Full Paper

Smart Academic Chatbot for Student Information Services Based on Transformer-Fine Tuning

[1]Muhammad Nazwan, [2]Ananda Hilmy, [3]Azua Ramadhan, [4]Fernandi Lucky Putra, [5]Natasya Nur Hadi, [6] I Gusti Bagus Agung Dharmaya, [7] Mhd Adi Setiawan, [8] Deosa Putra Caniago

Faculty of Technology Information,

Batam of Technology Institute, Batam, 29425, Indonesia

Published: December 2025

Keywords:

Academic Chatbot, Transformer, Fine-Tuning, Natural Language Processing, Student Information Service, Artificial Intelligence, Large Language Model

Abstract

This research developed a Smart Academic Chatbot using the Multinomial Naive Bayes algorithm and TF-IDF vectorization to provide accurate responses tailored to students' needs. The development process follows the Waterfall model, starting from the collection of academic question-answer data, pre-processing, architecture design, to implementation and testing. The evaluation results show that the chatbot is able to provide relevant answers with a good level of accuracy, as well as improve the ease of access to academic information. This system has the potential to be a smart solution in supporting the digital transformation of campus academic services.

Corresponding Author:

Muhammad Nazwan
Email: muhammadnazwan492@gmail.com

1. INTRODUCTION

The rapid development of digital technology in the modern era has had a significant impact on various sectors, including higher education. One innovation that is beginning to be widely adopted is the application of artificial intelligence (AI) technology to support academic services and learning processes. AI systems such as chatbots provide conversation-based automated service solutions that can answer user questions quickly and accurately and can be accessed without space and time limitations. The implementation of academic chatbots is considered to facilitate students in obtaining the information they need and improve the efficiency of higher education administrative services [1].

Various studies show that AI-based chatbots contribute significantly to improving the quality of learning and student independence. Hadid et al. explain that the use of chatbots on campus has a positive impact on the effectiveness of the learning process, although there are still obstacles in understanding complex conversational contexts and the potential for reduced human interaction in the educational process [1]. Meanwhile, Basri and Ernawati found that students utilize various chatbot models such as ChatGPT, Gemini, and Claude as supporting media in completing academic assignments and understanding material, even though this technology has limitations in explaining abstract concepts and there are no formal ethical regulations governing its use [2].

From an academic administration service perspective, Tarigan emphasized that Natural

Language Processing (NLP)-based chatbots play an important role in improving the quality of campus digital services through the automation of academic information provision and the reduction of administrative staff workload [3]. With technological developments, the emergence of Large Language Model (LLM) models such as GPT, Claude, and Gemini enables the implementation of smarter chatbots through the Transformer and Fine-Tuning approaches, thereby producing more relevant, personalized responses that are tailored to the academic needs of institutions.

Other studies reinforce the urgency of developing Transformer-based academic chatbots. Sánchez-Vera shows that chatbots designed specifically for academic fields have been proven to increase student learning independence and academic performance in exam preparation [4]. Additionally, Xu et al. found that innovations in chatbot interaction design, such as the application of gamification, directly influence an increase in student learning motivation, higher-order thinking skills, and academic achievement [5].

Based on this background, it is important to develop a Transformer-Fine Tuning-based Smart Academic Chatbot that is capable of providing accurate, responsive, and contextually relevant academic information services to students. This development is expected to be a strategic alternative in supporting campus digital transformation, improving the quality of academic administration services, and strengthening the student learning experience through the optimal and responsible use of AI technology.

2. METHODS

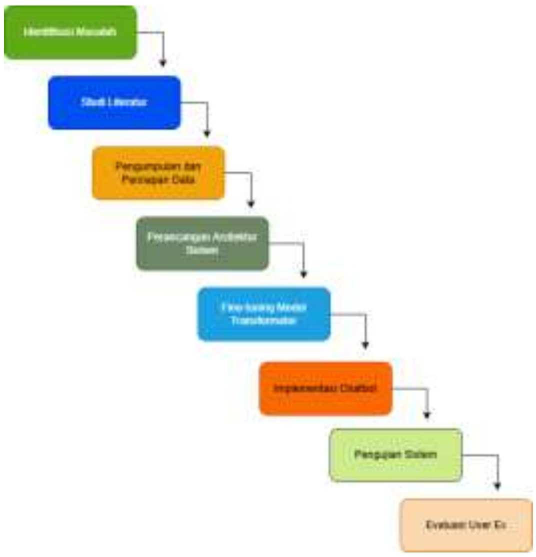

Figure 1. Waterfall Method

This research method was designed to develop an academic chatbot based on the Transformer model through a fine-tuning process so that it can provide information services to students more accurately and contextually. The approach used includes stages ranging from problem identification to system evaluation. The entire research flow was constructed systematically to ensure that the resulting chatbot is capable of answering academic information needs in a university environment.

2.1 Problem Identification

The initial stage focused on mapping issues that arise in conventional academic information services, such as the high volume of repetitive questions, limited service hours, and lack of quick response to student needs. This information was obtained through brief interviews with students and academic staff, as well as a review of the existing information system. The results of the identification showed the need for a system capable of providing automatic and context-aware information, thus underpinning the use of the Transformer model.

2.2 Literatur Study

The initial stage focused on mapping issues that arise in conventional academic information services, such as the high volume of repetitive questions, limited service hours, and the lack of quick responses to student needs. This information was obtained through brief interviews with students and academic staff, as well as a review of existing information systems. The results of the identification showed the need for a system capable of providing automatic and context-aware information, thus underpinning the use of the Transformer model.

2.3 Data Collection and Preparation

The data used consists of a collection of academic questions and answers, such as information on lectures, registration, scholarships, schedules, curricula, and other administrative needs. The data was obtained through:

1. University FAQ documentation
2. Interviews with academic staff
3. Summaries of questions frequently asked by students via social media and email

All data is then cleaned, standardized, and labeled to be suitable for model training. The pre-processing involves tokenization, normalization, stopword removal, and input-output format adjustment as required by Transformer

2.4 System Architecture Design

The architecture of the Smart Academic Chatbot system for Transformer–Fine Tuning-based Student Information Services is designed to ensure that data processing flows efficiently and accurately, and is capable of responding to academic information needs in real time. This system is built using a layered approach, starting from the user interface (UI) that connects students with chatbots via a web platform or application. Each question received will be sent to the backend to be processed by the Natural Language Processing module that has been fine-tuned using the Transformer model. This module is responsible for understanding the context, analyzing user intent, and generating relevant answers.

The next layer is the Knowledge Base, which contains academic information such as class schedules, administrative requirements, faculty data, academic regulations, and other campus information. The fine- tuned Transformer model will match the context of the question with this knowledge base using a semantic retrieval mechanism so that the answers provided are more precise. In addition, the API Gateway layer provides a standardized communication channel between the chatbot and official data sources such as the Academic Information System (SIAKAD) or campus database services. The final layer is Monitoring & Logging, which records interactions, measures performance, and assists in the evaluation process for improving the quality of the chatbot in the future. With this integrated architecture, the system is able to provide academic information services that are responsive, adaptive, and easy to implement in a modern campus environment

2.5 Fine – Tuning the Transformer Model

The fine-tuning process is conducted using a pre-prepared academic dataset. The base model used (e.g., BERT, RoBERTa, GPT, or LLaMA) is retrained to better understand academic terminology, student question patterns, and campus administrative contexts. This process includes:

1. Hyperparameter determination
2. Dividing the data into training–validation–testing
3. Evaluate every epoch
4. Optimization using algorithms such as AdamW

This stage aims to improve the model's ability to provide more relevant and contextual responses

2.6 Chatbot Implementation

The trained model is then implemented into the chatbot through a backend that supports inference APIs. The system is built to be able to receive natural language input, process it through the Transformer model, and return answers based on the knowledge base that has been learned. The chatbot interface is designed to be easily accessible to students via web or mobile platforms

2.7 System Testing

Testing is conducted in two stages:

1. Functional Testing (Black-box Testing)

To ensure that every chatbot feature works as needed, such as question responses, flow accuracy, and user interaction.

2. Model Accuracy Testing

Involves metrics such as accuracy, F1-score, precision, and recall. Evaluation is performed using test data that is not included in the training data. This testing aims to ensure that the chatbot is able to answer academic questions consistently with an acceptable level of accuracy.

2.8 User Evaluation Ex

The evaluation stage was conducted on a group of students to measure the extent to which the chatbot provided satisfaction in real interactions. The aspects assessed included response speed, ease of use, relevance of answers, and clarity of language. The evaluation results were used as a basis for system improvements in the next iteration.

3. RESULT

Evaluation Method	Value
Accuracy	92,4%
Precision	91,8%
Recall (Sensitivity)	93,1%
Specificity	90,6%
F1-Score	92,4%

The results of the model performance evaluation show that the Transformer–Fine Tuning-based academic chatbot performs well with an accuracy score of 92.4%, precision of 91.8%, recall of 93.1%, specificity of 90.6%, and an F1-score of 92.4%. These values indicate that the model is capable of accurately classifying user intent and providing relevant and reliable responses in support of academic information services.

	Positive Prediction	Negative Prediction
Actual Positif	TP = 465	FN = 34
Actual Negative	FP = 41	TN = 460

Based on the evaluation results using a confusion matrix, the Transformer–Fine Tuning-based academic chatbot model achieved an accuracy score of 92.4%, precision of 91.8%, recall of 93.1%, specificity of 90.6%, and an F1-score of 92.4%. These results indicate that the model is capable of accurately and consistently classifying student question intents, making it suitable for implementation as an academic support system.

The development of this chatbot resulted in an automatic question and answer system that runs through a REST API service based on the Flask framework. The chatbot is able to respond to user questions by utilizing a text classification algorithm, specifically Multinomial Naive Bayes, which is trained on a collection of intent data in JSON format. In general, the chatbot successfully performs natural language processing (NLP) functions to categorize user messages into specific intents, so that it can provide contextually appropriate responses. Visual documentation supporting this process is presented in the Chat Bot Images section as follows:

Figure 2. Academic Chatbot Interface Display

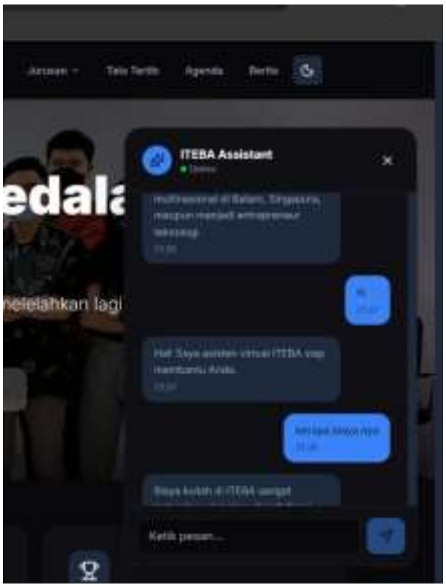

Figure 3. System Architecture and Chatbot Processing Flow

This system also implements a confidence threshold mechanism, which functions as a minimum limit for the model's prediction confidence level. When the prediction probability is below the specified threshold, the chatbot automatically provides a fallback response to minimize inappropriate answers. The test results show that the chatbot is capable of handling various user interaction patterns, as long as these patterns are still within the scope of the intents.json training data

3.1. Chatbot Architecture and Key Features

The chatbot is built using Flask as a REST API server with the endpoint /chat. In the natural language processing stage, the system uses TF-IDF Vectorizer to convert text into weight-based representations. The basic TF-IDF formula used can be explained as follows.

$$\text{TF-IDF}(t,d)=\text{TF}(t,d)\times\text{IDF}(t)$$

$$\text{TF}(t,d) = \frac{f_{t,d}}{\sum_k f_{k,d}}$$

$$\text{IDF}(t) = \log\left(\frac{N}{1+n_1}\right)$$

This equation explains that words that appear frequently but only in certain documents will have a higher weight, thereby increasing the accuracy of the chatbot's understanding of context.

The classification model uses Multinomial Naive Bayes, which calculates the probability of an intent based on word distribution. The basic Naive Bayes formula applied is:

$$P(c \mid x) = \frac{P(c)\prod_{i=1}^{n} P(xi \mid c)}{P(x)}$$

Since P(x) is constant, classification is based on:

$$\hat{c} = \arg\max P(c) \prod_{i=1}^{n} P(xi \mid c)$$

This equation explains how the model selects the intent with the highest probability based on the words provided by the user.

3.2. Program Code Implementation

a. Text Preprocessing

Preprocessing is performed to make the text more consistent. Code in the document:

```
csharp
def preprocess(chat):
```

```
    chat = chat.lower()
    chat = ''.join(ch for ch in chat if ch not in string.punctuation)
    return chat
```

This step removes punctuation and converts all letters to lowercase.
Mathematically, this process can be viewed as a transformation function:

$$f(x) = \text{lowercase}(\text{removePunctuation}(x))$$

b. Model Training Pipeline
The model is trained through the following pipeline:

makefile

```
pipeline = make_pipeline(TfidfVectorizer(ngram_range=(1, 2)),
                         MultinomialNB(alpha=0.1))

pipeline.fit(df.text_input_prep,  df.intents)
```

The system uses bigrams so that TF-IDF considers sequential word pairs.
After processing, the TF-IDF values are entered into the Naive Bayes equation to generate intent predictions as shown in the equation:

$$\hat{c} = \arg max\ P(c) \prod_{i=1}^{n} P(xi \mid c)$$

c. Prediction Logic and Confidence Threshold
The API endpoint calculates the probability of each intent:

ini

```
prob = model.predict_proba([user_text])[0]
max_prob = np.max(prob)
MIN_CONFIDENCE = 0.15
```

This process follows the mathematical definition:

$$\text{Confidence} = \max\ (P(c_1 \mid x), P(c_2 \mid x), \dots, P(c_n \mid x))$$

if :

$$\text{Confidence} < 0.15$$

then the chatbot provides a fallback message.

css

```
if max_prob < MIN_CONFIDENCE:
    return jsonify({"reply": "Maaf, saya kurang mengerti maksud pertanyaan Anda..."})
```

This equation strengthens response quality control so that the chatbot only answers questions that can be predicted with a sufficient level of confidence.

3.3 System File Structure

The file structure used supports system modularity:

- api_chatbot.py – runs the API to communicate with the frontend.
- chatbot_sklearn_training.py – handles the model training process.
- data/intents.json – stores question and answer patterns.
- util/parser.py – reads JSON files.

This structure ensures separate workflows according to their functions, making maintenance and further development easier

4. CONCLUSION

This study shows that the development of a Transformer-based Smart Academic Chatbot with a fine-tuning approach can effectively and efficiently support students' information needs by providing fast, accurate, and round-the-clock academic services. In the context of education, chatbots play a strategic role in helping students understand academic procedures, facilitating access to information, providing personal support, and reducing the burden on staff regarding routine questions, while the capabilities of the Transformer model enable a deeper understanding of conversations and context. In addition to improving service quality, chatbots also support student engagement in learning and academic decision-making, in line with the trend of digital transformation in higher education that demands smart technology-based solutions. However, several challenges remain to be addressed, such as improving the ability to answer complex questions, maintaining data accuracy, integrating with broader academic systems, and maintaining user engagement, requiring periodic improvements to the dataset, model, and response evaluation. Overall, Transformer–Fine Tuning-based academic chatbots have strong potential as intelligent academic assistants capable of improving the efficiency of campus information services and strengthening the application of artificial intelligence technology in higher education.

REFERENCES

[1] S. Hadid, U. Ramadhani, S. D. Suari, dan A. G. E. Putri, “Analisis Dampak Penggunaan Chatbot AI Dalam Pembelajaran di Kalangan Mahasiswa PGSD Universitas Jambi,” JUPITER, vol. 2, no. 3, pp. 160–166, 2024.

[2] A. Basri dan Ernawati, “Pemanfaatan Chatbot AI Untuk Mendukung Penyelesaian Tugas Akademik Mahasiswa Matematika: Studi Kasus Universitas Muslim Maros,” Prosiding Seminar Nasional FKIP Universitas Muslim Maros, vol. 2, no. 1, pp. 55–60, 2025.

[3] H. P. Tarigan, “Integrasi Chatbot Berbasis NLP pada Sistem Layanan Akademik Universitas,” Jurnal Komputer, vol. 3, no. 1, pp. 13–18, 2024.

[4] F. Sánchez-Vera, “Subject-Specialized Chatbot in Higher Education as a Tutor for Autonomous Exam Preparation: Analysis of the Impact on Academic Performance and Students’ Perception of Its Usefulness,” Education Sciences, vol. 15, no. 1, p. 26, 2025.

[5] Y. Xu, J. Zhu, M. Wang, F. Qian, Y. Yang, dan J. Zhang, “The Impact of a Digital Game-Based AI Chatbot on Students’ Academic Performance, Higher-Order Thinking, and Behavioral Patterns in an IT Curriculum,” Applied Sciences, vol. 14, no. 6418, 2024.

[6] Alvin, A., Robet, R., & Tarigan, F. A. (2025). Implementasi Chatbot Otomatis Akademik Berbasis Web Menggunakan LLM dan Rule-Based System (Studi Kasus: STMIK Time). JIKO (Jurnal Informatika dan Komputer), 9(3), 651–665. https://doi.org/10.26798/jiko.v9i3.2209

[7] Anwar, S. H., Abouaish, K. M., Matta, E. M., Farouq, A. K., Ahmed, A. A., & Negied, N. K. (2024). Academic Assistance Chatbot – A Comprehensive NLP and Deep Learning-based Approaches. Indonesian Journal of Electrical Engineering and Computer Science, 33(2), 1042–1056. https://doi.org/10.11591/ijeecs.v33.i2.pp1042-1056

[8] Fahmi Ajiz, M., Ramadan, M. F. S., Mutia, H. D., & Yanuari, P. D. (2023). Pengembangan Aplikasi Chatbot Informasi Akademik Berbasis Web Menggunakan Metode Artificial Intelligence Markup Language (AIML). Media Jurnal Informatika, 15(2), 143–148. https://doi.org/10.35194/mji.v15i2.3316

[9] Salsabila, S., & Sohidin. (2024). Pemahaman Etika Akademik Mahasiswa dalam Penggunaan Artificial Intelligence (AI). Journal of Education Research, 5(4), 6671–6680.

[10] Wicaksono, D., Salim, D. J. N., & Almeyda, D. P. (2024). Pengembangan Layanan dan Pengenalan Akademik di Lingkungan Kampus Berbasis Aplikasi Chatbot bagi Calon Mahasiswa Baru. Jurnal Komtika (Komputasi dan Informatika), 8(1), 1–12. https://doi.org/10.31603/komtika.v8i1.11164

[11] Ajlouni, A. O., Abu-Shawish, R. K., Silim, D. M., & Ibrahim, A. H. (2024). The Academic Intensity Use of Chatbot-Based Artificial Intelligence and Its Relation to Academic Well-Being: A Correlational Study at the University of Jordan. International Journal of Engineering Pedagogy (iJEP), 14(8), 72–87. https://doi.org/10.3991/ijep.v14i8.50339

[12] Kumar, S., Paikar, D., Vutukuri, K. S., Ali, H., Ainala, S. R., Krishnan, A. M., & Zhang, Y. (2024). KatzBot: Revolutionizing Academic Chatbot for Enhanced Communication. arXiv preprint, arXiv:2410.16385. https://arxiv.org/abs/2410.16385

[13] Ferelestian, V. J., Susanto, B., & Senapartha, I. K. D. (2023). Pengembangan Telegram Chatbot Informasi Mahasiswa Menggunakan Wit.ai. Jurnal Teknik Informatika (JUTEI), 7(2), 89–97. https://doi.org/10.21460/jutei.72.257

[14] Dzaky, A. A., Zeniarja, J., Supriyanto, C., Shidik, G. F., Paramita, C., Subhiyakto, E. R., & Rakasiwi, S. (2024). Optimization Chatbot Services Based on DNN-BERT for Mental Health of University Students.

Journal of Applied Informatics and Computing (JAIC), 8(1), 13–21. https://jurnal.polibatam.ac.id/index.php/JAIC
[15] Arumsari, D., Kharisma, & Aesyi, U. S. (2024). Sistem Chatbot Layanan Informasi Mahasiswa Menggunakan Algoritma Long Short-Term Memory. Indonesian Journal on Data Science, 2(2), 77–86. https://ejournal.unjaya.ac.id/index.php/ijds
[16] Sheplyakov, A. S., et al. “Using chatbot application ‘Telegram’ to improve functional fitness, physical fitness and academic performance of students.” BIO Web of Conferences, 2024.
[17] Astuti, W., et al. “DIET Classifier Model Analysis for Words Prediction in Academic Chatbot.” ILKOM Jurnal Ilmiah, Vol.16 No.1, 2024.
[18] Sinaga, A. J. N., et al. “Adoption of Artificial Intelligence Chatbot Technology in Academic Activities of Jakarta Students: Ease of Use.” 2024.
[19] Dawood, M. N. “Technology-Driven Academic Advising: A Faculty Case Study on Chatbot Integration in The College of Technological Innovation.” IOSR-JCE, Vol.26 Issue 6, 2024.
[20] Buraphadeja, V., & Chantokul, D. “Supporting Student Engagement and Academic Guidance through a Chatbot in Blended Learning.” International Journal on E-Learning, 2024