Chatbot for Complex Questions in University Admission using Bidirectional Long-Short Term Memory and Convolutional Neural Network

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Abstract*—Petra Christian University already has services to answer questions about new student admissions through WhatsApp, email, and Instagram. However, given the many inquiries, not all can be answered quickly, especially the complex and lengthy questions. There has been much research on chatbots for new student admissions, but the chatbots developed have not yet examined how well they can answer complex and lengthy questions. Therefore, this research will contribute by investigating how accurately the chatbot can answer short, medium, and long questions using Bidirectional Long-Short Term Memory and Convolutional Neural Network methods. The results show that the chatbot can answer short questions with the highest accuracy of 93%, but its accuracy drops below 80% when given medium and complex questions.

***Keywords*—chatbot, university admission, artificial intelligence, bidirectional long-short term memory, convolution neural network**

I. INTRODUCTION

Petra Christian University (PCU) offers several services to facilitate prospective students, parents, and the general public's acquisition of information about the university. These services include the university website, social media such as Instagram, which provides general information, and chat services with university staff via WhatsApp, email, and phone. However, obtaining information through chat services with staff takes considerable time. Therefore, a chatbot is needed to address this issue.

Previous research related to university admissions includes that conducted by Santoso H.A. et al. [1]. This study developed a web-based chatbot named Dinus Intelligent Assistance to serve prospective student inquiries using a dataset from the university guestbook. The method used was machine learning. Out of 10 questions, 8 were answered correctly, but the difficulty level was not specified. Presetya, M.R.A., and Prayitno, A.M. [2] developed a chatbot to handle student inquiries based on NLP using the TF-IDF method to assist customer service in answering questions from new students at Pahlawan Tuanku Tambusai University. The results obtained were a recall rate of 100% and a precision rate of 76.92%. Sakulwichitsintu, S. [3] developed a ParichartBOT chatbot to answer questions from master's degree students at Sukhothai Thammathirat Open University (STOU). This chatbot was developed using Agile principles. The participants were 24 master's degree students at STOU. Tommy, L. et al. [4] developed an Android-based chatbot for students to access academic information at ISB Atma Luhur. They used UML (Unified Modeling Language) with an NLP (Natural Language Processing) algorithm and entity extraction methods. The result was that students no longer had to zoom in and out on their phone screens. Hefny et al. [5] developed a bilingual chatbot named Jooka. This chatbot was designed to answer questions from high school graduates intending to enter university with a specific bilingual demographic target. Hence, the chatbot was designed to accept questions in both English and Arabic. Surveys were conducted among students and parents. The system can help significantly increase the number of admissions and the willingness to adopt new technology. Jhaerol, M.R., and Sudianto S. [6] developed a chatbot for the Merdeka Belajar Kampus Merdeka (MBKM) program aimed at students at Telkom Institute of Technology Purwokerto (ITTP). The method used was Deep Learning Long Short-Term Memory (LSTM). The precision, recall, and F1-score results were all 100%, but how the testing was conducted was not explained. Sarker, K.C., Rahman, M.M., and Siam A. [7] implemented an A.I. language-based chatbot using machine learning algorithms, including Logistic Regression (L.R.), Decision Tree (D.T.), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multinomial Naive Bayes (MNB). The chatbot model was used for the new student admission process, and it could answer prospective students' questions in English, Bengali, and Anglo-Bala. The Naive Bayes algorithm achieved the highest accuracy of 99.64%. [8]. Gbenga, O., Okedigba, T.O., and Oluwatobi, H. developed a chatbot model to handle admission inquiries using the IBM Watson artificial intelligence platform, achieving an accuracy of 95.9%. Aloqayli, A., & Abdelhafez, H.A. [9] developed an admission chatbot using the Naïve Bayes method, measured with a Confusion Matrix, and tested by 42 students from Princess Nourah University. The chatbot's accuracy was 91%. Atmauswan, P.S., & Abdullahi, A.M. [10] developed a chatbot for students interested in university enrollment using a dataset of frequently asked questions from students using Natural Language Processing. Nguyen, T.T., Le, A., Hoang, H., & Nguyen, T. [11] introduced an AI-based chatbot for prospective students at the National Economics University in Vietnam using Deep Learning integrated within the RASA framework, achieving an accuracy of 97.1%. Alabbas, A., & Alomar, K. [12] developed an Arabic-language chatbot named Tayseer based on artificial intelligence using the Rasa framework to bridge communication between students and the Technical College for Girls in Najran (TCGN). Tayseer identified 50 types of questions with 90% precision.

Fiddin, F.Y., Komarudin, A., & Melina, M. [13] researched chatbots using FastText as a text classification model and LSTM. The chatbot was used at the Faculty of Science and Informatics (FSI) at Jenderal Achmad Yani University (UNJANI) to provide new student admission services. Nguyen, M., Tran-Tien, M., Viet, A.P., Vu, H., & Nguyen, V. [14] developed a chatbot to support admissions at colleges in Vietnam using the RASA platform and an admissions dataset for bot training. To provide information on new student admissions at Indo Global Mandiri University, Heryati, D., Ir. Zulkifli, M., Fajri, R.M. [15] created a chatbot using deep learning and an artificial neural network model, tested with 15 conversations, achieving an accuracy of 86%. To facilitate students in obtaining information about courses and new student admissions, Prabha M. et al. [16] developed a chatbot that automatically answers student inquiries using artificial intelligence. To replace the IVR (Interactive Voice Response) system, Stepanov, M.S., Popov, V., & Fedorova, N. [17] conducted a comparative analysis of chatbots for admissions at universities and colleges in Russia, including Multichat, Webim, and Jivo. They successfully identified functional requirements for future development. To support the new student admission process at Cokroaminoto University of Palopo, Hamzah, M.A., Siaulhak, S., Iriansa, I., Jumardi, A., & Aman, A. [18] developed an artificial intelligence-based chatbot using the waterfall method. The expected result is an increase in the efficiency and quality of new student admission services at Cokroaminoto University of Palopo. To reduce the necessity for students to come to campus for information, Khan, Z.M., Rehman, H.U., Maqsood, M., & Mehmood, K. [19] built a university chatbot using machine learning algorithms, including Decision Tree, Random Forest, and Support Vector Machine. The result showed that Random Forest had the best performance. Pansombut, S. and Kirimasthong, K. aimed to study the development of a chatbot to answer questions about student admissions at Mae Fah Luang University (MFU) [20]. They successfully conducted a comparative analysis based on the format, structure, algorithms, and functions of the chatbot for creating a chatbot for prospective students.

From the previous research studies, it can be concluded that almost all papers focus on developing chatbots to help students, especially prospective new students, obtain information quickly without waiting for direct answers from authorities. However, their focus, methods, and success rates vary. Some conducted only comparisons and analyses [18], [20], some were only in the design phase [3], [10], [18]. Others focused on bilingual chatbots [5]. Some did not develop from scratch but used frameworks like RASA [11], [12], [14]. Some used cloud-based A.I. services, such as Watson [8]. Many used machine learning, A.I., and NLP methods [1]-[2], [3], [6]-[7], [9]-[10], [13], [15]-[16], [19]. Several used the LSTM machine learning algorithm [6], [13]. Many reported accuracy results [1]-[3], [6]-[9], [11]-[12], [15], while others mentioned more qualitative results [5], [13]-[14], [18].

However, none of the previous research has attempted to investigate the complexity level of the questions. Unlike previous papers, this study contributes to and fills the research gap by evaluating the complexity level of questions, ranging from short, medium, and long/complex questions. This study will experiment to determine how well the chatbot can answer questions from these three categories. The methods used are BiLSTM and CNN, which are used to determine which of the two methods yields higher accuracy.

II. Methods

A. Dataset

The data used in this study consists of a list of questions and answers related to new student admissions information at Petra Christian University. The dataset is stored in Excel format (.xlsx). This dataset consists of 1088 questions and 2 types of related answers for each question. The structure of the dataset can be seen in Figure 1. From the figure, it can be observed that there are 3 columns: the first column shows the question, and the second and third columns show answer 1 and answer 2.

	A	B	C
1	Pertanyaan	Jawaban 1	Jawaban 2
2	apa ada japres?	Kami masil	Jalur prestas
3	uang gedung/uang pangkal jurusan IBM berapa ya?	Jadwal adr	Untuk uang
4	uang semester apa sama dengan uang sks?	Info biaya	Untuk biaya
5	cara pembayaran uang gedung?	Info biaya	Cara pemba
6	cara pembayaran uang semester,uang sks.	Info biaya	Cara pemba
7	biaya pendaftaran	Cara pemb	Cara pembe
8	Informasi pendaftaran untuk Program Studi Bahasa Mandarin	Pembelian	Informasi pe
9	Jalur pendaftaran Sastra Tionghoa	Jadwal dar	Jalur pendaf
10	ini cara login di sim petra gimna yah?	Langkah D	Cara login di

Fig. 1. Example of Dataset

The dataset contains 1088 questions, but each has two types of answers. Each question will be duplicated in the initial data-loading stage to accommodate both answers. However, some questions in the dataset do not have answers and must be removed. The final total data obtained is 1962 questions and answers, with 1028 labels for the answers.

B. Questions and Answers

In this section, the questions and answers to be used for model testing will be explained, the system flow to be utilized will be described, the preprocessing methods to be employed will be detailed, the optional settings during testing will be specified, and the development of the chatbot model will be outlined.

The chatbot testing was conducted using a set of questions and answers obtained from two sources. The first source of questions is derived from the original dataset. These questions include short, medium, and long questions. Short questions have an average of 2-3 words, comprising 15 questions. Medium questions have an average of 4-7 words, comprising 15 questions. Long questions have an average of 8 words or more, comprising 15 questions.

The second source of questions and answers was created by following the rules for all 3 types of questions from the original dataset. These questions include short, medium, and long questions. Short questions have an average of 2-3 words, comprising 20 questions. Medium questions have an average of 4-7 words, comprising 20 questions. Long questions have an average of 8 words or more, comprising 20 questions.

C. System Flow

Figure 2 shows the chatbot flowchart. The system will wait for input from the user. Once the user submits a question, the system will process the question through text preprocessing. During this process, the question will undergo various preprocessing stages. After preprocessing, the data will proceed to the question clustering stage using the k-Means algorithm. At this stage, questions with similar features will be grouped into clusters to help the model handle false predictions. After clustering, each data point will go through the word embedding process. In this stage, feature extraction will be performed on the data, converting the original string format into numerical form that the computer can understand. Once complete, the data will be fed into the candidate models: Bidirectional Long-Short Term Memory (BiLSTM) or Convolutional Neural Networks (CNN). The best model will provide the final answer to the user's question.

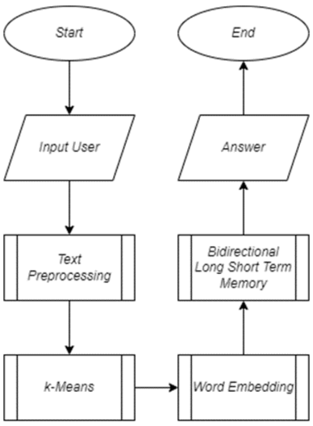

Fig. 2. System flowchart

D. Text Preprocessing

The preprocessing methods include lower casing, tokenization, stemming, and stopword removal. Lower casing is an important step to prevent data duplication due to differences in capitalization. Tokenization is a crucial step in converting sentences into separate words. Stemming is an important step in the preprocessing process, transforming inflected words into their root forms. The stemming can reduce the number of unique, less meaningful data points. Stopword removal is the stage where words without significant meaning are eliminated, and it ensures that the final data obtained is meaningful. The optional setting used is k-Means clustering. K-Means is optional to check whether text clustering impacts the candidate model's performance improvement.

E. Word Embedding

In Figure 3, the process of word embedding is explained. The types of word embeddings used in this research are Bag of Words (BoW), Word2Vec (W2V), and GloVe. The pre-trained GloVe model represents each word with a 50-dimensional vector. Testing is conducted using the average vector value, minimum vector value, maximum vector value, and the entire vector values as its word embeddings. The W2V methods employed are W2V Continuous BoW (CBoW) and W2V SkipGram. Additionally, the BoW Unigram is used.

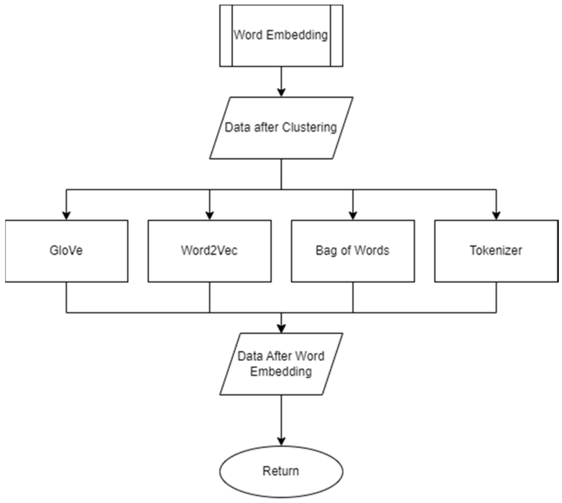

Fig. 3. Word Embedding

F. Deep Learning

The deep learning models used are the BiLSTM and the CNN models. The BiLSTM uses 2 LSTM layers arranged into a BiLSTM layer and 1 dense layer. The Convolutional Neural Network model will use 3 convolutional 1D layers and 1 dense layer.

III. EXPERIMENTAL RESULTS

This section investigated the combination of k-Means clustering, several word embeddings and deep learning models.

A. Type of Testing

The testing is conducted using several types of tests, and the complete list of their numbers can be seen in Table 1.

TABLE 1. LIST OF TYPES

Type	Model
1	Tokenizer with Splitting Data without Stopwords
2	Tokenizer with Splitting Data using Stopwords
3	Tokenizer with Splitting Data without Stopwords
4	GloVe Mean with Splitting Data without Stopwords
5	GloVe Mean with Splitting Data and Stopwords tidak Dihilangkan
6	GloVe Min with Splitting Data without Stopwords
7	GloVe Max with Splitting Data without Stopwords
8	GloVe Full without Splitting Data without Stopwords
9	Word2Vec CBOW Window=5 & Min_Count=1 with Splitting Data without Stopwords
10	Word2Vec CBOW Window=5 & Min_Count=2 with Splitting Data without Stopwords
11	Word2Vec CBOW Window=10 & Min_Count=1 with Splitting Data without Stopwords
12	Word2Vec CBOW Window=10 & Min_Count=2 with Splitting Data without Stopwords
13	Word2Vec SkipGram Window=5 & Min_Count=1 with Splitting Data without Stopwords
14	Word2Vec SkipGram Window=5 & Min_Count=2 with Splitting Data without Stopwords
15	Word2Vec SkipGram Window=10 & Min_Count=1 with Splitting Data without Stopwords
16	Word2Vec SkipGram Window=10 & Min_Count=2 with Splitting Data without Stopwords
17	Bag of Words Unigram with Splitting Data without Stopwords
18	k-Means Tokenizer with Splitting Data without Stopwords
19	k-Means Tokenizer with Splitting Data and Stopwords tidak Dihilangkan
20	Word2Vec CBOW k-Means Window=5 & Min_Count=1 with Splitting Data without Stopwords
21	Word2Vec CBOW k-Means Window=5 & Min_Count=2 with Splitting Data without Stopwords
22	Word2Vec CBOW k-Means Window=10 & Min_Count=1 with Splitting Data without Stopwords
23	Word2Vec CBOW k-Means Window=10 & Min_Count=2 with Splitting Data without Stopwords
24	Word2Vec SkipGram k-Means Window=5 & Min_Count=1 with Splitting Data without Stopwords
25	Word2Vec SkipGram k-Means Window=5 & Min_Count=2 with Splitting Data without Stopwords
26	Word2Vec SkipGram k-Means Window=10 & Min_Count=1 with Splitting Data without Stopwords
27	Word2Vec SkipGram k-Means Window=10 & Min_Count=2 with Splitting Data without Stopwords
28	Tokenizer CNN with Splitting Data without Stopwords
29	Tokenizer CNN Without Splitting Data without Stopwords
30	Word2Vec SkipGram Window=5 & Min_Count=2 CNN with Splitting Data without Stopwords
31	Word2Vec SkipGram Window=5 & Min_Count=2 CNN 3 Layer without Splitting Data without Stopwords
32	Word2Vec SkipGram Window=5 & Min_Count=2 CNN 2 Layer without Splitting Data without Stopwords
33	Word2Vec SkipGram Window=5 & Min_Count=2 CNN 1 Layer without Splitting Data without Stopwords
34	Word2Vec SkipGram Window=5 & Min_Count=2 BiLSTM without Splitting Data without Stopwords
35	GloVe Full CNN without Splitting Data without Stopwords
36	GloVe Full CNN with Splitting Data without Stopwords
37	GloVe Full with Splitting Data without Stopwords

B. Performance Testing

This section investigated the combination of K-means clustering, several word embeddings and deep learning models. Some of the best combinations can be seen in Table 2. In Table 2, there is a column for experiment codes; their corresponding test types are listed in Table 1.

TABLE 2. THE SETTING OF SEVERAL BEST COMBINATIONS OF CLUSTERING, WORD EMBEDDINGS AND DEEP LEARNING MODELS

Experiment Code	K-means Clustering	Word-Embedding				DL Model	
		BoW Unigram	W2V CBoW	W2V SkipGram	GloVe	BiLSTM	CNN
9/BiLSTM			✓			✓	
10/CNN			✓				✓
13/ BiLSTM				✓		✓	
14/ CNN				✓			✓
20/ BiLSTM	✓		✓			✓	
25/ BiLSTM	✓			✓		✓	
28/ CNN		✓					✓
30/ CNN				✓			✓
37/ CNN					✓		✓

The testing is conducted using 2 datasets. The first dataset, dataset I, utilizes the original dataset consisting of 1088 questions and answers. Dataset II employs an updated set of questions, totalling 1962 questions and answers, as explained in the Methods section. The difference between dataset 1 and dataset 2 is that dataset 2 includes many new data representing short questions (2-3 words), medium questions (4-7 words), and long questions (8 words or more), allowing the model to learn further.

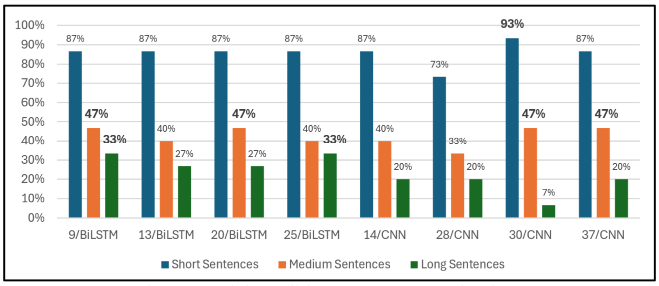

Fig. 4. Model candidates' accuracy to the dataset I

Figure 4 for dataset I shows that all tests yield high accuracy for short questions, whether with BiLSTM or CNN. The highest accuracy is achieved in test 30/CNN with 93%, whereas for BiLSTM, all tests have 87% accuracy. However, for medium questions, both BiLSTM and CNN show a decrease in accuracy to 47%. on 9/BiLSTM, 20/BiLSTM, 30/CNN, and 37/CNN. Meanwhile, the BiLSTM method yields higher accuracy for long questions than CNN, specifically in tests 9/BiLSTM and 25/BiLSTM, with 33% accuracy. The CNN method only achieves a maximum accuracy of 20% for tests 14/CNN, 28/CNN, and 37/CNN.

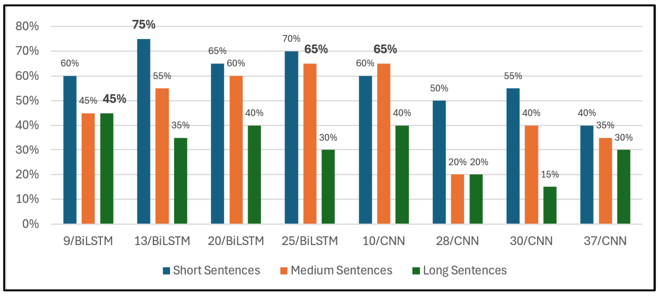

Fig. 5. Model candidates' accuracy to the dataset II

Figure 5 for dataset II shows that for short questions, the maximum accuracy is 75%, obtained from test 13/BiLSTM. In comparison, the CNN method only achieves a maximum accuracy of 55% for short questions obtained from test 30/CNN. For medium questions, the highest accuracy is obtained from the BiLSTM test, at 65% for test 25/BiLSTM, and from the CNN test for test 10/CNN. For long questions, the highest accuracy is obtained from test 9/BiLSTM with 45% accuracy, while the CNN test only manages to achieve 40% accuracy from test 10/CNN.

From the comparison of tests with dataset I and dataset II, for short questions, the accuracy result from dataset I is 93%, higher than the accuracy of tests with dataset II, which is only 75%. However, for medium questions, the testing result using the updated dataset II obtained a higher result of 65% compared to the testing with dataset I, which only reached 47%. A similar outcome is obtained from testing with long questions, with the highest testing result for dataset II reaching 45%, compared to testing with dataset I, which only reached a maximum of 33%. By improving the dataset, higher accuracy results are obtained for medium and long question types.

IV. CONCLUSIONS

The highest training and testing accuracy was 93% for dataset 1 with short questions. This result was obtained from testing the CNN with W2V SkipGram. The chatbot accuracy for medium and long questions on the dataset I was low, below 50%, specifically 47% for medium questions and 33% for long questions, using the BiLSTM method. The low accuracy was due to the lack of diverse data in the model training process. Another reason was the numerous typos in the dataset that the program could not yet address.

However, the accuracy of medium and long questions is increased using the updated dataset II. 65% Accuracy for medium questions is achieved by the BiLSTM method with W2V SkipGram combined with k-Means clustering and CNN with W2V CBoW. Similarly, for long questions with dataset II, the accuracy increased to 45% using the BiLSTM method with W2V CBoW. To improve the accuracy of medium and long questions, a suggestion for future research is to use LLM (Large Language Model) to understand and generate human-like language.

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