Transforming Student Advising in Smart Cities: A Deep Learning Conversational AI Chatbot

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***Abstract*— Citizens, including students, teachers and parents can all be significantly involved in the smart cities, as smart education is one of the main key drivers in developing smart citizens. Indeed, high school plays an essential role not only in shaping students' future career, but also in contributing to the development of smart citizens. High school students who benefit from college-career advising will be more prepared and motivated to universities compared to students from other schools. Because the availability of college-career guidance position can vary in schools, students might not get the proper guidance equally. Therefore, in this paper a novel deep learning based chatbot is implemented by using the Seq2Seq model trained on 2944 students' inquiries for taking the role of a college-career guidance in high schools. In this model a BiLSTM layer is configured with 400 units in each direction of LSTM layer and a single dense layer with Softmax activation is included in the decoder component. The model is evaluated by using ROUGE-N measures. The results revealed a high precision score of 92% in ROUGE-1 metric.**

Keywords— Artificial Intelligence, BiLSTM, Chatbot, Generative, NLP, Smart City, Seq2Seq

I. INTRODUCTION

The emerging technologies of artificial intelligent (AI) algorithms and the Internet of Things (IoT) play an essential role in making the city more sustainable and smarter [1, 2]. However, according to Duan et al. [3] the smart city includes other important sub components such as smart management, smart health, smart energy, smart infrastructure, smart transportation, and smart citizen, which can add all more value to the smart city. Consequently, not all cities can be smart in same degrees, as some cities might be smarter in terms of education and others in transportation, however, the common primary goal of most of smart cities is providing a high quality of life for their citizens including their well-being, security, health, and economy [4]. Citizens, including students, teachers and parents can all be significantly involved in the smart cities since the smart education is one of the main key drivers in developing the smart citizens. Smart schools and universities can promote the smart education by providing the state of the-art technologies in campuses and classes to be connected efficiently and effectively, which can eventually improve the students' satisfactions as well as increasing the productivity and saving money [5]. Nevertheless, several authors conducted imperial studies about the impact of high school students' college preparedness on students' success at universities. Oripova [6] conducted a quantitative study to determine the impact of integrating effective academic advising process into the high school programs on students' university degree attainment rate, the findings show a positive impact of including effective academic advising into high schools' programs. In fact, high school students who benefit from college-career advising will be more prepared and motivated to universities compared to students from other schools [7], aaccordingly, these prepared students will be able eventually to save more money and time in completing their higher education degrees successfully. On the other hand, the economically disadvantaged schools and parents cannot afford to hire academic advisers during high school. Henceforth, this paper aims to offer a smart and affordable chatbot to support students and parents in smart cities, preparing them effectively toward their careers and future. In this paper a novel generative chatbot will be implemented by using the Seq2Seq model for taking the role of a college-career adviser. It works by combining different machine learning algorithms and deep learning neural networks, which in turn works as an affordable high school college-career adviser. This conversational chatbot offers benefits to both students and schools within smart cities. As a result, students from various educational and socioeconomic backgrounds across different schools can get advised fairly and effectively.

A. College-Career Guidance

Students begin planning for their future during the high school typically in grade 10, grade11 and grade12, they need to select the elective subjects, advanced courses such the advanced placement subjects (AP) and pre-admission and standardized test such as Preliminary Scholastic Aptitude Test (PSAT), as well as English proficiency tests for international students such as International English Language Testing System (IELTS) and the Test of English as a Foreign Language (TOEFL). Moreover, during this stage student needs advices to explore the majors and universities that can fit them academically, economically and socially. Therefore, the college-career counselor plays an effective role in assisting students in college and career readiness [8]. Students around the world need advices before applying to universities, since most universities have application deadline besides some required national and international standardized tests need to be completed. Moreover, advisers can provide students with major and career assessments that can help them to select the best-fit majors.

B. *Converstaional AI agent (Chatbot)*

Conversational Artificial Intelligence (AI) is an advanced technology that acts as an AI agent or a chatbot. It is driven by using neural networks algorithms and other techniques from Natural Language Processing (NLP) in order to mimic human conversation [9, 10]. Nonetheless, a various of the state-of the-art machine learning models are developed and integrated into chatbots including the LSTM, GPT, and BERT. Interestingly, that using the advanced AI algorithms and models has improved the chatbots' ability to generate new responses without necessarily using pre-define answers. In this paper, a generative chatbot will be developed to support the high school students to receive a generative answer effectively and instantly.

II. RELATED WORK

There are limited studies that have focused on developing college-career advising chatbots for high school students, since most of previous advising chatbots are for supporting matriculated students at universities. Le Hoanh et al. [11] and Goyal et al. [12] developed a machine learning chatbot for admission and career guidance for universities as students can be exposed to the future career. However, it is not a generative chatbot, it's built by using NLP and SVM model as classification model for predicting the future career based on particular question. Moreover, Zaidi et al. [13], Cont et al. [14] and Kumbhar et al. [15] developed other smart applications performing the same tasks in predicting students' careers but by using different techniques, such as Dialogflow and Microsodt zure BOT Service. Some universities request students to declare their majors in their second year at universities and students might feel confusing in deciding their majors, and such chatbots can help them effectively. Lee et al. [16] developed an AI chatbot for college students to expose them more about the STEM majors as well to predict their careers based on their personality strengths. Whereas Dongre et al. [17] designed a chatbot for assisting high school students particularly in career planning by using the Dialogflow and the ASP Framework, this chatbot predicts the future's career based on students' skills and experiences. However, the college-career guidance is not limited to career advising as students need more advising on university' application, admission tests, application deadline, academic plan, and etc. In summary, the below Table 1 shows several previous studies about developing college guidance chatbots for high schools and university students.

TABLE 1. PREVIOUS CONVERSATIONAL AI SERVICES AND CHATBOTS FOR COLLEGE CAREER GUIDANCE.

Author	AI-Chatbot	Domain	Task
Le Hoanh et al.(2020)	SVM	University	Admission and Career
Goyal et al. (2023)	Random Forest & SVM	University/ School	Career Counselling Chatbot (ICCC)
Zaidi et al.(2021)	Dialogflow	University	career counselling chatbots
Cont et al.(2022)	Microsoft zure BOT Service & ML	Alumni (University Graduates)	Career Counseling and Orientation (Job interview/ CV/career plan)
Kumbhar et al.(2023)	Decision Tress, Random Forest & RNN/LSTM	University	Career/Majors
Dongre et al. (2021)	Dialogflow	High School	Career/Major
Lee et al. (2019)	AI Chatbot	University	Exploring Majors that fit students

Despite the importance role of college and career counselors for high school students and parents [18], the summary reviews in Table 1 as well as the systematic literature review of chatbots in academic advising conducted by Assayed et al. [19] suggest that most previous chatbots and conversational AI services for college-career advisers are focused on either university' students or alumni, rather than high school students. To bridge this gap, this study aims to develop a generative model that support high school students as well as parents to answer to their different enquiries and concerns including admission tests, advanced courses, standardized exams, applying to universities, majors and future careers.

III. EXPERIMENT AND DEVELOPMENT

A. *Corpus Collection*

In this paper we built a corpus consisting of 2944 questions and answers within the college-career high school domain. To insure the quality of data, we collected the data from authorized academic websites, including universities, schools, academic organizations and other educational consultant providers.

B. *Preprocessing Phase*

Pre-processing is an essential step for any application of Natural Language Processing System [20], in this stage, multiple functions are implemented in order to make the data readable for the neural network algorithms. The dataset in this study is cleaned first by removing the duplicates data, it's normalized by converting all texts to lowercase using the function lower() then the regular expression function "re" is implemented to replace and update some texts, for example we used it to replace the " i'm" to "i am", "he's" to "he is" and etc. Then each text in the corpus is divided into tokens by using the split() function from python's library. Since we are using deep learning algorithms, making all students' inquiries same length will increase the performance during the training process, so we used the function pad_sequences to make it all same length. Afterward, the vocabulary was created from the unique tokens and indexed accordingly. As results the size of vocabulary in our study is 3367.

C. *Word Embedding*

This process improves the efficiency of the model, as it can reduce the dimensionality of the data by capturing the semantic relationships between all tokens in the dictionary [21], and accordingly reducing the waste of memory. In our experiment we represented the embedded layer with 50 columns rather than having 3367 columns -which is the size of the vocabulary-.

D. *Model Building and Compilation (Encoder-Decoder Architecture)*

The model in this study is constructed by main two components, the first one is the encoder which takes student's enquiry for reading it and then encapsulate the meaning of the text into a fixed length vector "a context vector". We used the Bidirectional Long Short Memory (BiLSTM) as it can process the input texts for both directions, the forwards and backwards in order to encapsulate the meaning from both sides. Afterward, the decoder takes the context vector as input during the training process. (see Fig.1). Then, the loss function and parameters are updated accordingly. However, during the testing phase the decoder is fed by the prediction from the previous step, rather than the training process as it's fed by the (real token) at each step.

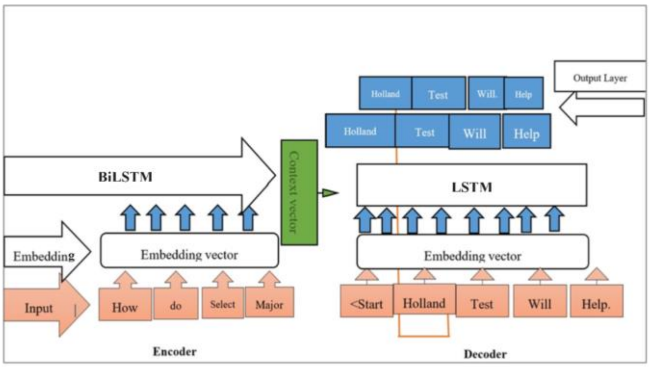

Fig. 1. The Architecture of Encoder-Decoder in this study

E. *The Bidirectional Long Short-Term Memory (BiLSTM)*

The Bidirectional Long Short-Term Memory is type of the recurrent neural networks (RNN), it processes the information in two directions, by using two hidden layers. According to different papers that the BiLSTM model outperforms the normal LSTM models [22] since BLSTM can train the input data in two sides (from past to future, from future to fast) which can see the words in future and accordingly will be able to predict the next words. Whereas, the unidirectional LSTM only recall the information of the past as it's the only data that are seen. According to the survey of the state of the art architecture of LSTM models that conducted by Lindemann et al. [23] the BiLSTM architecture can detect more time dependencies than unidirectional LSTM networks. In this experiment we used 400 units in each of LSTM direction as shown in Fig. 2. However, in order to predict the output text sequence, we used a single dense layer with Softmax activation in the decoder component.

```
=================================================================
============
 input_2 (InputLayer)          [(None, 13)]

 input_1 (InputLayer)          [(None, 13)]

 embedding (Embedding)         (None, 13, 50)


 bidirectional (Bidirectional)  [(None, 13, 800),
                                 (None, 400),
                                 (None, 400),
                                 (None, 400),
                                 (None, 400)]

 concatenate (Concatenate)     (None, 800)
[1]',

[3]']

 concatenate_1 (Concatenate)   (None, 800)
[2]',

[4]']

 lstm_1 (LSTM)                 [(None, 13, 800),
                                 (None, 800),
                                 (None, 800)]
[0]']

 dense (Dense)                 (None, 13, 3367)

=================================================================
============
Total params: 7,031,767
Trainable params: 7,031,767
```

Fig. 2. The description of the deep learning layers that are used in this study

F. *Model Compilation*

In order to improve the performance during the training and testing phase, we used the optimization algorithms to minimize the loss function and increasing the accuracy rate. In our experiment, we applied both optimizers the Adaptive Moment Estimation (Adam) and the Stochastic Gradient Descent (SGD) during the hyperparameter tuning, and accordingly we calculated the performance and the accuracy. However, the Adam optimizer outperforms the SGD optimizer in terms of the accuracy as shown in Table 2, the accuracy score reached 99%.

TABLE 2. THE ACCURACY RATE DURING THE HYPERPARAMETER TUNING

Optimizer	**Epochs**	**Loss Function**	**Accuracy**
Adams	100	0.0450	0.9908
SGD	100	4.7276	0.2754

G. Running The Model

The inference or predictive model can be used to run the BiLSTM or any other sequential [24]. However, this chatbot is performed by feeding the inference model with new five questions which have posed by high school students. Initially, the authors tested the model by using the SGD optimizer, however the model performed poorly as shown in Table 3.

TABLE 3: TESTING THE MODEL WITH FIVE NEW QUESTIONS BY USING SGD OPTIMIZER.

Enquiry	Answer (Chatbot)- SGD Optimizer
Show me the top universities in UK	the university of a a univer sities of university of unive rsity of
Where can I study Medicine in UAE	you university of a a a univ ersities of universities of
Should i study IB or ALevel	the you is a a a a universities of a universities
How can I apply to USA universities	you you to a a a your your you and
How can I select my major?	you you to a a a a college of you

Interestingly, the same model was tested using Adam optimizer and the results show a significant performance improvement compared to the SGD optimizer as shown in Table 4.

TABLE 4: TESTING THE MODEL WITH FIVE NEW QUESTIONS BY USING ADAM OPTIMIZER.

Enquiry	**Answer (Chatbot)- Adam optimizer**
Show me the top universities in UK	university of oxford and th e university of cambridge a re top universities
Where can I study Medicine in UAE	american university emirates and university of sharjah
Should i study IB or ALevel	the ib is more challenged than alevels the ib students must
How can I apply to USA universities	you might use the common application or universal application to usa
How can I select my major?	this test holland theory can help you to decide on your

H. Evaluating the Model

This Conversational AI adviser (chatbot) is evaluated by using the performance metrics precision, recall and F1-score of ROUGE-1gram, ROUGE-2 gram, and ROUGE-L. However, the maximum score is achieved in ROUGE-1 with a precision score of 92%

I. Chatbot Interface

In this study, we used the *Tkinter* Library from Python in order to create the Graphical User Interface (GUI). Two simple boxes are created, one for the student's inquiry and the other for the chatbot's answer. Fig. 3 shows the interface after running the inference model.

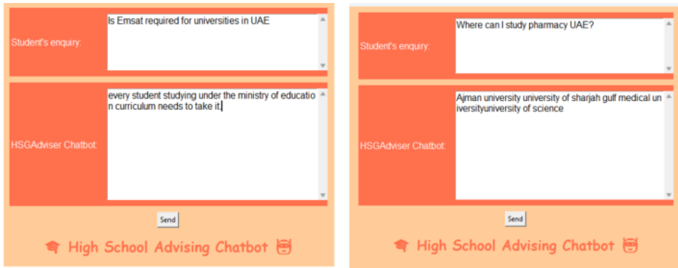

Fig. 3. The interface of the College-Career Guidance chatbot after running the inference model

IV. RESULTS AND DISCUSSION

In this paper, the authors implemented the Bidirectional Long Short Memory (BiLSTM) model within a sequential architecture (Seq2Seq) for the college-career guidance chatbot in order to provide effective guidance and advice to high school students. During the training process the Adam optimizer shows a high performance in training the data, compared to the Stochastic Gradient Descent (SGD) (See Fig.4). Consequently, the model performs a good performance by efficiently answering to five questions as depicted in Table 5 with average precision scores of 92%%, and 71%, and 88% for ROUGE-1, ROUGE-2 and ROUGE-L respectively. The recall score of 81% for ROUGE-1, 61% for ROUGE-2 and 77% for ROUGE-L. Moreover, the F1 score indicates good score with achieving 86%, 69% and 81% for ROUGE-1, ROUGE-2 and ROUGE-L respectively.

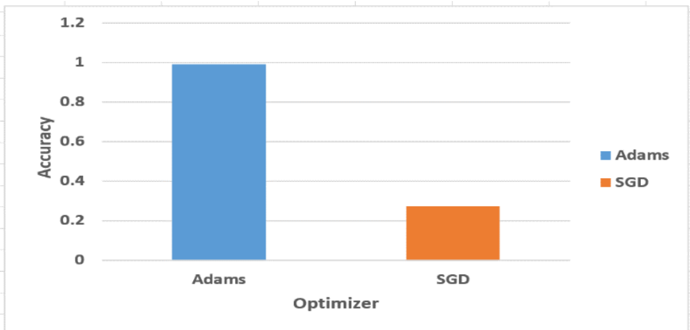

Fig. 4. the Adam optimizer shows a high performance compared to the SGD optimizer

TABLE 5. THE MODEL PERFORMANCE USING THE ROUGE METRICS BY ANSWERING TO FIVE HIGH SCHOOL QUESTIONS.

Enquiry	ROUGE-1			ROUGE-2			ROUGE-L		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Show me the top universities in UK	100%	85%	92%	90%	75%	82%	100%	85%	92%
Where can I study Medicine in UAE	86%	67%	75%	67%	50%	57%	86%	67%	75%
Should I study IB or A Level	82%	90%	86%	50%	56%	53%	64%	70%	67%
How can I apply to USA universities?	100%	79%	88%	80%	62%	88%	100%	79%	88%
How can I select my major?	91%	83%	87%	70%	64%	67%	91%	83%	87%
Average Score	92%	81%	86%	71%	61%	69%	88%	77%	81%

V. CONCLUSION AND FUTURE WORK

This study fills the gap in developing an AI-college career adviser in smart cities to guide high school students toward their future careers. Since the smart chatbot can promote a sustainable education with ensuring the equality and fairness in students advising [25]. Henceforth, this novel generative chatbot was developed by using Seq2Seq architecture trained on corpus of 2944 high school questions and answers within the college-career domain. The BiLSTM layer is configured with 400 units in each direction of LSTM layer. Additionally, a single dense layer with Softmax activation is included in the decoder component in order to predict the student's answers. The model is evaluated by using ROUGE-N measures into different n-grams, as answers are compared between the chatbot-generated and the human answer (reference). When the chatbot was provided with new five questions, the chatbot responded effectively to them. The results revealed a high precision score of 92% in ROUGE-1. In future, the model will be developed to include a bilingual corpus supporting the Arabic language, and additionally neural network layers will be integrated in the model.

REFERENCES

1. Wang, K., Zhao, Y., Gangadhari, R. K., & Li, Z. (2021). Analyzing the adoption challenges of the Internet of things (Iot) and artificial intelligence (ai) for smart cities in china. *Sustainability*, *13*(19), 10983.
2. Alsamhi, S. H., Ma, O., Ansari, M. S., & Almalki, F. A. (2019). Survey on collaborative smart drones and internet of things for improving smartness of smart cities. *Ieee Access*, *7*, 128125-128152.
3. Duan, W., Nasiri, R., & Karamizadeh, S. (2019, December). Smart city concepts and dimensions. In *Proceedings of the 2019 7th International Conference on Information Technology: IoT and Smart City* (pp. 488-492).
4. Chang, S., & Smith, M. K. (2023). Residents' Quality of Life in Smart Cities: A Systematic Literature Review. *Land*, *12*(4), 876.
5. Assayed, S. K., Alkhatib, M., & Shaalan, K. (2023, June). Advising chatbot for high school in smart cities. In *2023 8th International Conference on Smart and Sustainable Technologies (SpliTech)* (pp. 1-6). IEEE.
6. Oripova, M. (2022). The impact of intrusive college academic advising on high school students' college degree attainment commitment levels: A quantitative quasi-experimental study. *Social Sciences & Humanities Open*, *6*(1), 100315.
7. Perry, J. (2023). Providing College and Career Counseling to Students in Rural Settings. *Post-Secondary Planning for All: Approaches to College and Career Readiness Counseling for Special Populations*, 105.
8. Paolini, A. C. (2019). School counselors promoting college and career readiness for high school students. *Journal of School Counseling*, *17*(2), n2.
9. Kulkarni, P., Mahabaleshwarkar, A., Kulkarni, M., Sirsikar, N., & Gadgil, K. (2019, September). Conversational AI: An overview of methodologies, applications & future scope. In *2019 5th International Conference On Computing, Communication, Control And Automation (ICCUBEA)* (pp. 1-7). IEEE.
10. Meshram, S., Naik, N., Megha, V. R., More, T., & Kharche, S. (2021, June). Conversational AI: Chatbots. In *2021 International Conference on Intelligent Technologies (CONIT)* (pp. 1-6). IEEE.
11. Le Hoanh Su, T. D. H., Thi-Yen-Linh, T., Thi-Duyen-Ngoc, N., Bao-Tuyen, L., & Ha-Phuong-Truc, N. (2020). Development of an AI Chatbot to support admissions and career guidance for universities. *International Journal of Emerging Multidisciplinary Research*, *4*(2), 11-17.
12. Goyal, R., Chaudhary, N., & Singh, M. (2023, January). Machine Learning based Intelligent Career Counselling Chatbot (ICCC). In *2023 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1-8). IEEE.
13. Zaidi, D., Raza, S., & Sharma, L. (2021). Artificial intelligence based career counselling chatbot a system for counselling. *Annals of the Romanian Society for Cell Biology*, *25*(6), 11732-11735.
14. Conţ, M., Ciupe, A., Orza, B., Cohuţ, I., & Niţu, G. (2022, March). Career counseling chatbot using microsoft bot frameworks. In *2022 IEEE Global Engineering Education Conference (EDUCON)* (pp. 1387-1392). IEEE.
15. Kumbhar, V. R., Maddel, M. M., & Raut, Y. (2023, March). Smart Model For Career Guidance Using Hybrid Deep Learning Technique. In *2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP)* (pp. 327-331). IEEE.
16. Lee, T., Zhu, T., Liu, S., Trac, L., Huang, Z., & Chen, Y. (2021, October). CASExplorer: A Conversational Academic and Career Advisor for College Students. In *The Ninth International Symposium of Chinese CHI* (pp. 112-116).
17. Dongre, G., Vadraiwala, F., Upadhyaya, J., & Ghosal, D. (2021). Web-Based Career Counselling System With Chatbot. *International Research Journal of Modernization in Engineering Technology and Science*, *3*, 571-579.
18. Novakovic, A., Patrikakou, E. N., & Ockerman, M. S. (2021). School counselor perceptions of preparation and importance of college and career readiness counseling. *Professional School Counseling*, *25*(1), 2156759X21998391.
19. Assayed, S. K., Alkhatib, M., & Shaalan, K. (2024). A Systematic Review of Conversational AI Chatbots in

Academic Advising. In *BUiD Doctoral Research Conference 2023* (pp. 346-359). Springer, Cham.

20. Assayed, S., Shaalan, K., & Alkhatib, M. (2023). A chatbot intent classifier for supporting high school students. *EAI Endorsed Transactions on Scalable Information Systems*, *1*.
21. Selva Birunda, S., & Kanniga Devi, R. (2021). A review on word embedding techniques for text classification. *Innovative Data Communication Technologies and Application: Proceedings of ICIDCA 2020*, 267-281.
22. Mahmoud, A., & Zrigui, M. (2021). BLSTM-API: Bi-LSTM recurrent neural network-based approach for Arabic paraphrase identification. *Arabian Journal for Science and Engineering*, *46*, 4163-4174.
23. Lindemann, B., Müller, T., Vietz, H., Jazdi, N., & Weyrich, M. (2021). A survey on long short-term memory networks for time series prediction. *Procedia CIRP*, *99*, 650-655.
24. Ramirez-Alcocer, U. M., Tello-Leal, E., Romero, G., & Macías-Hernández, B. A. (2023). A Deep Learning Approach for Predictive Healthcare Process Monitoring. *Information*, *14*(9), 508.
25. Assayed, S. K., Alkhatib, M., & Shaalan, K. (2023, May). Artificial Intelligence based Chatbot for promoting Equality in High School Advising. In *2023 4th International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 1-4). IEEE.