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TRANSFORMING ENROLLMENT ADVISING IN EDUCATION WITH DEEP LEARNING MODELS AND CHATBOTS

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ABSTRACT: *Enrollment advising plays a pivotal role in guiding aspiring students throughout the university admissions process. The emergence of deep learning models and chatbot technologies has opened up new avenues for redefining the approach to enrollment advising. This article centers its attention on the creation of customized datasets catered specifically to admissions consultants, elucidating the data preprocessing procedures employed to enhance the quality of information utilized in advising. Furthermore, the article demonstrates the effective application of deep learning models in analyzing and interpreting the acquired data, facilitating precise predictions and individualized recommendations for prospective students. Lastly, the exploration extends to the implementation of these deep learning models within chatbot interfaces, offering an engaging and accessible platform for students to interact with enrollment advisors. The fusion of deep learning models and chatbots harbors the potential to revolutionize the landscape of enrollment advising, leading to enhanced efficiency, scalability, and an enriched student experience.*

Keywords: *Enrollment advising, Chatbots, Recurrent neural networks, Long short-term memory, Bidirectional-LSTM.*

I. INTRODUCTION

Enrollment advising is vital in education, especially in higher education institutions, as it guides and supports students during the enrollment process [1]. Its multifaceted functions are fundamental to students' academic journeys. Chatbots have the potential to revolutionize education by engaging learners, personalizing activities, supporting educators, and gaining insights into learner behavior [2]. They are computer programs that interact with users using natural language through user-friendly interfaces. Chatbot research focuses on developing intelligent dialogue models, utilizing natural language processing. Chatbots and Frequently Asked Questions (FAQs) are increasingly popular virtual assistants in domains like healthcare, education, and museums.

Chatbots, known as conversational agents, use natural language processing techniques to facilitate interactions between humans and computers [3]. They are gaining popularity in healthcare, consumer services, education, and academic advising, as they emulate human conversations and automate various services [4]. Educational chatbots are on the rise due to their cost-effectiveness and ability to engage students with personalized learning experiences [5]. In online classes with a large student population, where individual support may be challenging, chatbots play a crucial role [6].

The integration of chatbot technology in Enrollment Advising enhances operational efficiency and effectiveness by providing enhanced accessibility, streamlined communication, and increased student support. Chatbots ensure continuous engagement, surpassing office hours, and promptly respond to student inquiries, expediting issue resolution. Leveraging student-specific information, they offer personalized recommendations, empowering students to make informed choices aligned with their academic journey.

This research endeavor aims to make notable contributions by investigating the potential of utilizing deep learning models and chatbots to transform the landscape of enrollment advising within university settings. The study centers its attention on the critical undertaking of constructing datasets tailored explicitly for admissions consultants, acknowledging the fundamental significance of comprehensive and pertinent information within the advising domain. Through the implementation of data preprocessing techniques, the study enhances the quality of the gathered data, ensuring its appropriateness for subsequent analysis.

The application of deep learning models assumes a pivotal role in extracting valuable insights from the datasets. By leveraging these models, admissions consultants are empowered to make precise predictions regarding student preferences, behavior, and requirements, thus enabling the provision of highly personalized recommendations and guidance. The integration of deep learning methodologies affords universities the opportunity to optimize the enrollment advising process, resulting in heightened efficiency and effectiveness for both students and advisors alike.

II. RELATED WORKS

A. Traditional method

Approach based on <*question, answer*> sets and predefined rules [7]: A common technique in chatbot development involves creating question-answer sets with predefined rules. These sets are used to match user input with the most appropriate answer pattern. Artificial Intelligence Markup Language (AIML), which resembles XML, is often used to create these question-answer datasets. While this approach is straightforward and user-friendly, it requires significant time investment for data construction and may result in limited diversity and monotony in the generated responses.

Approach based on Ontology [8]: Ontology refers to a hierarchical model of data structures that define relationships and rules within a specific domain. It provides a shared vocabulary and facilitates inference about objects and their connections. By combining ontology with relational databases, knowledge bases for chatbots and question-answering systems can be created, enabling the extraction of answers from documents and establishing connections using inference. Approach based on corpus [9]: Recent research has utilized corpora, consisting of multiple documents, to search for the most relevant answer based on user input. Information retrieval methods, including corpus search and semantic parsing frameworks, are employed to retrieve accurate answers.

In article [10], the author adopts an approach based on corpus and machine learning to develop a chatbot for students. A dataset of questions and answers was collected from learning materials and a technology blog. The questions were represented using a bag-of-words model, and classifiers such as Support Vector Machines, Neural Networks, Random Forests, and k-Nearest Neighbors (k-NN) were trained. The accuracy rates achieved were 76.77%, 72.73%, 71.72%, and 65.66% for the respective classifiers.

B. Deep learning approaches

Deep learning methods have gained attention for their ability to uncover complex patterns in large datasets without explicit feature engineering. In admissions consulting, deep learning shows promise in handling diverse data points and revealing patterns. Using advanced models like RNN (recurrent neural network), LSTM (Long short-term memory), and Bi-LSTM (Bidirectional Long short-term memory), we can analyze student profiles and extract key features such as academic achievements, extracurricular activities, skills, preferences, and career goals.

1) Recurrent Neural Networks (RNN): Recurrent Neural Networks (RNNs) have emerged as a powerful neural network architecture for processing sequential data, making them particularly suitable for analyzing the temporal structure present in text [11]

A simple RNN has three layers which are input, recurrent hidden, and output layers. The input layer has N input units. The inputs to this layer is a sequence of vectors through time t such as $\{\ldots, x_{t-1}, x_t, x_{t+1}, \ldots\}$, where $x_t = (x_1, x_2, \ldots, x_N)$. The input units in a fully connected RNN are connected to the hidden units in the hidden layer, where the connections are defined with a weight matrix W_{IH}. The hidden layer has M hidden units $h_t = (h_1, h_2, \ldots, h_M)$, that are connected to each other through time with recurrent connections. The initialization of hidden units using small nonzero elements can improve overall performance and stability of the network. The hidden layer defines the state space or "memory" of the system as

$$h_t = f_H(o_t) \tag{1}$$

where,

$$o_t = W_{IH}x_t + W_{HH}h_t + b_h \tag{2}$$

f_H is the hidden layer activation function, and b_h is the bias vector of the hidden units. The hidden units are connected to the output layer with weighted connections W_{HO}. The output layer has P units $y_t = (y_1, y_2, \ldots, y_P)$ that are computed as:

$$y_t = f_O(W_{HO}h_t + b_o) \tag{3}$$

The activation function f_O and the bias vector b_o are fundamental components in the output layer of a recurrent neural network (RNN). As the input-target pairs unfold sequentially through time, the aforementioned processes are iterated continuously over a defined time period $t = (1, \ldots, T)$. The equations (1) and (3) elucidate the essence of an RNN, which comprises a collection of non-linear state equations capable of being traversed iteratively over time. At each time step, the hidden states generate predictions at the output layer based on the input vector, thus contributing to the overall functionality of the RNN architecture.

2) Long short-term memory (LSTM): is a specialized type of RNN that addresses the vanishing gradient problem by introducing memory cells and gating mechanisms. These features allow LSTMs to effectively learn and retain long-range dependencies in sequences, improving their performance in various text-based tasks. The forward training process of the LSTM can be formulated with the following equations:

$$y_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$
$$i_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$
$$C_t = f_t \times C_{t-1} + i_t \times tanh(W_f \cdot [h_{t-1}, x_t] + b_c) \tag{6}$$
$$O_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0) \tag{7}$$
$$h_t = o_t \times tanh(C_t) \tag{8}$$

where i_t, o_t, and f_t denote the activation of the input gate, output gate, and forget gate, respectively; C_t and h_t denote the activation vector for each cell and memory block, respectively; W and b denote the weight matrix and bias vector, respectively. In addition, σ denotes the sigmoid function.

3) Bidirectional Long short-term memory (Bi-LSTM): The bidirectional LSTM (Bi-LSTM) is an extension of the LSTM architecture that offers a solution to the limitations posed by traditional RNNs. By processing the input sequence in both the forward and backward directions, Bi-LSTMs have the ability to capture dependencies and context from both past and future elements within the sequence. This bidirectional processing empowers Bi-LSTMs with a more comprehensive understanding of the question content, rendering them advantageous for text classification tasks.

The Bidirectional RNN (BRNN) model was conceived as a means of circumventing the constraints of conventional RNNs. Specifically, the LSTM variant of the BRNN architecture is referred to as Bidirectional LSTM (Bi-LSTM). This particular version exhibits the potential to enhance the performance of LSTM models in classification procedures. Distinct from the conventional LSTM structure, the Bi-LSTM architecture entails the training of two distinct LSTM networks to process sequential inputs.

The utilization of bidirectional LSTM (Bi-LSTM) structures has demonstrated superior performance compared to alternative network architectures, depending on the specific problem domain. Notably, Bi-LSTMs have exhibited significant successes in natural language processing tasks where content comprehension holds paramount importance. These architectures offer distinct advantages in text classification tasks.

III. DATA PREPROCESSING

As illustrated in Figure 1, the workflow encompasses both data collection, data clear and data augmentation processes.

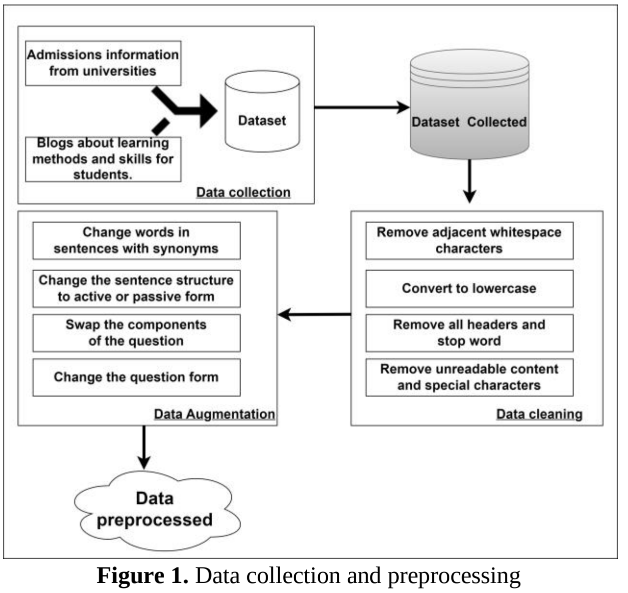

Figure 1. Data collection and preprocessing

A. Data collection

In this study, we undertook an investigation into data collection and representation techniques tailored for chatbot applications. Our approach centered around curating a comprehensive corpus of <*question, answer*> pairs pertaining to the domain of university education, vocational skills, and emerging technological trends for students. As a valuable resource, we drew inspiration from the insightful Blog Science Technology [12] authored by Professor John Vu from Carnegie Mellon University (CMU). Professor Vu's blog serves as a platform for disseminating cutting-edge information on learning methodologies, specialized skills, soft skills, and advancements in the fields of science and technology. Notably, a significant portion of the blog content adopts a question- and-answer format. However, due to our specific focus on the task of question classification for chatbots, we assembled additional questions to correspond with existing answers or topics discussed.

```
{
    {
        "qa list":[
            {
                "no":"1",
                "q":"What should a freshman
                     do?",
                "a":"The answer for this
                    question;etc;"
            },
        ]
    }
}
```

To facilitate efficient data organization, we devised a structured storage system json. Each question is represented by three key components: a unique sequence number ("no"), the textual content of the question ("q"), and the corresponding answer associated with the question ("a").

B. Data cleaning

In natural language processing (NLP), data cleaning is crucial for optimizing the performance of NLP models. The data cleaning phase employs various techniques, including sentence processing, special character removal, whitespace elimination, and lowercase conversion. These techniques enhance the ac- curacy and effectiveness of the models. The methods involved in this phase are as follows:

- Removing punctuation and special characters: Punctuation marks and special characters often do not carry much meaning in language processing and can introduce noise to the model.
- Normalizing capitalization: Normalizing the capitalization of words ensures consistency in the data.
- Removing stop words: Removing stop words from the data helps reduce the vocabulary size and focuses on more important words.
- Handling white spaces: This process improves the training of the model and focuses on more relevant words.

C. Data augmentation

Upon acquisition of the question sets, our endeavor encompasses the consolidation and categorization of these inquiries, yielding an exhaustive compilation of the most prevalent topics and content. Subsequently, an extensive repertoire of question sets, accompanied by their respective topics and content, is meticulously devised.

To create equivalent questions, we will apply the following principles:

- Replace words in the sentence with synonyms.
- Change the sentence structure to active or passive form.
- Rearrange the components of the question.
- Modify the question patterns

To further amplify the dataset's comprehensiveness, we meticulously gather question-answer pairs from specialized study materials. Following this meticulous data collection process, subsequent stages entail data cleaning and augmentation, culminating in a dataset comprising interconnected question- answer pairs. It is this enriched dataset that shall be harnessed for training and evaluating the model, leveraging prominent deep learning algorithms such as RNN, LSTM, and Bi-LSTM.

IV. METHODOLOGY

The essence of this investigation unfolds through a well- defined sequence of steps, as depicted in Figure 2. Commencing with meticulous data preparation, we proceed to employ the technique of word embedding, which facilitates the conversion of textual data into a numerical representation that deep learning models can comprehend. Subsequently, we harness the power of sophisticated deep learning architectures, including RNN, LSTM, and Bi-LSTM, to undertake the crucial task of data classification. Through the application of these cutting-edge models, we aim to unravel the underlying patterns and structures within the dataset, thereby advancing our under- standing and enabling more accurate classification outcomes. The application of data preprocessing techniques holds promising potential for enhancing the outcomes of classification tasks. In the context of this investigation, it is postulated that every query possesses an accompanying response. Consequently, this particular inquiry is aptly labeled as a binary classification quandary, where the ascertained outcomes are appraised as either accurate or erroneous rejoinders for each respective question, aligning with the numerical values of 1 or 0.

A. Word embedding

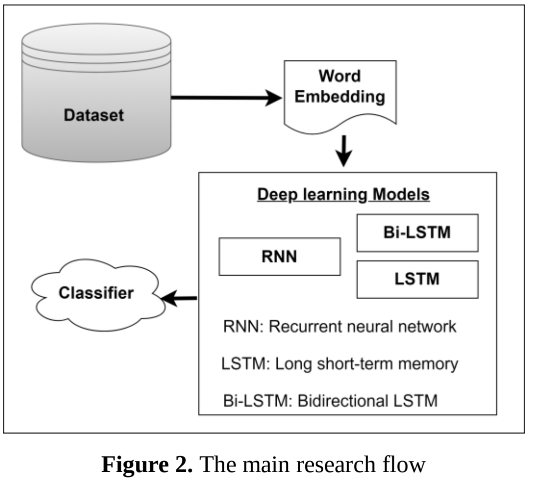

Figure 2. The main research flow

After data preparation and preprocessing, the original data is transformed through vectorization. One approach involves creating a word library from the training dataset, where each word is assigned a unique index based on its frequency. The text is then converted into a vector representation by replacing each word with its corresponding index. An embedding class is employed to convert each word into a numerical vector, establishing a connection between indices and vector representations.

With the vectorized dataset, experiments are conducted using deep learning models such as RNN, LSTM, and Bi-LSTM. These models analyze the dataset and extract meaningful insights, enabling accurate classification outcomes. With the foundation of the vectorized dataset established, subsequent experiments are conducted utilizing prominent deep learning models such as RNN, LSTM, and Bi-LSTM. These models serve as powerful tools to analyze and extract meaningful insights from the dataset, facilitating accurate classification outcomes.

B. Evaluation criteria

In this study, we will utilize metrics such as Accuracy, Precision, Recall, and F1-score to compare and evaluate the results.

Evaluation metrics such as Accuracy, Precision, Recall, and F1-score are crucial in assessing classification models. Accuracy measures the percentage of correct predictions out of all predictions, while Precision focuses on the accuracy of positive predictions. Recall evaluates the model's ability to capture all positive instances, and F1-score combines Precision and Recall to evaluate overall performance. These metrics are widely used in tasks such as label prediction, fraud detection, and image classification. However, the choice and evaluation of these metrics depend on the specific context and goals of the classification model.

V. RESULTS AND ANALYSIS

In this research, experiments are conducted to explore the performance of recurrent neural network (RNN) architectures, including RNN, LSTM, and Bi-LSTM models. These models are designed with specific layers to optimize functionality and classification outcomes. The aim of this research is to investigate the capabilities and performance of RNN, LSTM, and Bi-LSTM models in classification tasks.

A. With RNN model

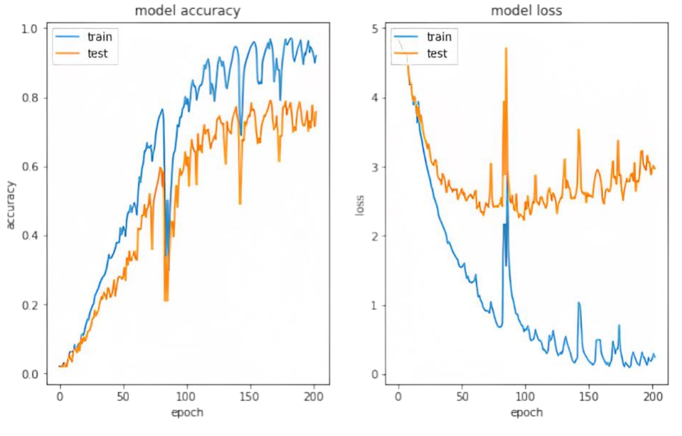

Figure 3. Accuracy and loss value on RNN model

Figure 3 presents a visual representation showing the accuracy and loss values during the implementation phase of the Recurrent Neural Network (RNN) model.

Accuracy Graph: The accuracy trajectories of the training and test data exhibit an ascending pattern, indicating the model's learning proficiency without overfitting. However, further training may be required to achieve enhanced performance.

Loss Graph: If the training data curve consistently declines while the test data curve does not show a corresponding de- crease, it suggests overfitting. This means the model performs well on the training data but struggles to generalize to new instances.

The classification accuracy on the test dataset is approximately 79,48%, which is considered modest. Both graphs show noticeable oscillation, indicating a lack of stability in the model's performance.

B. With LSTM model

Figure 4 shows the accuracy and loss values achieved during the implementation of the Long Short-Term Memory (LSTM) model.

Accuracy Graph: The training and test data curves consistently rise together with each epoch, indicating effective learning without overfitting.

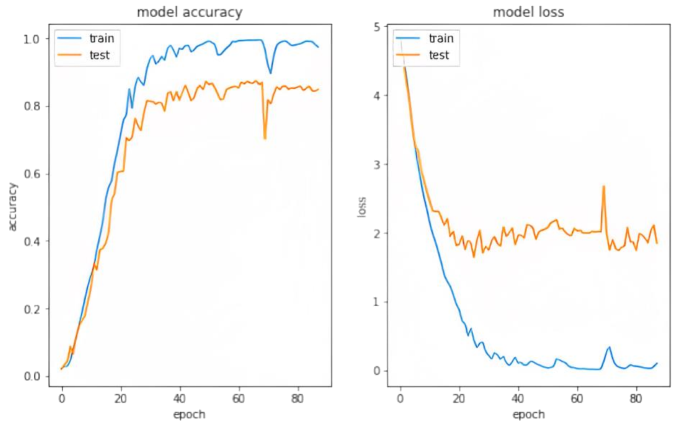

Figure 4. Accuracy and loss value on LSTM model

Loss Graph: Both the training and test data curves show a downward trend, with some intermittent fluctuations. This suggests that the model requires adequate training time to reach optimal performance.

The classification accuracy on the test dataset is approximately 83.34%, surpassing the accuracy of the Recurrent Neural Network (RNN) model. Notably, both graphs exhibit minimal fluctuations, demonstrating the model's remarkable stability.

C. With Bi-LSTM model

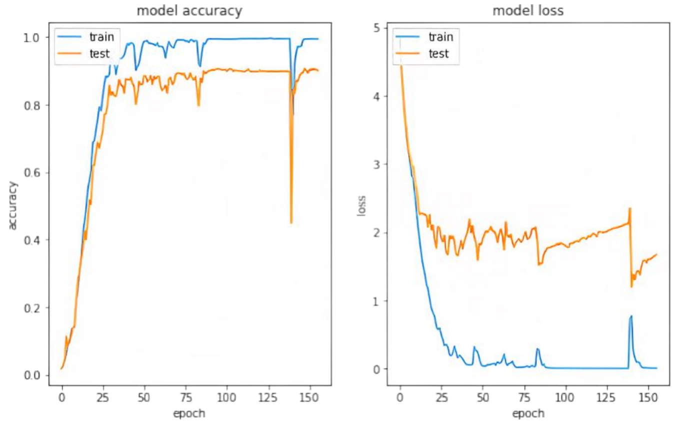

Figure 5. Accuracy and loss value on Bi-LSTM model.

Figure 5 presents the accuracy and loss values achieved using the Bidirectional Long Short-Term Memory (Bi-LSTM) model.

Accuracy Graph: Both the training and test data curves consistently and synchronously rise with each epoch, converging towards a stable value. This pattern indicates the model's ability to acquire knowledge without overfitting.

Loss Graph: The training and test data curves exhibit a simultaneous and continuous decrease, reflecting effective learning within the model.

The classification accuracy on the test dataset is approximately 91.5%. The graphs show limited fluctuations, with instances of accuracy reaching 1.0 and maintaining stability over time. Similarly, the model's loss follows a similar pattern, occasionally reaching 0, indicating high performance and the ability to provide highly accurate responses.

These findings highlight the significant advancements achieved by the Bi-LSTM model compared to RNN and LSTM architectures. The model excels in generating accurate answers, making it highly relevant for real-world applications.

D. Comparison and evaluation

Figure 6 showcases a Comparative Analysis table, presenting an array of measures across various algorithms. The findings elucidate that the utilization of the Bi-LSTM model yields the most favorable outcomes in relation to essential evaluation metrics, namely Accuracy, Precision, Re- call, and F1 score, when employed in the context of this classification problem. Notably, the Bi-LSTM model attains impressive performance levels with corresponding values of 91.5%, 84%, 86%, and 84%, respectively.

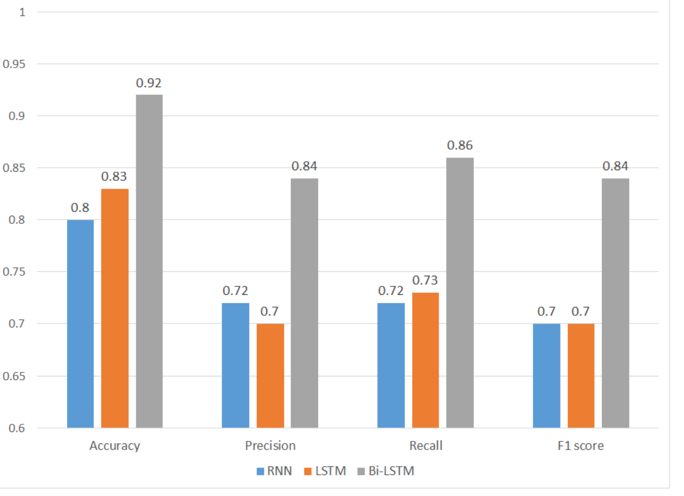

Figure 6. Comparison table of measures between algorithms

E. Deployment

The deployment of a sophisticated chatbot system for enrollment advising necessitates the establishment of a dedicated website, the construction of specialized datasets for admissions consultants, and the application of deep learning models like LSTM, RNN, and Bi-LSTM. This comprehensive approach aims to enhance the user experience, deliver personalized guidance, and optimize the efficiency of the enrollment advising process. By seamlessly integrating cutting-edge technology with personalized support, universities can transform the way they engage with prospective students, ultimately leading to improved enrollment outcomes and student satisfaction.

Upon completion of the deep learning model training, seamless integration of these models within the chatbot system facilitates real-time interactions with students. The chatbot interface is meticulously designed to deliver a natural and conversational experience, providing prompt responses and adaptive dialogues based on the models' predictions. The chat- bot assumes a multifaceted role, aiding students in navigating the intricacies of the enrollment process, addressing frequently asked questions, providing personalized recommendations, and, when necessary, connecting students with admissions consultants for further assistance.

VI. CONCLUSION

In conclusion, the study dedicates specific attention to the development of datasets tailored specifically for admissions consultants, recognizing the paramount importance of reliable and pertinent information in the advising domain. By employing meticulous data preprocessing techniques, the study enhances the quality and applicability of the gathered data, ensuring its appropriateness for subsequent analysis.

Furthermore, the study explores the application of deep learning models, including RNN, LSTM, and Bi-LSTM, to extract valuable insights from the datasets. Notably, the experimental outcomes demonstrate promising levels of accuracy, with the RNN achieving a notable accuracy rate of 79.48%, while LSTM attains 83.34%, Bi-LSTM reaches 91.45%. These models afford admissions consultants the ability to make precise predictions, comprehend student behaviors, preferences, and needs, and offer personalized recommendations and guidance throughout the enrollment journey.

The study investigates the integration of deep learning models into chatbot interfaces, revolutionizing the advising ecosystem. By implementing chatbots, students gain accessible and user-friendly platforms to interact with enrollment advisors, receiving prompt responses and support. This integration enhances scalability and empowers students with instant access to valuable information, enriching their overall experience.

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CẢI THIỆN TƯ VẤN ĐĂNG KÝ HỌC TRONG LĨNH VỰC GIÁO DỤC THÔNG QUA MÔ HÌNH HỌC SÂU VÀ CHATBOT

Nguyễn Năng Hùng Văn, Hồ Lê Minh Nhật, Võ Đức Hoàng, Đỗ Phúc Hảo

TÓM TẮT: *Tư vấn tuyển sinh đóng vai trò then chốt trong việc hướng dẫn các sinh viên có nguyện vọng trong suốt quá trình tuyển sinh đại học. Sự xuất hiện của các mô hình học sâu và công nghệ chatbot đã mở ra những con đường mới để xác định lại cách tiếp cận tư vấn tuyển sinh. Nghiên cứu này, tập trung chú ý vào việc tạo ra các bộ dữ liệu tùy chỉnh dành riêng cho các nhà tư vấn tuyển sinh và làm sáng tỏ các quy trình tiền xử lý dữ liệu được sử dụng để nâng cao chất lượng thông tin trong tư vấn. Hơn nữa, nghiên cứu đã chứng minh việc ứng dụng hiệu quả các mô hình học sâu trong việc phân tích và biểu diễn dữ liệu thu được, tạo điều kiện cho những dự đoán chính xác và đề xuất riêng cho từng sinh viên tương lai. Cuối cùng, việc khám phá mở rộng sang việc triển khai các mô hình học sâu này trong giao diện chatbot, cung cấp một nền tảng hấp dẫn và dễ tiếp cận để học sinh và phụ huynh tương tác với cố vấn tuyển sinh. Sự kết hợp giữa mô hình học sâu và chatbot mang lại tiềm năng cách mạng hóa lĩnh vực tư vấn tuyển sinh, giúp nâng cao hiệu quả, khả năng mở rộng và trải nghiệm phong phú cho người dùng.*

Từ khóa: *Enrollment Advising, Chatbots, Recurrent Neural Networks, Long Short-Term Memory, Bidirectional - LSTM.*