Design of an Academic Services Chatbot at Asia Institute Malang

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Abstract

This study successfully developed and evaluated an academic services chatbot utilizing Natural Language Processing (NLP) and Artificial Neural Networks (ANN), showcasing a comprehensive methodology that encompassed data collection, preprocessing, model training, and performance evaluation. We meticulously derived the dataset from frequently asked questions at the Asia Institute of Technology and Business Malang, ensuring its relevance and applicability to the target audience. Rigorous preprocessing techniques, including tokenization, stemming, and stop words removal, were employed to enhance the quality of the input data for the ANN model, which significantly improved its performance. The training results revealed a strong correlation between the number of training epochs and the accuracy of the chatbot's responses, indicating that increased training led to enhanced performance. Furthermore, a Cronbach's Alpha coefficient of 0.965 confirmed the validity and reliability of the measurement tool for user feedback, highlighting the robustness of the collected data. User testing involving 37 students indicated a high level of satisfaction with the chatbot's performance, as it achieved a perfect accuracy score of 100%. These findings highlight the potential of NLP-based chatbots to enhance academic information services, effectively addressing student inquiries while significantly reducing the workload on academic staff. This study serves as a valuable model for other educational institutions aiming to implement AI-powered solutions to improve their academic support services and overall student experience.

1. Introduction

The development of technology is accelerating in the modern day. These advancements are important in many different disciplines. But it's imperative to make sure that technology is usable and appropriate for every group in society. People from all walks of life utilize computers, smartphones, and other electronic gadgets, demonstrating the rapid development of technology. The development of technology based on artificial intelligence (AI) is one of the major developments brought about by this rapid growth in human life (Apriliani et al., 2023).

Artificial intelligence (AI) technology enables electronic devices to carry out particular tasks that closely resemble human traits and behavior. Chatbots—computer programs that mimic human discussions via voice commands or text chats—are one prominent application (Hikmah et al., 2023). Natural language processing (NLP), an inventive method, enables computers to automatically comprehend and evaluate human language, providing new insights into users' perceptions and reactions to these apps (Nurwanda et al., 2024).

Chatbots converse with users in a genuine human language to assist them in finding the information they need. Academic services use chatbot technology in education to address frequently asked questions by students about campus information. We anticipate that this technology will enhance the quality of services provided to students. It is crucial to have simple access to academic information, including schedules, tuition costs, scholarships, and more. Even though the university's official website provides these details, students frequently seek more thorough information, which usually necessitates speaking with school representatives.

Managing academic information services at the Asia Institute of Technology and Business Malang is extremely difficult, especially given the frequency of recurring inquiries from students regarding lecture schedules, study plan submissions, and graduation procedures. Academic staff currently manually respond to these inquiries, which leads to ineffective time management and an increased burden. This impacts the staff members focus on other academic assignments. Furthermore, the lack of an automated method for prompt responses results in information delivery delays, particularly during peak times like registration or study plan submissions filing.

Putting in place an NLP-based chatbot could be a way to increase productivity when responding to routine questions, simplify the information retrieval process for students, and lessen the workload of academic staff. By improving service quality, creating academic services that are directly available to students will benefit educational institutions. The Asia Institute of Technology and Business Malang requires an innovative approach to website building using AI technology. This necessitates an information system that can effectively collect and display data to pupils. At the Asia Institute of Technology and Business Malang, chatbot creation may be a viable way to deliver academic and informational services.

1.1 Literature Review

1.1.1 Natural Language Processing

NLP is a branch of artificial intelligence (AI) that focuses on training computers to understand, process, and generate language. This technology powers search engines, machine translation services, and voice assistants. Today, NLP is widely integrated into everyday life in the form of virtual assistants like Siri, Alexa, or Google Home. In the industrial world, NLP is also highly valuable for businesses to gain a competitive edge. NLP applications can assist in various fields, especially in analyzing and extracting value from unstructured data (Ahda et al., 2024; Rumaisa et al., 2021).

1.1.2 Chatbot

A chatbot is a computer program that mimics human conversation through voice commands or text-based interactions. To understand natural human language, chatbots utilize Natural Language Processing (NLP) approaches to analyze and process each word conveyed by users in the form of text messages. Chatbots are programmed to operate independently and are capable of responding to questions formulated based on predefined scripts in natural language, providing responses that mimic real human interactions. Essentially, a chatbot consists of two main components: "Chat," which refers to the conversation aspect, and "Bot," which represents a program containing a database that processes input to generate responses. Chatbots can answer questions by interpreting the text typed by users through a keyboard (Hikmah et al., 2023).

1.1.3 Artificial Neural Network

Artificial Neural Network is a machine learning model inspired by the human brain's neural networks. It can independently learn data patterns and provide responses based on inputs through a structured process, ultimately producing appropriate outputs (Hikmah et al., 2023).

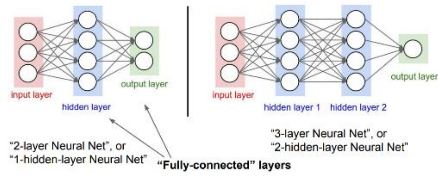

Fig. 1. *Structure of Artificial Neural Network (ANN)*

1.1.4 Flask

Built using the Python programming language, Flask is a commonly used web service framework. Flask falls into the category of a microframework because it does not require specific libraries for its use. Flask serves as a framework and interface for building web-based applications. Additionally, this framework is designed to be simple and flexible, making it adaptable to the needs of users (Walingkas & Saian, 2023).

2. Research Methods

2.1 Dataset

The data used in this research were obtained from the Academic Administration Bureau at the Asia Institute of Technology and Business Malang. The dataset includes frequently asked questions (FAQs) from students to the academic services and the corresponding responses from the academic services to these questions.

The dataset is categorized into several types of data, as follows:

- Operating Hours
- Study Plan Card
- Academic Calendar
- Study Results Card
- Graduation Procedure
- Examination Card
- Academic Leave
- Program Transfer
- Certification

This data was manually entered and stored in a file in JSON (JavaScript Object Notation) format. Examples of the JSON data structure can be seen in Figures 2.

```
{
"intents":
[{
    "tag" : "Salam",
    "patterns" : [
        "halo","hai","hola",
        "hello","hei",
        "hi","halo teman","halo acabot",
        "halo bot","permisi, halo",
        "apakah kamu ada?","halo bot, bisa ngobrol?",
        "bisa bicara?","permisi","selamat pagi",
        "selamat siang","selamat sore","selamat malam",
        "assamualaikum","shalom","apakah ini chatbot baa?"
    ],
    "responses" : [
        "Halo, Selamat datang di Chatbot BAA Institut Asia Malang, Saya dapat membantu kamu u
        "Haii!!, Apa yang anda butuhkan?",
        "Halo, Silahkan bertanya pada kami.",
        "Selamat datang di Chatbot Biro Administrasi Akademik Institut Asia Malang - Tim BAA"
    ]
},
```

Fig. 2. *JSON Data Structure*

The following data structure is present in the JSON file:

- Tag: Groups similar text data as target outputs during neural network (Purwitasari & Soleh, 2022).
- Patterns: A series of letters or a question expected to match the user's input (Padhilah et al., 2022).
- Responses: Contains responses provided by the chatbot to users.

2.2 Chatbot Design System

Figure 3 displays the Chatbot System Design.

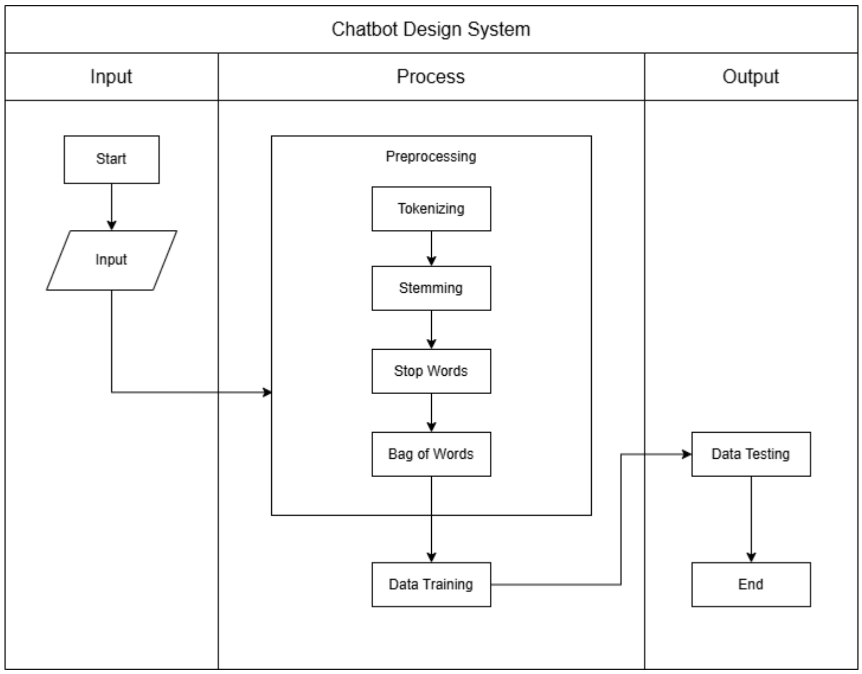

Fig. 3. Chatbot Design System

The chatbot system design in the diagram shows a structured flow for building a chatbot based on Natural Language Processing (NLP) techniques. The design of the system comprises three main components: Input, Process, and Output. The flow begins with the Input stage, where the user provides data in the form of text. This data then undergoes tokenizing, stemming, and stop words removal processes. A bag of words represents the outcome of these processes.

The system then moves on to the training data phase, where it uses the processed dataset to train the artificial intelligence model. The goal of this process is for the chatbot to learn patterns from the data and generate appropriate responses based on the user's input. The next step involves testing new data against the trained model to assess the system's performance and accuracy. If the testing results are satisfactory, the system produces output in the form of a response relevant to the user's input. Ultimately, the chatbot provides an appropriate response, and the process ends.

This flow illustrates a systematic approach to building a chatbot, with a focus on effective text data processing to achieve optimal performance. Through this process, the chatbot system can better understand user input and respond accurately.

2.3 Data Preprocessing

A crucial step in preparing raw text data for further analysis is the data preprocessing stage, which ensures the cleaning, standardization, and formatting of the data to make it compatible with machine learning models. This process transforms text data into a structured and usable form, facilitating better understanding and response generation by the chatbot system. The primary steps involved in data preprocessing are:

- Tokenizing
  Tokenizing is a process of providing a sequence of characters and a defined unit of a document (Rianto et al., 2024). This is significant because, in many natural language processing tasks, the relationship between words in a sentence is not always immediately relevant. By analyzing each word separately, the model can better recognize patterns and learn from them. Tokenizing enables the model to concentrate on examining the relevance and presence of each word in the dataset, which helps it discover word correlations and relationships for further processing steps. Here are the results of the tokenization process.

Fig. 4. Tokenizing Result

- Stemming
  Stemming is one method used for upgrading performance summary text with the method transforming the words in a module learning to the basics for then the base word is given weight to achieve aim summary text that can represent the whole from the document original (Sulistyo et al., 2023; Tuhpatussania et al., 2022). For example, the terms "running," "runner," and "ran" all stem from the term "run." By combining related terms into a single representation, this phase helps to simplify the language and facilitates the processing of information by the machine learning model. Because stemming enables the model to interpret several word forms (such as the past tense and plural) as the same root word, it is very helpful in natural language processing. This makes the dataset simpler, lowers the dimensionality, and helps concentrate on the words' essential meaning rather than their particular grammatical forms. Here are the results of stemming process (Ashari et al., 2024).

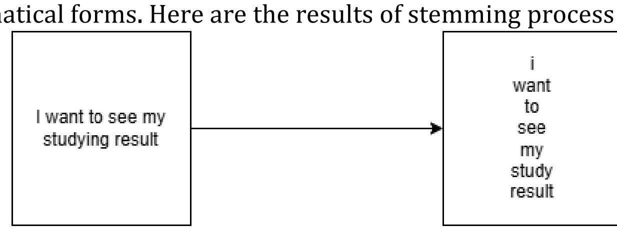

Fig. 5. Stemming Result

- Stop Words Removal
  The stop words removal will remove common words that usually appear in large quantities and are considered to have no significant meaning (Santosa et al., 2022). In this case, punctuation marks like "?", ".", and "!" are the stop words that are disregarded. In many NLP applications, these punctuation marks don't give more information about the meaning or context of the surrounding words, even though they are crucial in the context of a sentence. The stop words removal stage eliminates these punctuation signs to reduce data complexity and enable the model to focus on more relevant words. Here are the results of the stop words removal process.

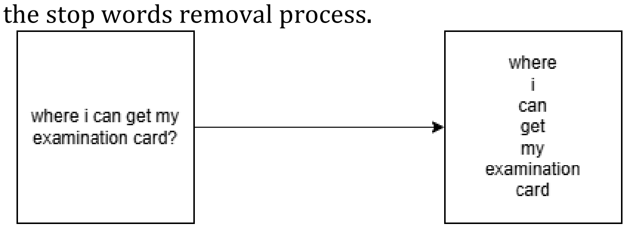

Fig. 6. Stop Word Removal Result

- Bag of Words
  By disregarding syntax and word order, the Bag of Words (BoW) model represents text data as a collection of words and their frequency in a document or corpus. This method treats each word in the text as a feature, noting its frequency of appearance.

In order for machine learning algorithms to comprehend the data, the BoW model converts the language into a numerical representation. The BoW model assigns a distinct index to each word in the text and counts its frequency or existence. A vector representing the frequency of words throughout all text data is the final product. The stop words removal stage of Natural Language Processing (NLP) aims to eliminate words deemed unimportant for analysis or providing little information.

3. Result and Discussion

3.1 User Testing

User testing was conducted to evaluate user satisfaction in utilizing this academic service chatbot. The testing involved distributing a questionnaire designed to measure the level of comfort, effectiveness, and accuracy of the chatbot's responses to user inquiries. The questionnaire was shared with students of the Asia Institute of Technology and Business Malang as the primary target users.

3.1.1 User Testing Result

From the user testing conducted, 37 students from various years and departments at the Asia Institute of Technology and Business Malang provided feedback regarding their experience interacting with the chatbot. A Likert scale with values ranging from 1 to 5 represents the responses from the participants to the 15 questions in the questionnaire or survey. Here are the descriptions for the Likert scale.

Table 1. Likert Scale

Description	Value
Very Poor	1
Poor	2
Average	3
Good	4
Verry Good	5

3.1.2 Validity Testing

Validity testing serves as a measurement tool to ascertain the validity of the data under examination. If the results exhibit a high level of validity, it indicates that the data accurately measures its intended purpose. High validity guarantees the relevance, reliability, and trustworthiness of the data in drawing accurate conclusions.

item2	Pearson Correlatio	,661**
	Sig. (2-tailed)	0,000
	N	37
item3	Pearson Correlatio	,917**
	Sig. (2-tailed)	0,000
	N	37
item4	Pearson Correlatio	,834**
	Sig. (2-tailed)	0,000
	N	37
item5	Pearson Correlatio	,815**
	Sig. (2-tailed)	0,000
	N	37
item6	Pearson Correlatio	,886**
	Sig. (2-tailed)	0,000
	N	37
item7	Pearson Correlatio	,823**
	Sig. (2-tailed)	0,000
	N	37
item8	Pearson Correlatio	,860**
	Sig. (2-tailed)	0,000
	N	37
item9	Pearson Correlatio	,898**
	Sig. (2-tailed)	0,000
	N	37
item10	Pearson Correlatio	,823**
	Sig. (2-tailed)	0,000
	N	37
item11	Pearson Correlatio	,848**
	Sig. (2-tailed)	0,000
	N	37
item12	Pearson Correlatio	,867**
	Sig. (2-tailed)	0,000
	N	37
item13	Pearson Correlatio	,826**
	Sig. (2-tailed)	0,000
	N	37
item14	Pearson Correlatio	,908**
	Sig. (2-tailed)	0,000
	N	37
item15	Pearson Correlatio	,706**
	Sig. (2-tailed)	0,000
	N	37
total	Pearson Correlatio	1
	Sig. (2-tailed)	
	N	37

Fig. 7 Validity Testing Result

The validity of the questions can be assessed by referring to the Significance column. If the value in the significance column is less than 0.05, it indicates that the questions are valid. Based on the results above, all 15 questions are valid. Another method of determining validity is by examining the Pearson Correlation column. If a star symbol appears in this column (indicating a value above 0.632), it signifies that all the questions are valid.

3.1.3 Reliability Test Results

The purpose of the reliability test is to evaluate the measurement tool's consistency under repeated testing conditions. A measurement tool is considered dependable if it consistently produces consistent results across multiple measurements. A validity test must precede the reliability test to ensure the data is reliable and accurately reflects the construct under assessment. In order to guarantee the dependability of the data for subsequent analysis, the reliability test helps ascertain whether the instrument can consistently measure the same parameter under similar conditions. The Cronbach's Alpha technique is used in the reliability test.

```
RELIABILITY
  /VARIABLES=item1 item2 item3 item4 item5 item6 item7 item8 item9 item10 item11 item12 item13
    item14 item15
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	37	100,0
	Excluded[a]	0	,0
	Total	37	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,965	15

Fig 8. Reliability Test Result

The reliability test's Cronbach's Alpha coefficient, which is significantly higher than the 0.6 threshold, was 0.965. Given that it shows consistency in measurement across multiple tests, this suggests that the study's questionnaire is extremely dependable. The outcome implies that the tool can yield consistent and reliable findings, which qualifies it for evaluating user satisfaction in this situation.

4. Conclusions

It can be inferred from the outcomes of the construction and testing of this chatbot utilizing an artificial neural network that:

- The Artificial Neural Network (ANN) Method's Use: The chatbot can effectively respond to customer inquiries with relevant and accurate responses thanks to the ANN approach. The chatbot can recognize patterns and provide responses that are contextually appropriate to the user's input by using preprocessed data throughout the training phase. According to the testing results, the chatbot's accuracy increases as the number of epochs increases, suggesting that the ANN model can adapt to different question types and produce reliable results.
- The findings of the validity and reliability tests showed that all of the examined questions had a high degree of validity, with significant values less than 0.05. This suggests that the data utilized in this study is both valid and reliable. Furthermore, the Cronbach's Alpha reliability test yielded a result of 0.965, above the cutoff value of 0.6, suggesting that the questionnaire employed to assess this chatbot is dependable and consistent. Therefore, we can rely on the testing data to objectively evaluate the chatbot's functionality.

All things considered, the outcomes of the validity, reliability, and ANN method tests demonstrate that this chatbot does a decent job of giving pertinent answers, which makes it helpful for supporting academic information services with a high enough degree of accuracy.

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