Comparison of Neural Network Models for the Implementation of a Chatbot in the University Admission Process

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Abstract. Universities face a growing demand for information during admission processes, leading to an administrative overload due to the large number of individual and in-person inquiries from applicants. This work proposes the development of a chatbot based on Natural Language Processing (NLP) to automate and optimize the management of inquiries in admission processes, taking the National University of Moquegua (UNAM), Peru, as a case study.

A specific corpus was built from the UNAM General Admission Process Regulations, supplemented with real inquiries from institutional sources. The corpus was segmented and preprocessed to train five neural network architectures: RNN, CNN, LSTM, GRU, and BiLSTM. Each model was evaluated in terms of accuracy and generalization capability using a preprocessing pipeline that included tokenization, lemmatization, stopword removal, and conversion to numerical sequences.

The proposed chatbot uses a neural network architecture with a 300-dimensional embedding layer, followed by different sequential processing layers depending on the selected architecture, and an output layer with softmax activation for multi-class classification. The models were trained using categorical cross-entropy loss and the Adam optimizer, with 60 training epochs.

The results show that the architectures based on BiLSTM and RNN outperform the others in terms of accuracy and robustness, suggesting their suitability for implementation in university admission environments. The developed system has the potential to significantly reduce the workload of administrative staff and improve the experience of applicants by providing quick and accurate responses to their inquiries.

Keywords: NLP · Chatbots · University · Admission · RNN · CNN · LSTM · GRU · BiLSTM

1 Introduction

Universities play a crucial role in the professional training of individuals, and during admission processes, they face a high demand for information from applicants. Each year, admission processes attract numerous candidates who visit offices with questions about requirements and procedures. This situation represents a significant burden for administrative staff, as communication is largely individual and in-person. This method proves inefficient, especially when applicants have to wait in long lines for answers, leading to high costs and considerable time loss.

The admission process requires the submission of several documents and the fulfillment of various requirements, regulated by a legal document detailing the types of exams, protocols for the exam day, application document specifications, deadlines, and other requirements. Reading and understanding these regulations can be tedious and often leads to misunderstandings or disappointments. To avoid these issues, applicants tend to seek sources of information that offer quick and accurate answers [1].

The increasing number of inquiries and the insufficient staff to respond efficiently represents a major challenge. As questions about document submission and requirements rise, administrative staff become overwhelmed. Chatbots can be an effective solution to this problem, as they can address frequently asked questions using a history of inquiries, thereby reducing backlogs and delays [2].

Currently, artificial intelligence, particularly Natural Language Processing, is widely used to enhance interaction between businesses and clients. Chatbots employing advanced NLP models can interpret natural language and generate appropriate responses, improving efficiency in handling inquiries. NLP models have advanced significantly, and neural chatbots now offer smoother and more natural communication compared to previous rule-based systems [3] [4].

This research focuses on the issue of increasing inquiries about the admission process in public universities in Peru and proposes a solution through the development of a prototype chatbot based on NLP models. The study uses data from the National University of Moquegua to train the NLP model, evaluating models such as RNN, CNN, LSTM, GRU, and BiLSTM. The goal is to provide a technological tool that benefits both applicants and administrative staff by optimizing the admission process with quick and accurate responses.

To gain further insight into the progress and results obtained in similar research, a search for related works was carried out, which are presented in Chapter 2. Chapter 3 presents the methodological proposal for the development of the research, which includes processes such as corpus construction, data preprocessing, and modeling, where the previously mentioned neural network architectures are implemented. Chapter 4 shows the results obtained in the evaluation of the models and the developed prototype. Chapter 5 evaluates the contribution to previous works, Chapter 6 includes the conclusions of the study carried out, and finally, in Chapter 7, we will present the Future Work section, where recommendations for future research are provided.

2 Related work

Weizenbaum introduced ELIZA in 1966, a pioneering program that allowed natural language conversation with a computer using keywords to generate responses, laying the groundwork for future chatbots [5]. Over time, chatbots have proven to be effective tools for replacing human effort in repetitive tasks without compromising quality, as evidenced by their preference among staff and students due to their ability to provide direct answers [6, 7].

The development of a chatbot largely depends on the quality of the dataset it is based on [8]. A successful example is DINA, a chatbot that responds to frequently asked questions from prospective students based on reliable data from Universitas Dian Nuswantoro [9]. Chatbots such as NEU-chatbot, applied in the admission process at the National Economics University in Vietnam, have shown that implementing chatbots helps reduce staff workload and minimizes the spread of false information [10].

The use of advanced models like Seq2Seq and BiLSTM has significantly improved chatbot performance. For example, a chatbot developed for Telkom University Admission achieved a BLEU Score of 44.68 using BiLSTM [11], while subsequent studies suggest that extending traditional LSTM models to BiLSTM or advanced LSTM variants can further enhance results, though at a higher computational cost [12].

The implementation of chatbots in universities, such as UNIBOT, has proven useful by providing a user-friendly environment through a GUI similar to messaging applications, and it is recommended to integrate natural language processing to improve interaction [13]. Depending on the range of input data, it is suggested to use retrieval-based chatbots, with JSON being an ideal file format due to its organized structure [14, 15]. Recent studies have shown that models like BiLSTM outperform other approaches, such as RNN, LSTM, and CNN, in accuracy. In [16], two chatbots based on retrieval and generation were developed, to answer frequently asked questions about psychological well-being, where the results of retrieval-based chatbots showed that Vanilla Recurrent Neural Network (RNN) has an accuracy of 83.22%, Long Short Term Memory (LSTM) has an accuracy of 89.87%, Bidirectional LSTM (Bi-LSTM) has an accuracy of 91.57%, Gated Recurrent Unit (GRU) has an accuracy of 65.57%, and Convolution Neural Network (CNN) has an accuracy of 82.33%, so the favorable results of implementing chatbots to answer frequently asked questions can be seen.

3 Proposal

The methodological proposal for the development of the research is presented in Figure 1. The process begins with the construction of the corpus, where various textual sources are selected and organized following a JSON file structure. Subsequently, in the preprocessing phase, a series of data cleaning and preparation techniques are carried out for use in model training. During the modeling stage, five different neural network architectures are implemented and evaluated. In the training phase, the learning process of the models is executed on the preprocessed dataset. Finally, the effectiveness of the models' learning is assessed by applying various performance metrics.

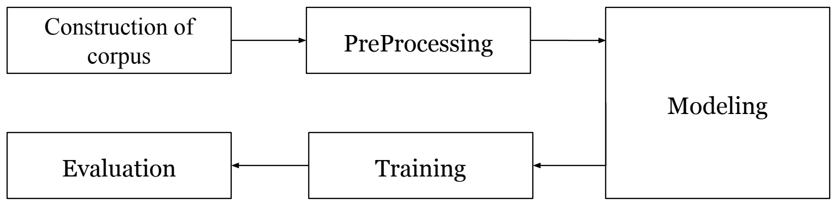


Fig. 1: Research methodology.

3.1 Construction of Corpus

In this research, a question-and-answer corpus was constructed based on the General Regulation of the Admission Process, supplemented with questions sourced from official university channels such as email, WhatsApp, and other institutional communications. To ensure the quality and representativeness of the corpus, stratified sampling was employed to create separate training and testing datasets. This method guarantees that the test questions are significantly different from the training questions, leading to more accurate test results.

As a result, two JSON files were generated: `intents.json` for training and evaluation (80% and 20%, respectively), and `test.json` for final model testing. The dataset consists of 79 classes in Spanish, organized into 60 articles and 22 procedural formats from the regulation. The distribution of the articles in the general format, adapted as questions for training, is shown in Table 1.

Each class defines a unique category of information, represented by three fundamental labels: 'tag', 'patterns', and 'responses', as illustrated in the JSON structure 1.1. This design allows each class to encapsulate specific topics related to the admission process, such as an article from the General Regulations, which is a numbered section that establishes specific rules or procedures, or a particular procedure format, providing details on how certain tasks or actions should be carried out during the admission process.

The training set includes multiple questions associated with each answer for every class, while the test set features a single question per class, aimed at assessing the models' effectiveness and generalization capabilities. The corpus was validated by the call center team for the 2024-I admission process, ensuring its relevance and accuracy. Below is the structure of the data in the JSON file:

Regulations		**Training Data**	
Regulation Article	**Description**	**JSON Class**	**Example of questions**
Article 11	El concurso de admisión a la Universidad se efectúa en las Modalidades siguientes: A) Por CEPREUNAM B) Por Examen Extraordinario C) Por Examen Ordinario General	articulo11	¿Cuáles son las modalidades de concurso de admisión a la Universidad?, ¿Qué métodos existen para ingresar a la universidad?, ¿Qué modalidades hay para ingresar a la UNAM?, ¿Qué alternativas existen para ingresar a la UNAM?
Article 13	Para acceder a la modalidad de ingreso por CEPREUNAM, el postulante debe estar matriculado en el Centro Preuniversitario de la Universidad Nacional de Moquegua (CEPRE) y rendir un examen de conocimientos. Para el proceso de admisión 2024-I el CEPRE dispone de dos fases y el número de vacantes está establecido en la tabla N°1.	articulo13	¿Cuáles son los requisitos para acceder a la modalidad de ingreso CEPREUNAM?, ¿Qué necesito para participar del proceso de admisión a través de CEPREUNAM?, ¿Qué se necesita para ingresar a la UNAM por CEPREUNAM?, ¿Qué requiero para participar en el proceso de admisión a través de CEPREUNAM?
Article 28	La inscripción del postulante será únicamente a través de la plataforma virtual de la Universidad Nacional de Moquegua `https://unam.edu.pe/admision/`.	articulo28	¿Cómo realizo la inscripción para el examen de admisión?, ¿La inscripción al examen de admisión es en línea?¿Dónde debo inscribirme para el examen de admisión?, ¿Cuál es el link para inscripciones?

Table 1: The table shows the equivalence between admission regulation articles and JSON training data classes, along with sample questions used to train the admission process chatbot.

```
"tag": "articulo11",
       "patterns": [
         "Cuales son las modalidades de concurso de admision a la Universidad",
         "que metodos existen para ingresar a la universidad",
         "que modalidades hay para ingresar a la UNAM",
         "que alternativas existen para ingresar a la UNAM",
         "cuantas formas hay de ingresar a la UNAM"
       ],
       "responses": [
         "El concurso de admision a la Universidad se efectua en tres
              modalidades: CEPREUNAM, Examen Extraordinario y Examen Ordinario."
       ]
```

Listing 1.1: JSON format example

Where:

- "tag": This key represents the label or unique identifier of the class.
- "patterns": A list of patterns or questions that the applicant may ask related to the admission process regulation.
- "responses": A list of responses based on the regulation that the chatbot will provide to the applicants.

3.2 Data preprocessing

Data preprocessing is essential in the creation of deep learning models, directly affecting the model's quality and performance. In this work, a preprocessing pipeline was implemented that includes data loading and structuring, text tokenization, stop word removal, lemmatization, text cleaning, and conversion of labels to categorical format.

- **Data Loading and Structuring**: Data was loaded from the `intents.json` file and split into training (80%) and validation (20%) sets using the `train_test_split` function from the Scikit-learn library.
- **Text Tokenization**: Tokenization was performed using the `Tokenizer` class from TensorFlow. Stop word removal was carried out using the `remove_stop_words` function, and Spanish stopwords were downloaded using `nltk.download('stopwords')`.
- **Lemmatization and Text Cleaning**: `lemmatize_text` from spaCy, a Python NLP library, was used for lemmatization. The text was cleaned by removing special characters and normalized to lowercase.
- **Sequence Conversion**: The `preprocess_data` function was implemented to convert questions into numerical sequences. This function applies padding using `pad_sequences` from TensorFlow, ensuring all sequences have uniform length for processing in the model.
- **Conversion of Labels to Categorical Format**: Labels were converted to categorical format using the `to_categorical` function from Keras, facilitating multiclass classification during model training.

3.3 Modeling

For the retrieval chatbot, five neural network architectures were implemented: RNN, CNN, LSTM, GRU, and BiLSTM. Each model was selected for its ability to process text sequences and capture relevant contextual patterns in the input data.

- **RNN**: This architecture uses a 300-dimensional *Embedding* layer and an RNN layer with 100 units. It includes a *Dropout* layer with a rate of 20%, and ends with a dense layer with *softmax* activation. The model was trained for 60 epochs with categorical cross-entropy, the Adam optimizer (learning rate of 0.001), and a batch size of 32.

- **CNN**: The CNN architecture employs a 300-dimensional *Embedding* layer, followed by a *Conv1D* layer with 64 filters, kernel size of 3, and *ReLU* activation. A *MaxPooling1D* layer with a pooling size of 6 is applied, followed by a *Flatten* layer and two dense layers: one with 64 units and *ReLU* activation, and another with *softmax* activation. The model was trained for 60 epochs with categorical cross-entropy, the Adam optimizer (learning rate of 0.001), and a batch size of 32.
- **LSTM**: The LSTM architecture includes a 300-dimensional *Embedding* layer and an LSTM layer with 250 units, followed by a dense layer with *softmax* activation. Training was conducted for 60 epochs using categorical cross-entropy, the Adam optimizer with a learning rate of 0.001, and a batch size of 32.
- **GRU**: The GRU architecture includes a 300-dimensional *Embedding* layer, followed by two GRU layers with 250 units each, interspersed with *Dropout* layers (20%). The output is obtained through a dense layer with *softmax* activation. The model was trained for 60 epochs with categorical cross-entropy, the Adam optimizer (learning rate of 0.001), and a batch size of 32.
- **BiLSTM**: This model includes a 300-dimensional *Embedding* layer and a bidirectional LSTM layer with 250 units. The output is determined through a dense layer with *softmax* activation. This model was trained for 60 epochs using categorical cross-entropy, the Adam optimizer with a learning rate of 0.001, and a batch size of 32.

In a summarized and comparative manner, it can be seen in Table 2.

Model	**Embedding Layer**	**Main Layer**	**Units / Filters**	**Epochs**	**Optimizer**
RNN	300 Dim.	SimpleRNN	100 units	60	Adam (0.001)
CNN	300 Dim.	Conv1D	64 filters, kernel=3	60	Adam (0.001)
LSTM	300 Dim.	LSTM	250 units	60	Adam (0.001)
GRU	300 Dim.	2x GRU	250 units, Dropout 0.2	60	Adam (0.001)
BiLSTM	300 Dim.	Bidirectional LSTM	250 units	60	Adam (0.001)

Table 2: Comparison of different recurrent and convolutional neural network model architectures, highlighting the used Embedding layer, the main layer of each model, the number of units or filters, training epochs, and the applied optimizer.

4 Results

4.1 Evaluating

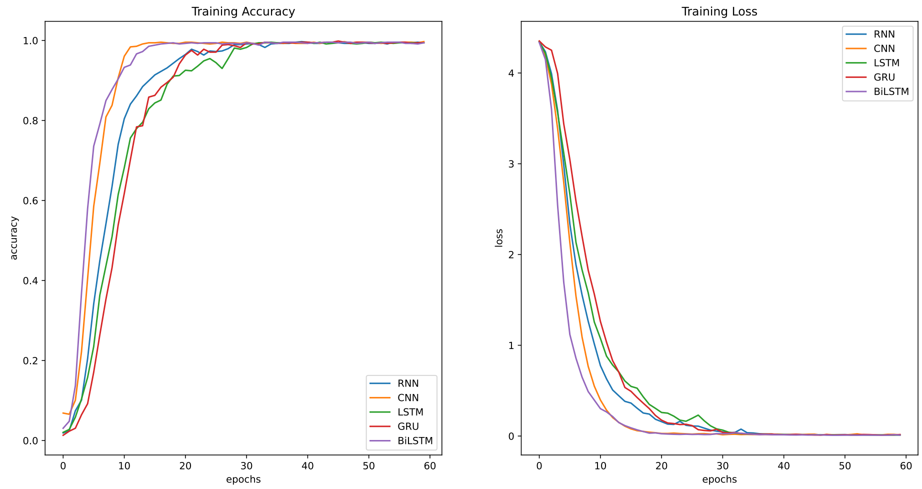
The empirical results of training and validation reveal that the BiLSTM and CNN models outperform the others in terms of convergence speed, final accuracy, and loss minimization. These models demonstrate superior capability in capturing long-term bidirectional dependencies, which is crucial for optimizing both accuracy and loss reduction. On the other hand, GRU, RNN, and LSTM models require more time to reach convergence, suggesting that their effectiveness is lower compared to BiLSTM and CNN for this task. These results are reflected in Figures 2a and 2b, which present the Accuracy and Loss curves over the 60 epochs of training and validation.

Table 3 shows the results of the five evaluated models: RNN, CNN, LSTM, GRU, and BiLSTM. The metrics of Accuracy (Ac), Recall (Rc), F-Score (F1), Precision (P), and BLEU (B) are displayed for each model.

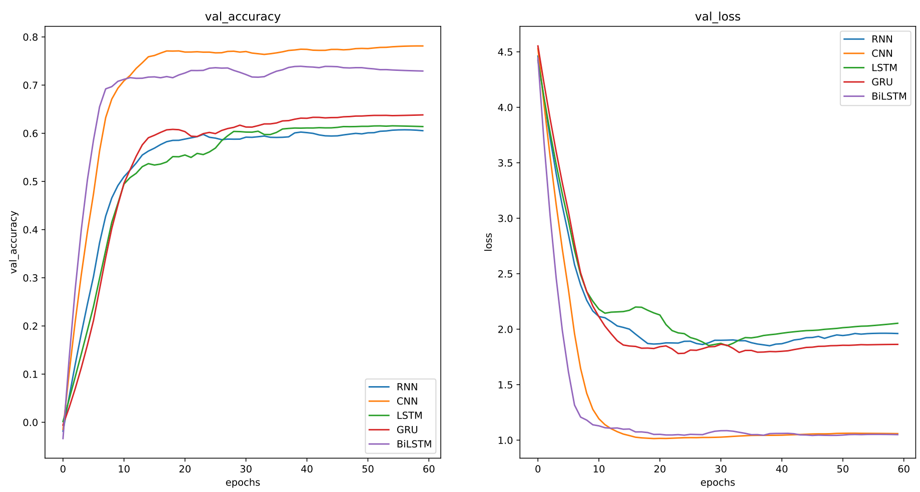
Model	**Accuracy**	**Recall**	**F-Score**	**Precision**	**BLEU**
RNN	0.800	0.813	0.772	0.735	0.775
CNN	0.725	0.725	0.681	0.642	0.713
LSTM	0.775	0.775	0.740	0.708	0.763
GRU	0.750	0.750	0.714	0.682	0.738
BiLSTM	**0.825**	**0.825**	**0.795**	**0.767**	**0.813**

Table 3: Comparison of models with different metrics.

The BiLSTM model achieves the best results across all metrics, with an Accuracy of 82.5%, a Recall of 82.5%, an F-Score of 79.5%, a Precision of 76.7%, and a BLEU score of 81.3%. This suggests that the BiLSTM model is the most effective for the information retrieval task.



(a) Accuracy and Loss of training.



(b) Accuracy and Loss of validation.

Fig. 2: Comparison of training and validation performance.

4.2 Prototype

To progress to the next phase of the research, the optimal model was deployed in a real environment. The BiLSTM model was implemented on a web platform using the Flask framework, enabling real-time execution through an intuitive and efficient user interface. Figure 3 shows the system interaction diagram between the User, Interface, and Model.

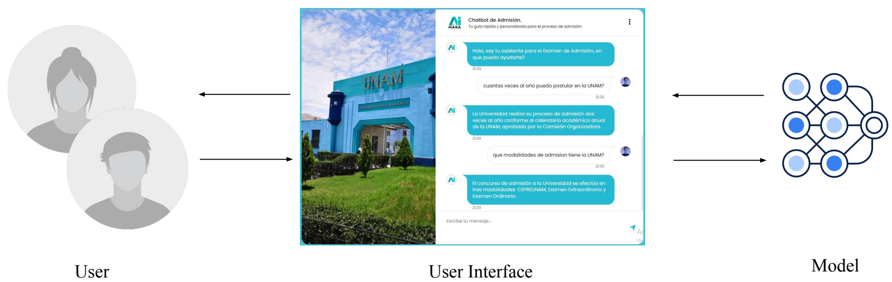


Fig. 3: Interaction Scheme

5 Discussions

The development of the chatbot's graphical interface was inspired by the design principles of a messaging application, as proposed in [13]. Additionally, the integration of Natural Language Processing (NLP) was considered essential. To ensure optimal performance, a comparative study of various NLP models, including RNN, CNN, LSTM, GRU, and BiLSTM, was conducted.

[10] highlights the importance of annually updating the dataset by incorporating new queries and relevant information from the academic year. This is crucial for addressing the potential issue of understanding intents during the query process. To mitigate this problem, we decided to include information from the General Admission Process Regulations of the University and queries made by users through communication channels. This strategy allows for comprehensive training of the chatbot, improving its ability to understand user writing styles and extract key terms. This approach aligns with the need to update the dataset according to the most recent revisions of the General Admission Process Regulations of the University.

The implementation of the BiLSTM model, as recommended by [12], achieved a BLEU score of 81.3%, surpassing other models in metrics such as Recall, F-Score, and Precision, while also showing outstanding performance in the training set, similar to the CNN. However, in the test set, BiLSTM and RNN demonstrated better generalization capability. Although BiLSTM is effective, its high computational cost and extended training time are important factors to consider [18]. In contrast, the RNN, with a lower cost, could be a viable alternative in contexts that require frequent training. Therefore, results will depend on the nature of the data; in similar projects, a CNN model could be ideal for optimizing resources, BiLSTM for greater precision in complex data, or RNN for a balance between performance and efficiency in final testing.

6 Conclusions

The comparative analysis of different recurrent neural network architectures for intent classification in the UNAM admission chatbot reveals that the BiLSTM model demonstrated superior performance across all evaluated metrics. With an accuracy of 82.50%, BiLSTM outperforms the other evaluated architectures, including RNN (80.07%), CNN (72.50%), LSTM (77.50%), and GRU (75.00%). These results highlight the importance of capturing long-term bidirectional dependencies to enhance performance in intent classification tasks.

The study demonstrates the feasibility of implementing a deep learning-based chatbot to automate and improve the query handling process for admissions at UNAM. The accuracy achieved by the BiLSTM model suggests that this approach could significantly enhance the efficiency and quality of service in handling applicant inquiries, providing accurate responses related to the admission process.

The developed chatbot has the potential to significantly reduce the workload of administrative staff, improving the efficiency and effectiveness of the admission process. Future work may involve refining the chatbot's capabilities and expanding its application to other areas of university administration.

7 Future Work

Based on the promising results obtained with our BiLSTM chatbot and recent advancements in educational chatbot technology, we propose several technical improvements for its future development:

- Integrate pre-trained models in Spanish, such as BERT, for text classification. This will allow us to evaluate how it adapts to our dataset and improve accuracy compared to the current model.
- Evolve from a classification to a generative chatbot, providing more dynamic and contextually relevant responses capable of addressing a wider range of queries.
- Integrate contextual memory and user profile creation mechanisms, enabling the chatbot to personalize responses based on previous interactions and user preferences.
- Implement continuous learning processes, allowing the chatbot to refine its responses over time, adapting to the changing needs of users and the evolution of language patterns.

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