted in [16] which focused on developing an NLP-based chatbot for the Directorate General of Budget Performance Monev application, aiming to improve the quality of service to users of the Directorate General of Budget information system. The framework used is RASA with the NLP model. The results showed that the chatbot has an intent prediction accuracy of 0.986 and a response prediction accuracy of 0.980. Research in [17] developed a chatbot to provide the right information and make it easier for students at Duta Wacana Christian University (UKDW). This application uses the Wit.ai NLP service, with the results of the study showing an accuracy of 97%.

This research aims to develop a chatbot that not only provides information when requested, but also interacts more actively by providing advice or asking back to the user regarding whether the information provided is appropriate. The goal is to create a more interactive conversation and improve the user experience in interacting with the chatbot. The main focus of this research is on testing the performance of chatbots that use NLP and NLU technologies to measure their ability to respond to questions, understand natural language, and provide relevant solutions. Through this test, it is expected to be proven that the integration of

NLP and NLU can improve service efficiency, reduce customer service workload, and improve the quality and efficiency of PT XYZ's asset management application. This research offers innovative technological solutions while focusing on optimizing user experience through an adaptive and responsive chatbot.

METHOD

Research Stages

The stages of research are a series of procedures that must be followed step by step in accordance with what is the goal. The stages carried out in this study are shown in Figure 2.

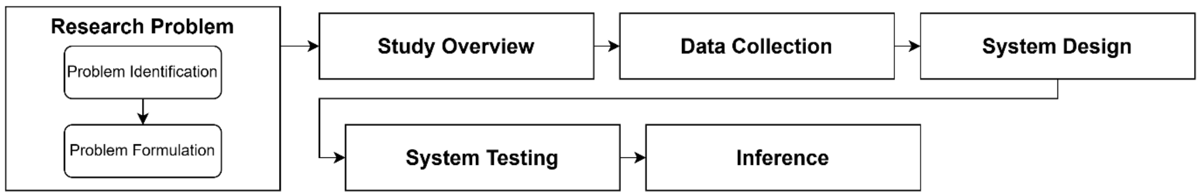


Figure 2. Research Stages

Problem Identification

In this research, the first step taken is the identification of problems at PT XYZ, specifically related to the provision of information services for users of the asset management application that has been developed. Through analysis and evaluation, this stage aims to highlight areas that require attention to improve service quality and efficiency. From the identification results, the problems encountered will be clearly formulated, forming the basis for the problem-solving steps that will be implemented in this research.

Problem Formulation

The problem formulation includes important parameters for the chatbot to provide optimal responses to various user questions. Another focus is the assessment of the success of the integration of NLP and NLU in providing responses, expressed in percentage of success. In addition, the problem also includes building an effective database to support the chatbot functions, ensuring adequate access and understanding in answering user queries appropriately. These aspects are expected to be a strong basis for developing an effective and solutive research strategy.

Study Overview

This stage involved searching and reviewing previous research to understand the methods and conceptual frameworks related to NLP and NLU-based chatbot development. The review aimed to assess the contribution of the research to existing knowledge, with references from books, theses, and scientific publications.

Data Collection

At this stage, the data obtained consists of general questions asked by users of the asset management application, along with the answers given by customer service. Data was obtained through interviews with PT XYZ customer service staff and records of frequently asked questions. The author also conducts application tests to ensure the dataset covers all application functions, so that the chatbot can answer general questions and other functions in the application.

System Design

At this stage, the chatbot was designed using Python and the RASA platform that integrates NLP and NLU. The initial NLP process includes lower casing, word replacing, removing punctuation, stemmer, stopword and text tokenization. After the text is processed, further processing will be carried out by two components in RASA, namely RASA NLU plays a role in understanding the meaning of the text and RASA CORE manages conversational logic and decision making [7][18]. The system implementation flow can be seen in Figure 3.

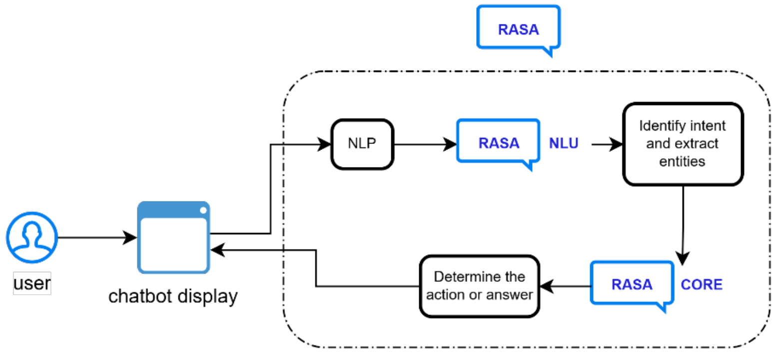


Figure 3. Overview of System Implementation

System Testing

System testing is carried out to evaluate the performance and accuracy of the chatbot that has been developed. In this research, two testing approaches are confusion matrix and black box testing.

Confusion Matrix

Confusion matrix is a table that serves to assess the performance of a classification model, by showing the number of correct and incorrect predictions generated by the model. [19].

Table1. *Confusion matrix*

	Actual Positive	*Actual Negative*
Predicted Positive	TP	FP
Predicted Negative	FN	TN

There are four terms in the confusion matrix to describe the classification results: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The following is an explanation of each term:

a. TP: Correct positive prediction (the model predicts positive, and it actually is positive).
b. FN: Incorrect negative prediction (the model predicts negative, but it is actually positive).
c. FP: False positive prediction (the model predicts positive, but it is actually negative).
d. TN: Correct negative prediction (the model predicts negative, but it is actually negative).

With confusion matrix, we can calculate model performance metrics such as precision, recall, accuracy, and f1-score.

a. *Precision*: Measures how many positive predictions are correct compared to all positive predictions. Formula:

$$\boldsymbol{Presisi = \frac{TP}{TP + FP}} \quad (1)$$

b. *Recall*: Measures how many positive examples the model successfully found compared to all positive examples. Formula:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}} \quad (2)$$

c. *F1-score*: It is a harmonic average between precision and recall, providing a more balanced measure of performance. Formula:

$$\boldsymbol{F1 - Score} = \boldsymbol{2} \times \frac{\boldsymbol{Precision} \times \boldsymbol{Recall}}{\boldsymbol{Prescission} + \boldsymbol{Recall}} \quad (3)$$

d. *Accuracy*: Measures how many predictions are correct (both positive and negative) compared to the total predictions. Formula:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}} \quad (4)$$

Black Box Testing

Black box testing methods, or functional testing, focus on the output of the system based on inputs without looking at its internal mechanisms. The advantage is that testers do not need to understand programming languages and can test from the user's perspective. Black box testing can be performed early in application development, allowing developers and testers to work independently. [20].

Penarikan Kesimpulan

The final stage of this research is to draw conclusions from the results of testing the chatbot system, as well as provide suggestions to improve the shortcomings in the research. The conclusions reflect the evaluation of the performance and effectiveness of the chatbot, while the suggestions aim to improve the quality of service in the future. This stage is crucial to assess the contribution of the research results in the further development of the chatbot system.

RESULTS AND DISCUSSION

Dataset

This research dataset is divided into two: first, related to the functions of the asset management application (264 data), and second, general conversations such as greetings and thanks (275 data). The addition of general conversations aims to make the chatbot able to interact more naturally. The total data used was 539, which allowed for a more in-depth analysis of the chatbot's capabilities in various communication situations.

Table 2. Chatbot Intent List

Intent Type	Description	Sample Quantity
informasi_aplikasi	Explanation of asset management application	9
pengajuan_pinjam_aset	Search for information on how to borrow assets	21
laporan_rusak_aset	Looking for information on how to report damaged assets	38
pengajuan_pengembalian_aset	Seek information on how to make asset returns	23
laporan_hilang_aset	Looking for information on how to report missing assets	19
pengajuan_pemindahan_aset	Looking for information on how to apply for asset transfer	15
pengajuan_pembuangan_aset	Search for information on how to apply for asset disposal	23
penambahan_aset	Looking for information on how to add asset data to the system	38
info_aset	Looking for information on how to view asset details	35

pembaharuan_data_aset	Search for information on how to make data changes	43
salam_umum	Greetings	25
ya	Answer with yes	21
tidak	Answer with no	15
suasana_bahagia	Expressing happy news	67
suasana_sedih	Expressing sad news	70
tantangan_bot	Ask about bots	25
ucapan_terima_kasih	Expressing gratitude	13
tokenisasi_pesan	Testing tokenization on messages	7
selamat_tinggal	The closing sentence of the conversation	32

Cleansing Data

The dataset that has been obtained will go through a cleansing process to make the data more structured and relevant for the next stage of analysis. NLP simplifies data processing by removing irrelevant words that can overload the system and reduce efficiency. In this research, data processing is done through several main stages: lowercasing, word replacing, removing punctuation, stemming, stopword removal, and tokenization.

a. Lowercasing: Changes all letters in the text to lowercase to equalize word forms that differ only due to capitalization.
b. Word Replacing: Replacing certain words, such as abbreviations or nonstandard words, with more formal or standardized word forms to improve consistency.
c. Removing Punctuation: Removing punctuation marks such as periods, commas, question marks, and others so that they do not interfere with text analysis.
d. Stemming: Changing words to their basic or root form to simplify variations of words that have similar meanings (e.g. "melaporkan" becomes "lapor").
e. Stopword Removal: This process involves the removal of common words that are less meaningful in the analysis, such as "yang", “dan”, and “di”.
f. Tokenization: Breaking the text into small units such as words or phrases to facilitate further analysis.

Table 3. NLP Process on Dataset

Steps	Results
Original Text	Bgmn cara melaporkan aset yang rusak?
Lowercasing	bgmn cara melaporkan aset yang rusak?
Word Replacing	bagaimana cara melaporkan aset yang rusak? (bgmn → bagaimana)
Removing Punctuation	bagaimana cara melaporkan aset yang rusak
Stemming	bagaimana cara lapor aset yang rusak
Stopword	cara lapor aset rusak
Tokenization	["cara", "lapor", "aset", "rusak"]

Define Intents and Responses

Intents group phrases with the same intent, so that the chatbot can recognize what the user wants. Each intent contains example phrases to help the RASA model understand input variations. In chatbot development with RASA, the dataset is organized in .yml files in the /data/nlu/namafile.yml directory. Each question category is integrated as an intent, with example questions added as examples to be processed by RASA.

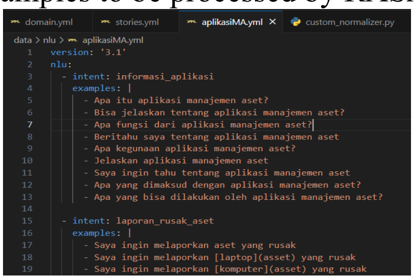


Figure 4. Intent Writing Structure in RASA

Responses are how the chatbot responds to recognized intents. Responses can use variables to include dynamic information, such as names or specific data. Responses can be simple text or interactive components such as images, buttons or cards. In RASA, responses are written in the domain.yml file and labeled according to the associated intent.

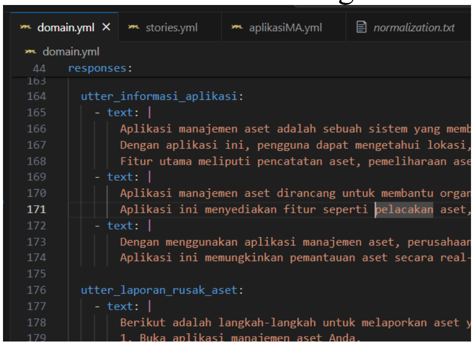


Figure 5. Structure of Writing Responses in RASA

Configure Stories

Stories connect intents with responses and actions to create complex conversational flows. By defining interaction scenarios, stories help chatbots understand context and maintain a logical flow. Stories allow the chatbot to follow the conversation naturally and handle branching conversations based on user responses.

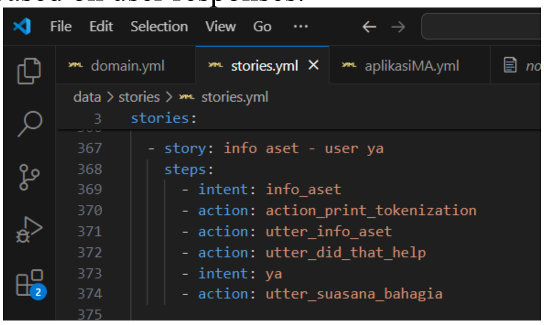


Figure 6. Structure of Writing *Stories* in RASA

Modeling

In the RASA framework, the modeling process is done through the terminal command "rasa train". This modeling is run using various predefined configurations.

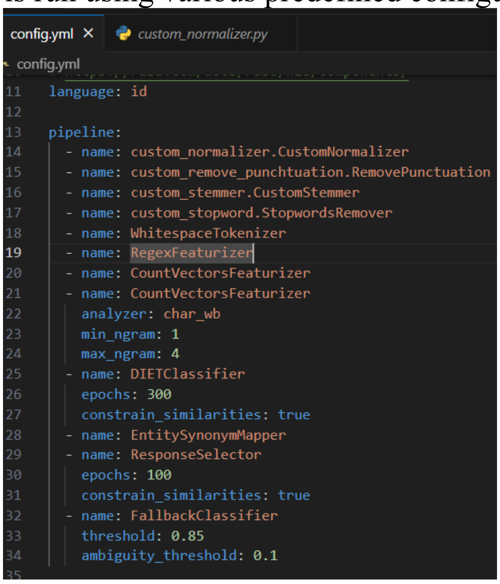


Figure 7. RASA NLU Configuration

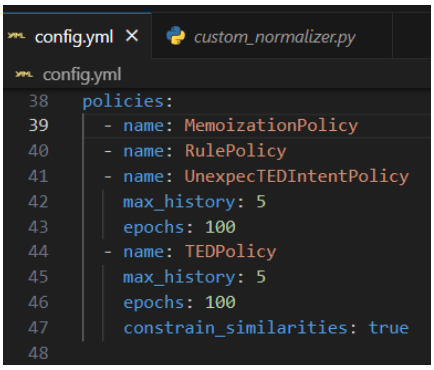


Figure 8. RASA Core Configuration

An explanation of the configuration of RASA NLU and RASA Core will be explained in the table below.

Table 4. RASA NLU Configuration

Pipeline	Explanation
CustomNormalizer	Data processing to perform lower casing and word replacing.
RemovePunctuation	Removes all punctuation marks in the data.
CustomStemmer	Change a word to its root form.
StopwordsRemover	Removing common words that don't have much meaning.
WhitespaceTokenizer	Convert text into words/tokens that are separated by spaces.
RegexFeaturizer	Regular expressions (regex) are used to recognize patterns in text, such as dates or emails. This helps extract specific information and improves accuracy in identifying intent and entities in conversations.
CountVectorsFeaturizer	Convert text into a numerical representation by counting the frequency of occurrence of words in the text.
DIETClassifier	The Dual Intent and Entity Transformer (DIET) Classifier serves to identify intent and extract entities from the input provided by the user.
EntitySynonymMapper	Natural language processing used to map synonyms or variations of words that have the same meaning into a single entity.
ResponseSelector	Components used to build response recovery models that directly predict bot responses from a number of available candidate responses.
FallbackClassifier	The message will be put into the nlu_fallback category if the NLU classification value is below the limit specified in the configuration file.

Tabel 5. RASA Core Configuration

Pipeline	Explanation
MemoizationPolicy	MemoizationPolicy remembers the conversation patterns from the training data and evaluates the match of the current conversation with the patterns contained in the stories.yml file. If a match is found, the system predicts the next action based on the memorized pattern.
RulePolicy	RulePolicy is a rule that manages short conversations based on the training data contained in the rules.yml file.
UnexpecTEDIntentPolicy	UnexpecTEDIntentPolicy is a multitasking architecture developed to predict unexpected actions.
TEDPolicy	TEDPolicy is a multitasking architecture designed to predict the next step and recognize entities in the conversation.

Analysis of Test Results

In this research, two testing methods are applied: the first is confusion matrix testing, and the second is black box testing.

Confusion Matrix

To validate the accuracy of the model, testing was conducted using Confusion Matrix. In this analysis, the percentage of successful predictions for each intent and response is evaluated, ensuring that the chatbot model's interpretations and responses match the given data. The following are the steps performed:

a. Dataset Sharing: The total dataset available amounted to 539 data. To split the data proportionally between training and testing, the “rasa data split nlu” command was used in the Rasa framework. This procedure automatically split the dataset into 80% for training, which is 431 data, and 20% for testing, which is 108 data. This ensures that the chatbot model is developed using a sufficient dataset for adequate training and validation.
b. Modeling using training data: From a total of 431 training data that has been collected, a model will be created by running the following command: “**rasa train nlu --nlu .\train_test_split\training_data.yml**”.
c. Model testing using test data: After the model has been trained, the next step is to test the model using test data. Testing is done by running “**rasa test nlu --nlu .\train_test_split\test_data.yml**” command. The Rasa framework automatically generates a confusion matrix that is used to analyze the intent prediction as well as the response generated by the model.

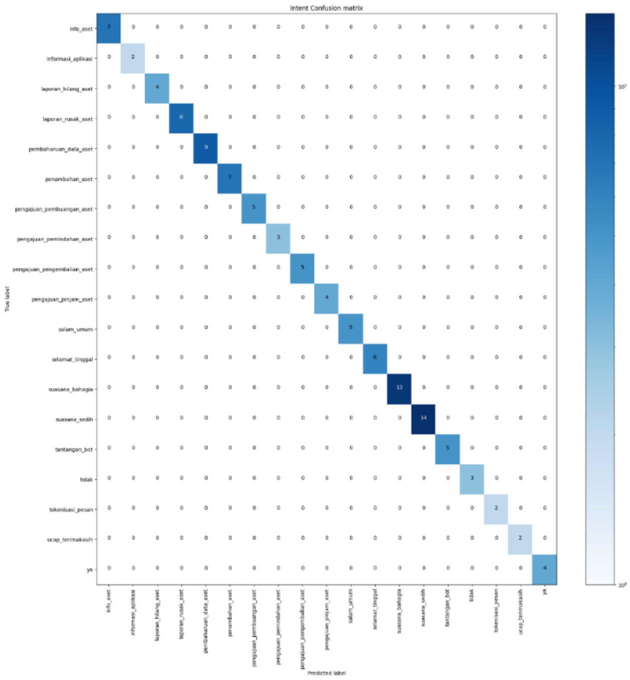


Figure 9. Confusion Matrix Predicted Intent (NLU)

From the results obtained through the confusion matrix in Figure 9, precision, recall, accuracy, and f1-score can then be calculated using the equation. The results of calculations that have been carried out for each precision, recall, accuracy, and f1-score on intent testing (RASA NLU) on the model produce an average of 1.0.

d. Modeling response testing: To test the accuracy of the response, a model created with the “**rasa train**” command will be used. This model uses the entire existing dataset of 539 data.
e. Testing the response of the model: Next, the “**rasa test core**” command will be executed to test the accuracy of the model's response.

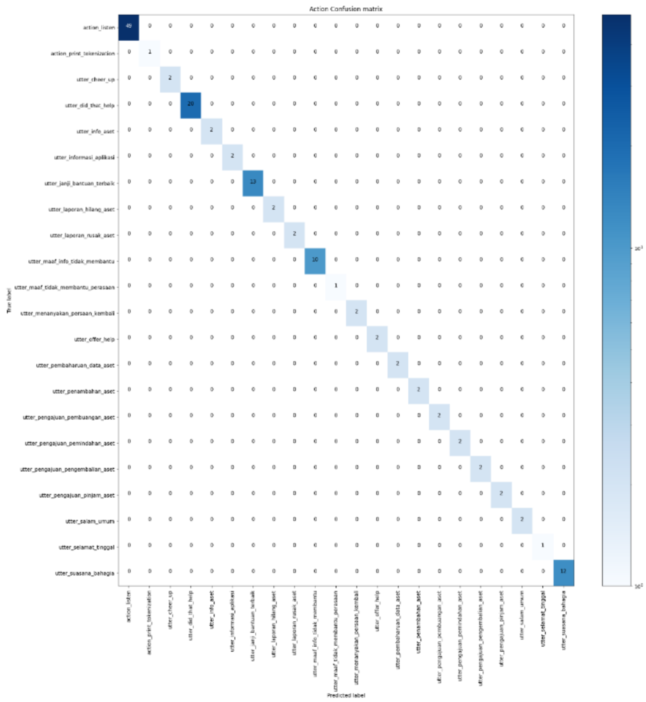


Figure 10. Confusion Matrix Predicted Response (Core)

From the results obtained through the confusion matrix in Figure 10, precision, recall, accuracy, and f1-score can then be calculated using the equation. The results of calculations that have been carried out for each precision, recall, accuracy, and f1-score on intent testing (RASA Core) on the model produce an average of 1.0.

Black Box Testing

Here, testing is done by the researchers themselves by giving 100 different questions with various sentence variations to ensure the model can recognize the intent contained in the sentence.

Table 6. A portion of the Black Box Testing Results

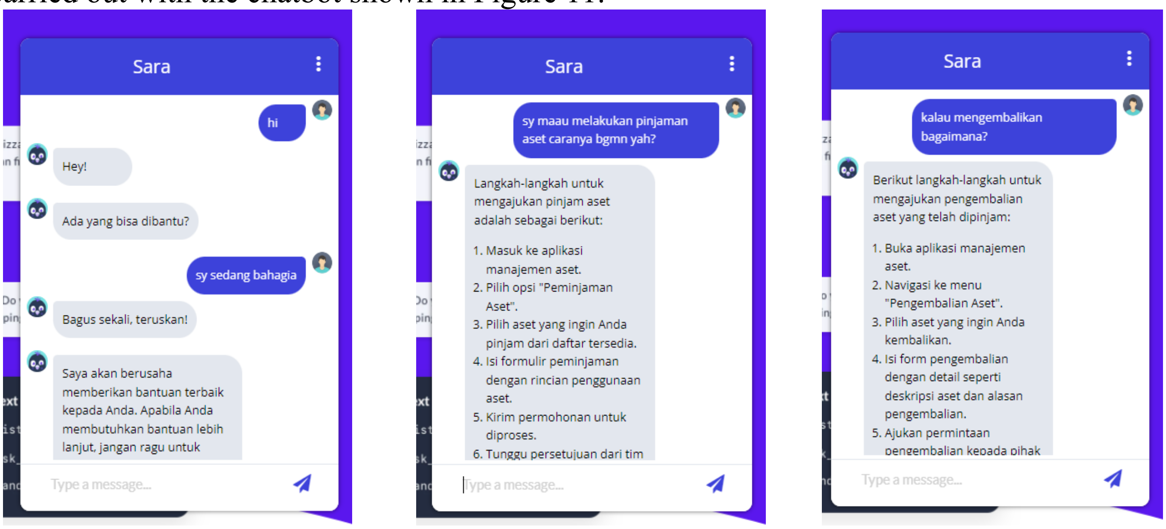
No	Question	Intent detected	Intent should be	Results
1	Apa yang dimaksud dengan aplikasi manajemen aset perusahaan?	informasi_aplikasi	informasi_aplikasi	Correct
2	Bisa berikan gambaran umum tentang aplikasi manajemen aset ini?	informasi_aplikasi	informasi_aplikasi	Correct
3	Apa saja fungsi utama dari aplikasi manajemen aset?	informasi_aplikasi	informasi_aplikasi	Correct
4	Tolong berikan deskripsi mengenai scanner yang ada di lantai dua	info_aset	info_aset	Correct
5	Bagaimana cara melihat informasi lengkap tentang monitor yang digunakan di departemen IT?	info_aset	info_aset	Correct
6	Bagaimana cara melaporkan kulkas di dapur yang tidak dingin?	laporan_rusak_aset	laporan_rusak_aset	Correct
7	Saya menemukan motor yang rusak di area parkir, Apa yang harus saya lakukan?	laporan_rusak_aset	laporan_rusak_aset	Correct

8	Bagaimana cara melaporkan lampu yang mati di koridor lantai 3?	laporan_rusak_aset	laporan_rusak_aset	Correct
9	Apa langkah-langkah untuk mengembalikan komputer setelah penggunaan selesai?	pengajuan_pengembalian _aset	pengajuan_pengembalian _aset	Correct
10	Bagaimana cara saya mengembalikan laptop yang sedang saya pinjam?	pengajuan_pengembalian _aset	pengajuan_pengembalian _aset	Correct
11	Tolong tunjukkan cara menambahkan meja ke dalam sistem	penambahan_aset	penambahan_aset	Correct
12	Bagaimana cara saya bisa meminjam laptop untuk acara di luar kota?	pengajuan_pinjam_aset	pengajuan_pinjam_aset	Correct
….	….	….	….	….
98	Berikan saya panduan untuk memperbaharui detail aset	pembaharuan_data_aset	pembaharuan_data_aset	Correct
99	Apa yang perlu saya lakukan untuk mengubah deskripsi monitor di database aset?	pembaharuan_data_aset	pembaharuan_data_aset	Correct
100	Bagaimana cara menghapus monitor dari sistem aplikasi ini?	pembaharuan_data_aset	pembaharuan_data_aset	Correct

The test results show the success of the chatbot in understanding the intent of each question or statement given gets accurate success in each test, namely with an accuracy of 100%.

Prototype View

The screen display in this chatbot application uses a chatbot widget whose display is built using html and javascript as the programming language. In the picture below is the display when the chatbot answers a variety of different questions and provides the appropriate response from the text or question entered by the user. The following are some views of the interactions carried out with the chatbot shown in Figure 11.



(a) (b) (c)

Gambar 11. (a) Ordinary conversation, (b) Conversation about requesting to borrow assets, (c) Conversation about returning assets

Figure (a) shows a chatbot interaction that starts with the greeting “hi,” to which the chatbot replies. The chatbot then asks about the user's needs and offers help. When the user enters random text about their feelings, the chatbot responds with appreciation for the user's happiness. After that, the chatbot again offers help until the user's needs are met.

Figure (b) shows a conversation between a user and a chatbot where the user's current need is to ask about the steps that must be taken in the asset management application if the user wants to borrow goods or assets. It can be seen that the chatbot can understand the intent of the user's question so that it can provide an appropriate response, namely providing the steps that the user must take to make a loan.

Figure (c) shows the interaction that occurs after the borrowing process shown in figure (b). In this interaction, the user wants to return the previously borrowed asset and asks the chatbot a question about how to return the asset. In figure (c) it can be seen that the chatbot is able to understand the user's intention to know the procedure for returning the borrowed asset. The chatbot provides a response that is in accordance with the user's request, namely explaining the steps that must be followed to return the asset through the asset management application. Thus, the chatbot is not only able to understand the user's needs but also provides clear and useful guidance in the process of returning the borrowed asset, making it easier for users to complete their tasks more efficiently.

CONCLUSION

From the results of the design, creation, and testing of the chatbot system that has been carried out, it can be concluded that the system has succeeded in responding to user needs very well. This can be seen during testing, especially black box testing, where the system is able to recognize the intent of the text given by the user with an accuracy level of 100%. In addition, in testing using a confusion matrix, the chatbot obtained a prediction accuracy of 1.0 for intent and response testing. The precision, recall, and f1-score metrics also show a perfect value, namely 1.0, which reflects the success of the chatbot in recognizing user intent and providing the right response.

The use of Natural Language Processing (NLP) and Natural Language Understanding (NLU) in chatbot development has proven to be crucial. NLP allows chatbots to parse and process text, while NLU allows chatbots to understand the context and intent behind user messages. This allows chatbots to provide relevant responses, understand the context of conversations, handle language variations, analyze sentiment, and learn from user interactions. This provides a more natural, responsive, and satisfying experience for users, and ensures that the system can evolve over time.

However, although the results obtained are quite satisfactory, there are still some things that can be improved for future development. One suggestion for further development is the addition of datasets to the chatbot knowledge base, so that the chatbot can answer more questions from users. In addition, integration with customer service or human operators needs to be considered, especially to handle questions that cannot be answered by the chatbot automatically. The system also needs to be improved to be able to automatically add data from user questions that have not been answered by the chatbot, so that it can facilitate direct knowledge base updates.

Thus, these suggestions are expected to improve the ability of the chatbot system to provide more optimal and efficient services in the future.

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