Received: 4 January 2023 | Revised: 9 May 2023 | Accepted: 9 June 2023 | Published online: 25 June 2023

RESEARCH ARTICLE

Artificial Intelligence and Applications
2024, Vol. 2(2) 140–148
DOI: 10.47852/bonviewAIA3202631

University Auto Reply FAQ Chatbot Using NLP and Neural Networks

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Abstract: When new students enter college, they often have similar questions – "Where to study for this subject?," "How to prepare Data Structures and Algorithms?," "How to connect with seniors?," and so on. The use of chatbots can help them get answers to their questions quickly and efficiently. This study proposes a deep learning (DL) chatbot for addressing common doubts of university students, providing efficient and accurate responses to college-specific questions. A self-curated dataset is used for the purpose of building the chatbot, and natural language processing techniques are utilized for the pre-processing of raw data gathered. The study compares two deep learning models – a bidirectional long- and short-term memory network and a simple feed-forward neural network model.

Keywords: chatbot, deep learning, bidirectional LSTM, NLP

1. Introduction

One of the most popular research areas nowadays is natural language processing (NLP). Many different applications of NLP have been constructed, including sentiment analysis (Astya & Shahnawaz, 2017; Chakraborty et al., 2020), question-answering (Hirschman & Gaizauskas, 2001), information extraction (Lewis & Jones, 1996), and machine translation (Shahnawaz & Mishra, 2013), among many others. Chatbots such as Weizenbaum (1966) and Zemčík (2019) were early attempts to create programs that could make a real human think they were speaking with another human. In the early 1970s, an adaptation of the Turing test was used to evaluate PARRY's effectiveness. In a Turing test (French, 2000), a computer tries to trick a human interrogator into thinking it is another person by communicating in writing. In the field of machine-human interaction, chatbots are regarded as one of the most advanced and promising technologies. Users can use chatbots for getting answers to their questions in any particular domain where they are used.

College websites are often confusing, and it is difficult to find information or get questions answered quickly. Additionally, it becomes difficult for a non-student or employee to access information. An effective college information chatbot is a probable solution to the above problems. It is a fast, standard, and informative widget that is designed to enhance the college experience and provide effective information to users.

Using Artificial Intelligence (AI) and NLP, chatbots allow users to interact with each other in a conversational manner (Adamopoulou & Moussiades, 2020). Users can ask questions about examinations, admissions, academics, users' attendance, grade point averages, placements, and other miscellaneous matters using the application. There is a need for a college inquiry system due to various reasons. A fresher at college or a person with a lack of adequate sources might have a lot of doubts regarding academics, college facilities, fees, etc. Answering all these questions individually might be difficult even for teachers or the college executive board. This calls for a smart solution.

The topics covered by the current bot are admissions, examinations, notice boards, attendance, placements, and other miscellaneous topics. Users' queries would be analyzed by the bot, and it will understand their message and then reply appropriately. It uses state-of-the-art methods like bidirectional long- and short-term memory (LSTM) and NLP to give an accurate response to user queries. This way users' time and efforts will be saved, and they will be equipped with appropriate answers. Now, the question arises – what will this bot be able to accomplish?

- Time-saving: The user would not have to look out for sources to seek information regarding college.
- One-stop destination for all answers: The answers will be thorough and aim to clear all the doubts of the user.
- The bot will reply using an effective GUI, which will give a feeling of actual human conversation.
- To analyze the needs and demands of the user through their messages.
- To add new questions to the data set built by surveying so that new doubts also get answered effectively.

The main contribution of our paper includes the following:

1. We are using a new self-curated query dataset to evaluate both models.
2. The research evaluates and contrasts the performance of two deep learning models: a bidirectional LSTM network and a basic feed-forward neural network model.

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Our project revolved around first creating the dataset using the results of a survey form that was circulated among the college students to gather the questions for the chatbot. We proceeded with carrying out data pre-processing on the dataset. Two models were used – a feed-forward neural network model and a BiLSTM model. Results for each model were calculated and evaluated.

The remainder of the article is organized in the following sections: A literature review of previous work done in the field of NLP and chatbot building using deep learning, Methodology used in the study including data collection, preparation, and pre-processing followed by model architectures, Evaluation, and results elaborating on the results obtained in case of both models BiLSTM and feed-forward neural network, and lastly, Conclusion and future work.

2. Literature Review

Chatbots have evolved numerous times since their introduction. Their use is on the rise in the business and consumer markets (Adam et al., 2021). As they are upgraded, consumers have lower to argue about while interacting with them. The paper by Patel et al. (2019) describes a web-based chatbot called "UNIBOT" that provides college-related information to users in a conversational manner. The user interface is designed to resemble a messaging application to make it user-friendly. The user inputs a question, and the chatbot prepossesses the message to provide a relevant response from its database. The chatbot solves the problem of visiting colleges to gather information and can be accessed from anywhere at any time. The chatbot is designed to be efficient with a minimal response time and low memory usage, and it provides relevant and satisfactory answers to the user's queries. The algorithm used in the chatbot can also be applied to other domains, such as healthcare and Android chatbot applications, for faster and more efficient responses. Table 1 presents a comprehensive literature review of related works, summarizing various studies and their key findings. The table provides a comparative analysis of different approaches, highlighting the methodologies, datasets used, and notable outcomes of each study.

Every university office occasionally encounters a spike in incoming messages, which can make regular higher education staff workers seem like call center agents scrambling to handle the load for knowledge. There are frequently a lot of inquiries concerning registration, or even just clarifications about enrolling in new classes, from prospective students, staff, and parents. When it comes to selecting the ideal chatbot for higher education university's admissions department, one wants a bot that applies algorithms and is intelligent enough that students and professors don't feel the need to evade the system and call your help desk anyhow (Lalwani et al., 2018). Utilizing chatbots such as Mongoose Harmony powered by Drift, Amazon's QnABot (Rabuan & Ping, 2021), IBM's Watson (High, 2012), and HubBot by HubSpot instead of having to learn how to use a new virtual assistant, investing in tools which were created to make the work of higher education staff members easier can profitable in the long term.

College inquiry chatbot systems have become the need of the hour nowadays. Gawade et al. (2020) describe a method for finding the key information in biographies of historical figures in order to create a conversational agent that might be employed in middle school situations. Sperlí (2021) present a deep learning-based chatbot for university student services. The chatbot is trained on a large dataset of student queries and uses deep learning techniques to generate relevant responses. Lee et al. (2019) provide an analysis of the impact of university chatbots on student services. The study found that chatbots can significantly improve the efficiency of student services and provide students with quick access to information. Karri and Kumar (2020) discuss the design of chatbots using NLP techniques and compare several existing chatbots. The chatbot implemented in this paper uses NLP techniques such as the bag of words and seq2seq model to extract features from text and provide efficient and smart answers to users through a friendly interface. The chatbot can be improved by adding more text corpora to increase its vocabulary.

Another study (Dhyani & Kumar, 2021) describes the creation of an open-domain Chatbot using deep learning, specifically the neural machine translation model which is an improvement on the sequence-to-sequence model. The Chatbot uses a bidirectional recurrent neural network with an attention mechanism, which allows the model to have both forward and backward information at every step, receiving information from both past and future states.

Makhalova et al. (2019) propose an information retrieval chatbot model that uses a concept-based knowledge model and an index-guided traversal to provide relevant information to users based on their preferences. Lecerf et al. (2018) describe the design and development of a chatbot for university admission. The authors developed the chatbot using NLP techniques and trained it on a corpus of admission-related queries to provide relevant information to students. They then used NLP techniques to preprocess the data and train the chatbot using a machine learning algorithm.

Zhou et al. (2018) propose a deep learning-based approach for multi-turn response.

3. Materials and Methods

In this section, we describe the overall methodology for building a chatbot: Collection and preparation of data, data pre-processing using various Python libraries followed by data splitting, and finally the deep learning model architecture.

3.1. Data collection and preparation

In this section, we describe our setup for collecting data to be able to answer any questions students may have about the university or curriculum as well as their general queries. A novel dataset of frequently asked questions and their respective answers about the university was created. Students of the university were asked to fill out a survey form, jotting down any and all questions or queries they had regarding college life, for example, placement preparation, connecting with seniors, maintaining good grades, and many more. The form was distributed to every batch of each branch in the university. An Excel sheet was created to store the results of the survey. Students were given a suitable deadline of a week to complete the survey.

The next step was to curate the right and appropriate answers to the questions after they had been collected, which was done manually by college seniors and under the guidance of our faculty advisor. The data for this study were collected from students in Indira Gandhi Delhi Technical University for Women, Delhi (IGDTUW)1, consisting of a total of 75 query responses. A total of 70 students participated in the given survey after which 75 question-answer pairs were curated with the queries being answered manually.

For the purpose of processing and training, the raw data were converted to a JSON file having "intents" with pre-defined "tags," and "patterns" – for questions and "responses" for the answers to the respective "patterns." The created JSON format data were then further pre-processed using NLP libraries in Python like NLTK (Loper & Bird, 2002), SpaCy (Schmitt et al., 2019), etc. Figure 1

Table 1
Comparative analysis of various approaches used in chatbots

ID	Year	Approach	Dataset	LSTM	DL	Result
High (2012)	2012	ML+NLP +Reasoning	Self	No	No	The results showed that the Watson chatbot performed well and was able to engage in natural language conversations with humans.
Ranoliya et al. (2017)	2017	AI/ML + LSA	Self	No	No	The paper discusses the increasing popularity of AI conversational agents for web services and systems and proposes an interactive chatbot for the University environment using AI ML.
Sharma et al. (2017)	2017	Pattern-matching algorithm using DFS	Self	No	No	The paper examines chatbot systems like ELIZA and ALICE and finds that ALICE's pattern-matching technique is easier to use. It introduces ALICE as a domain-specific chatbot for a student information system
Patel et al. (2019)	2019	Rasa NLU + APIs	NLU	No	No	The evaluation of the chatbot involved a series of tests. The results showed that the chatbot performed well by providing helpful responses.
Bhartiya et al. (2019)	2019	Feed-forward neural network model	Self	No	Yes	Basic DL chatbot works well for university queries with optimized hyperparameters. AI chatbots in education can offer personalized, efficient, and cost-effective solutions.
Lee et al. (2020)	2020	Free cloud service Dialogflow (ML-based service)	Self	No	No	Infobot is a chatbot that can respond to students' inquiries in natural language, and preliminary evaluations indicate that it is effective as an online tutor. Infobot has the potential to lessen the teachers' workload and can be integrated into other e-learning platforms.
Karri and Kumar (2020)	2020	DL + NLP	Self	No	Yes	The paper concludes that the DL chatbot has the potential to revolutionize the way people interact with technology and can be used in a variety of applications.
Rabuan and Ping (2021)	2021	DL + Seq2Seq model	Self	Yes	Yes	The paper outlines the features of the chatbot, which includes integration with university databases and personalized responses based on the data.
Assayed et al. (2023)	2021	Multinomial Naive-Bayes +Random Forest classifiers	Self	No	No	The paper compares the performance of random forest classifier and multinomial Naive-Bayes classifier for sentiment analysis using different metrics like accuracy, precision, recall, and F1 score.

Figure 1
Example of data present in the JSON file

```
"tag": "society_manage",
"patterns": [
    "How many societies will i be able to manage in my first year?"
],
"responses": [
    "That depends on how you manage your time but 1 to 3 should be fine"
]
```

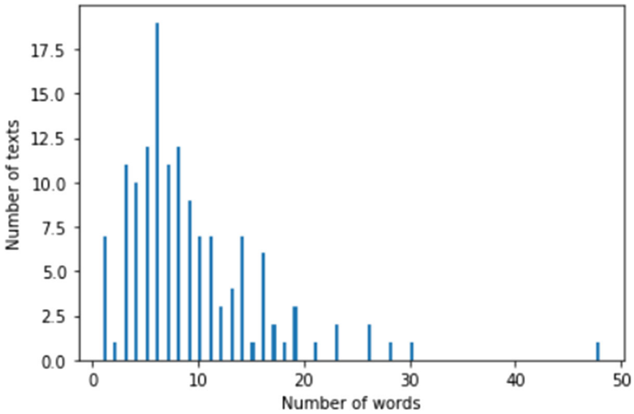
shows a glimpse of the JSON format file used in the study. As one can observe, similar questions were grouped under the same tags. Some of the examples of tags include – "time management," "online exams," "hostels Delhi," "seniors connect," "upgradation," "scholarship," etc.

3.2. Data pre-processing

In order to solve any text classification problem, data pre-processing is the necessary first step, and in order to process textual data efficiently, several steps need to be performed to transform words into numerical features that can be used by the deep learning models.

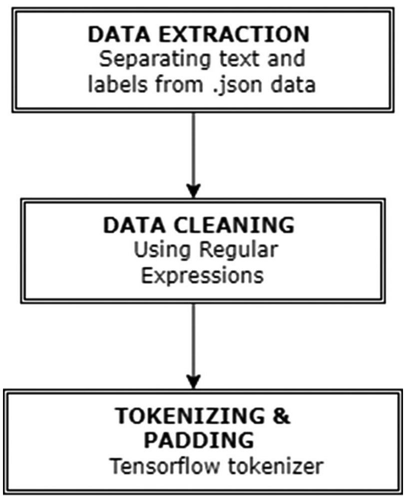
For this study, the raw data are first extracted from the JSON file, separating the text from the corresponding labels. The next step is performing data cleaning. This is achieved by using the re or regular expressions library in Python. RegEx (Erwig & Gopinath, 2012) or Regular Expressions are sequences of characters that form search patterns. It can be used to find out if a given string contains a particular pattern. Using the in-built RegEx library, this step consisted of deconstructing data (e.g., changing "weren't" to "were not," "didn't" to "did not," etc.), lower-casing, and removing punctuation. The last step in text pre-processing was Tokenization and Padding. The tokenization process involves breaking larger strings of text into smaller chunks (Mayo, 2017). For example, bigger portions of the text corpus can be tokenized into sentences, and sentences can be tokenized similarly into words, and so on. Padding is a method that is used for converting an integer array with variable length into a fixed-length array (by truncating or padding). It can be seen in Figure 2 the distribution of text length on the created dataset.

Figure 2
Distribution of text length on dataset



The Keras API with TensorFlow backend is used for importing the text Tokenizer utilized for this step. The data are then made ready to be trained on the model after performing padding with vocabulary size (vocab size) kept as 1000. The total number of words is 1288, and the number of tokens in a sentence/text is 48 after performing padding. Figure 3 shows the pictorial representation of the various data pre-processing steps performed.

Figure 3
Data pre-processing flow chart



3.3. Splitting data for testing and training

A different set of data was kept separated from the training sample for evaluating our model during testing. The test data include patterns (questions) and responses (answers) which are not present in the training data at all to observe the model's performance on unseen data.

3.4. Model architecture

The study implements two models for comparing the results of a bidirectional LSTM and a simple deep learning model in text classification. Keras sequential API is used for building the model architectures.

3.4.1. Model 1

Our baseline model architecture was a feed-forward neural network, refer to Figure 4a, that consisted of three dense layers, preceded by an embedding layer. Global average pooling (1D) was applied, and the optimizer used was Adam (Kingma & Ba, 2014).

Adam (Kingma & Ba, 2014) optimizer uses adaptive learning rates for each parameter, which means that the learning rate is adjusted based on the gradient variance. It also uses momentum, which helps to smooth out the optimization process by keeping a running average of the gradients. Overall, the adaptive learning rates and momentum used in Adam optimizer make it a powerful and efficient optimization algorithm for deep learning models.

3.4.2. Model 2

A BiLSTM model (bidirectional LSTM) (Schuster & Paliwal, 1997) was implemented by adding a bidirectional LSTM layer after an embedding layer, succeeded by two dense neural network layers and a dropout layer.

The model was compiled again with Adam as the optimizer and used categorical cross-entropy as the loss function. It was trained to fit for 550 epochs. Refer to Figure 4b for the summary of this model.

4. Experiments and Evaluation

After the process of learning was constructed, the model was trained by specifying the input, output, and setting the number of epochs (550). The two models were trained, and their different outputs were compared. Tables 2 and 3 show the responses our chatbot presented after the implementation of Model 1 and Model 2, respectively. We can observe from the responses that Model 1 performs better than Model 2. Responses 2 and 3 made by Model 2 are vague; on the other hand, Model 1 is able to answer more accurately.

Moreover, to ensure the accuracy of our chatbot, we have added a confidence value that is fundamentally a threshold value of 60 which helps the model to distinguish between appropriate responses and irrelevant ones. It gives a default answer for confidence below a certain threshold value. For the purpose of evaluating the model's effectiveness, two metrics were examined: loss and accuracy. For real experimental validation, we can confidently report that we have conducted a test of our chatbot model on university students and have received positive feedback. In this test, the students found the chatbot to be helpful and user-friendly, and we believe that this provides evidence of the effectiveness of our algorithm. While further testing is certainly warranted, we are encouraged by the results of this initial trial.

Figure 4
Model architectures

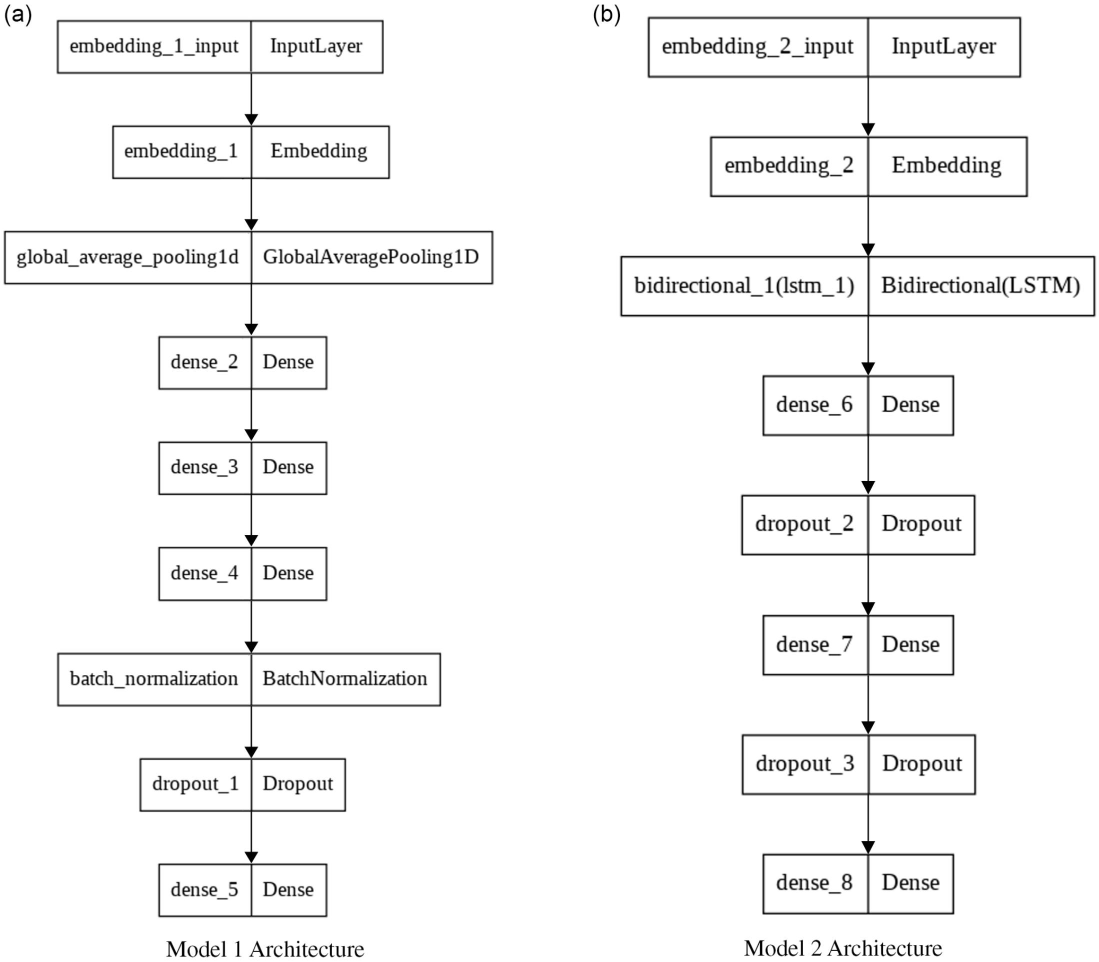


Table 2
Responses by chatbot built on model 1

S. NO.	QUESTION	ANSWER BY BOT
1.	Hey	Hey there
2.	How to connect with seniors?	Through societies! Societies are an excellent way to build connections and interact with your peers as well as your seniors. You can also use LinkedIn and interact with the alumni network and your seniors of IGDTUW.
3.	How to manage time?	Making proper schedules and timetable is the key. Devote 2–4 hours to coding daily as per your capacity and the rest to college studies and society-related work.

Table 3
Responses by chatbot built on model 2

S. NO.	QUESTION	ANSWER BY BOT
1.	Hi!	Hello
2.	Where is the library?	The college library is open on all working days till 5PM, and books can be issued from there using your ID card
3.	How to connect with seniors?	75% attendance is mandatory.
4.	How to manage time with studies?	Attend the classes regularly, make notes, and revise them. Join a couple of interesting societies and try not to waste your time in unproductive things like overusing social media websites, etc.

4.1. Analysis and testing

Testing is a significant step to ascertain the proper working of the chatbot. After the initial implementation of the deep learning model, our aim was to test the chatbot responses with new queries. Hence, for this task, we made an "intentstest.json" file containing a different set of test questions that were not previously used for training the model. A query list of 20 test cases was conveyed to the model, the answer tag was compared to the one that was anticipated. The chatbot responded with 75 percent of responses that can be termed as accurate, and the remaining responses can be termed as a little vague. Following the model generation, the user question was prepared, and tasks related to response prediction were carried out. Once the model's weights had been set, it would forecast the best-matching answer tag depending on the likelihood that the user question's input pattern would match one of the 77 pattern tags already in use for that inquiry. From the chosen tag class, a response is randomly chosen and presented to the user on the interface, the results of which can be observed from the tables. By choosing the pattern with the maximum probability in the model, it correctly determines the best-matched response tag for the query.

4.2. Results of deep learning approach

Table 2 shows the responses our chatbot presented after implementing the initial deep learning model. After a set number of epochs, from Figure 5, the model performance was seen to have improved steadily until it was essentially constant. Collectively, it can be shown that the model loss continuously drops until, after a particular number of epochs, it basically becomes steady.

With the epoch value set to 550, the model starts by learning the correct distribution of data, but after a definite number of epochs, the model starts over-fitting the data. Over-fitting (Hawkins, 2004) is a problem that arises when a model gains knowledge of the information and variability in the training data to the point where it has a negative effect on the model's effectiveness on new data. To address the problem of over-fitting in our model, we have used the dropout technique. Kamath et al. (2019) reasoned that because fully connected dense layers are the ones with the greater number of parameters, they are likely to excessively co-adapt themselves causing over-fitting. Dropout offers a highly efficient regularization technique that is also remarkably computationally inexpensive and helps to lessen over-fitting and enhance generalization error in all types of deep neural networks. This layer ignores a set of neurons (randomly) during training, and hence, their contribution to the activation of downstream neurons is temporarily removed. Figure 5 shows the model accuracy and loss results after removing the problem of over-fitting. However, it can be seen from the figures that the model is not able to perform well on the validation data with only a 48.27% accuracy as opposed to the 80% on the training set, leading to a case of over-fitting.

4.3. Results of bidirectional LSTM model

Bidirectional LSTM (Basaldella et al., 2018) is the technique of equipping any neural network with the ability to understand sequence data both forward (past to future) and backward (future to past). In situations involving sequence classification, they can enhance model performance. Bidirectional LSTMs train two LSTMs on the input sequence as opposed to only one. The first is on an original copy of the input sequence, and the second is on an inverted copy. This can give the network extra context and lead to a quicker and even more thorough learning process for the issue.

Table 3 shows the responses our chatbot presented after adding the bidirectional LSTM layer. From Figure 6, it is evident that the model's accuracy kept rising after a given number of epochs, eventually becoming practically constant. On the other hand, it can be shown that after a certain number of epochs, the model loss steadily drops until it practically becomes constant. In this model, categorical cross-entropy is used as a loss function. When there are two or more output labels for a multi-class classification model, it is utilized. One-hot category encoding value in the form of 0s and 1s is allocated to the output label. As the anticipated likelihood departs from the actual label, the loss grows. Chowdhary (2020) have also tackled the problem of over-fitting by using a dropout layer. And it can be seen that the problem of over-fitting also exists in the LSTM model. Model 2 gains a training accuracy of 88.6% with a very low accuracy of 27.56% on the validation data. Table 3 shows that some responses obtained by this model were not accurate despite expecting that this layer would improve the results; however, the desired outputs were obtained in a considerable amount.

Figure 5
Loss and accuracy graphs for model 1

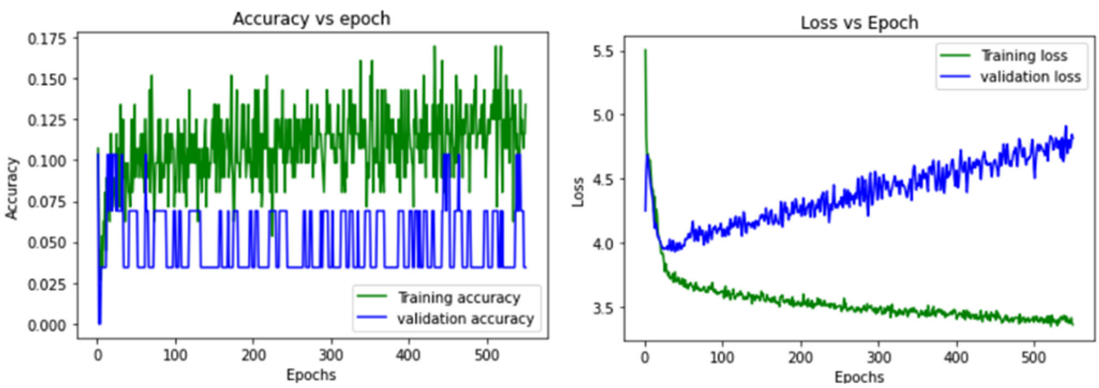
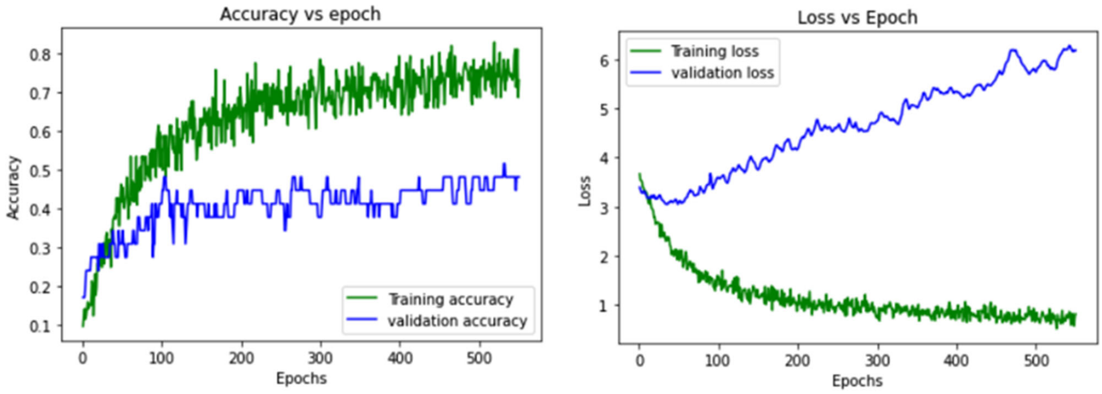


Figure 6
Loss and accuracy graphs for model 2



After comparing the results for both models, we observed that the deep learning model gave better results on unseen data.

5. Conclusion

In conclusion, our study has explored the potential use of the latest technology of Bidirectional LSTM – which is one of the most optimal neural networks for sequence learning problems and NLP techniques in designing chatbots for a university environment. By using a corpus dataset, the chatbot was able to provide intelligent responses to frequently asked questions.

The hyperparameters including learning rate, batch size, number of epochs, optimizer algorithm, dropout rate, activation functions, and number of hidden layers for the deep learning model were adjusted to effective values to maximize our chatbot's accuracy. This process was done through trial and error, where different hyperparameters were tested, and their impact on the model's performance was evaluated. The developed chatbot with the deep learning model was able to resolve user queries with fitting responses related to our university, IGDTUW considerably as shown in the responses table and the test results acquired.

Despite the promising results of our study, there are several limitations that should be considered when interpreting our findings. These limitations include the following: Small Dataset: At present, our available data are limited. As can be observed from the results, the deep learning models developed in the study tend to overfit upon validation. This seems to be due to the fact that the dataset curated is too small to fit into the model. To curb this limitation, the creation of a larger, more diverse dataset will be the next step in improving our chatbot. In addition to using larger datasets, we are also actively engaged in refining our data collection and analysis methods. We plan to explore more robust techniques for preventing over-fitting, such as fine-tuning a pre-trained model and data augmentation. These techniques can help to reduce the risk of over-fitting and improve the accuracy and robustness of our model. These limitations suggest that our findings should be viewed with caution, and further research is needed to confirm and generalize our results.

Here we have attempted to demonstrate how a chatbot can be helpful for college students, by reducing the efforts of the students to travel all the way to college or in general, looking for sources to solve their queries or questions. The use of such Chatbots using NLP as discussed in the paper will lead to effective user query resolution. Such chatbots provide a personalized and fast query resolution that can prove very beneficial to the users which include naive newcomers to the college. The results of this study demonstrate the effectiveness of NLP in creating chatbots with a friendly interface that can interact with users using natural language. The success of the current research highlights the potential of chatbots as a valuable tool in the university setting, providing students and faculty with accessible and convenient support.

In addition to the application of the proposed algorithm in the current study, there are several other potential applications that could be explored. One potential application is in the field of customer service, where chatbots could be used to answer common customer questions and provide support. Another application is in the field of education, where chatbots could be used to provide personalized learning experiences and support for students.

Chatbots could also be used in healthcare settings, to provide patients with quick and accurate answers to common health questions. These are just a few examples of the potential applications of the proposed algorithm, and further exploration is warranted.

6. Future Scope

The current extent of the proposed study was bounded to developing a prototype for guiding the freshmen of our college with their newbie doubts and queries. However, the model developed has the potential to be used by other universities as well. It is intended to analyze the potential risks and vulnerabilities of the developed chatbot while it is used by IGDTUW college students and further inculcate changes to improve the overall credibility of the chatbot.

In the study, we have chosen to use simple model structures instead of more complex models mainly because of limited data availability. When the amount of available data is limited, it can be challenging to train complex models with a large number of parameters. In such cases, simpler models with fewer parameters may be more appropriate. Simple models are often more interpretable than complex models. However, fine-tuning a pre-trained model can be an effective approach to tackling NLP tasks with limited data, but it requires careful consideration and tuning to achieve optimal results. This is one future aspect that we look forward to working on.

Some more future directions that can be looked upon are enlarging the dataset to incorporate a large number of data points as well as a huge variety of queries. We are in the process of expanding our dataset which will not only help in solving the problem of over-fitting but also help in making the chatbot more accurate and error-free. Moreover, it is essential to have more quality training data available in open repositories to enable progress in natural language understanding. Hence, sharing the collected database in an open repository for improving the resources available in natural language understanding would be considered.

Lastly, keeping in mind the emerging techniques for chatbot design and development, this chatbot model will be deployed on the IGDTUW university website. Using conversational interfaces as part of software-enabled services is an exciting direction for chatbot research and development. Consequently, its scope of query resolution will be increased upon deployment, so that it can accommodate all the different types of queries for university students as well as potential students or parents seeking admission to our University.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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How to Cite: Mangotra, H., Dabas, V., Khetharpal, B., Verma, A., Singhal, S., & Mohapatra, A. K. (2024). University Auto Reply FAQ Chatbot Using NLP and Neural Networks. *Artificial Intelligence and Applications*, *2*(2), 140–148. https://doi.org/10.47852/bonviewAIA3202631