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Designing a Chatbot for the College Website

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Abstract- This study focuses on developing a chatbot for a college website to enhance the user experience by automating responses to common inquiries, including FAQs, admissions, and student support. The backend uses Dialog flow, TensorFlow, and Python for NLP-based contextual intelligence, while the frontend uses HTML and CSS for smooth deployment. The system demonstrated the efficacy of AI-powered chatbots in enhancing accessibility, lowering workload, and offering ongoing support in academic settings with an 8.7/10 user satisfaction score and 91% response accuracy [1]– [5], [16].

Keywords: Artificial Intelligence, Chatbot, Dialogflow, NLP, Machine Learning, TensorFlow, and College Website Automation.

I. INTRODUCTION

AI tools are being used by academic institutions more frequently to enhance accessibility and digital transformation initiatives [1], [5], and [12]. Chatbots are an effective means of answering common inquiries, facilitating communication, and delivering prompt answers [2], [4], [7]. The suggested system lessens staff workload and improves user satisfaction by automating FAQs, admissions inquiries, and student support [3], [4], [13]. Additionally, AI-based conversational systems have demonstrated great promise in sustaining ongoing interaction with stakeholders and students [5, 16, 18].

II. LITERATURE REVIEW

AI-driven conversational systems in education have been the subject of numerous studies. Sharma et al. proposed a rule-based chatbot, though scalability remained a challenge [1]. Deshmukh and Patel implemented a Dialog flow-based NLP chatbot with 85% intent accuracy [2]. Gupta et al. later introduced machine-learning-based models that improved dynamic response generation [3]. Kumar et al. demonstrated the role of chatbots in improving student engagement [4].

Deep learning models such as LSTM and BERT further enhanced contextual understanding in chatbots, as shown by Wang and Liu [6] and Devlin et al. [14]. Hybrid AI architectures combining rule-based and neural models were discussed by Ghosh et al. [7], contributing to improved accuracy and conversational flow.

Comparative analyses of chatbot frameworks-including Dialog flow, Rasa, and IBM Watson-revealed that AI-based systems generally outperform traditional models in scalability and accuracy [8], [9], [17]. Additional research on intelligent agent alignment and communication systems further strengthens the reliability of chatbot architectures [16], [19].

III. METHODOLOGY

Data collection, preprocessing, model training, and frontend integration are all steps in the structured AI pipeline that the suggested system uses [10], [11]. First, student FAQs and past questions were gathered, and the text data was cleaned up using stop-word removal, tokenization, and stemming. Five thousand labeled queries from categories like "admission process," "course details," "fee structure," and "faculty information" were used to train a TensorFlow-based intent classification model.

On the training set, the model's accuracy was 93%, and on the validation set, it was 89%. NLP tasks like entity extraction, fallback intent handling, and intent mapping were handled with Dialogflow [2], [9]. The backend was powered by Flask and Python, which handled database interactions and API requests. Using HTML and CSS, the chatbot was integrated into the college website to guarantee accessibility and seamless device interaction [11], [20].

IV. SYSTEM ARCHITECTURE

The backend database, the NLP engine, and the user interface are three layers of the chatbot. Using HTML, CSS, and JavaScript, the user interface offers a chat panel for user interaction [11]. TensorFlow and Dialogflow enable the NLP layer, which interprets natural language inputs and determines user intent [10], [14]. A database with institutional data and frequently asked questions is accessed by the backend layer, which was created with Flask and Python. The NLP model first determines the user's intention through classification, integrates the appropriate answer and delivers it to the user without any delay [7], [17]. The layered structure allows for modularity, scalability, and easy maintenance of the system.

V. CHALLENGES

Limited training data and ambiguity in language are two of the challenges that come with designing an AI chatbot [6], [12]. It is difficult for rule-based systems to maintain contextual continuity in multi-turn conversations. It is essential to ensure privacy compliance and update the system with institutional changes [12], [13], [20].

VI. COMPARATIVE ANALYSIS AND DATA QUALITY

Accuracy of the chatbot depends on labeling accuracy and data quality. The accuracy of rule-based and AI-based models was compared and found to be 91% and 72%, respectively [9]. In line with earlier research by Ghosh et al. [7] and Kumar et al. [4], user satisfaction increased noticeably [19].

VII. MODEL ACCURACY COMPARISON

BERT, LSTM, and logistic regression are the three AI models which were tested by us. The BERT model with an F1 score of 0.92 came out to be the best when compared to the other two [6], [14]. BERT's contextual embeddings led to an increase in conversational understanding [16], [18].

VIII. PERFORMANCE EVALUATION

The system achieved a precision of 0.91, a recall of 0.90, and an F1 score of 0.905, with a latency of 1.3 seconds per response [3]. 87% of users rated it reliable and easy to use [5], [7], [13] which aligns with findings from other modern AI assistant evaluations [18], [19].

IX. CONCLUSION

Student and administrative interactions are efficiently automated by the AI chatbot. High accuracy, scalability, and reliability were attained by integrating Dialog flow and TensorFlow [10], [14], [16]. In terms of efficiency and satisfaction, it performed noticeably better than rule-based systems [1], [4].

Future Scope

Predictive analytics, voice-based help, and ERP system integration are examples of future improvements [14], [15], [18]. Features that are emotion-aware and multilingual may improve engagement [13], [17], [20].

REFERENCES

1. S. Sharma et al., “A Rule-Based Chatbot for Academic Queries,” International Journal of Computer Applications, vol. 182, no. 5, 2021.
2. R. Deshmukh and P. Patel, “Implementation of NLP Chatbots Using Dialogflow,” IEEE Xplore, 2020.
3. P. Gupta et al., “Machine Learning-Based Conversational Agent,” Proc. Int. Conf. on Artificial Intelligence, 2022.
4. R. Kumar et al., “Enhancing Student Communication via AI Chatbots,” IEEE Access, vol. 11, 2023.
5. A. Mehta et al., “AI in Educational Services,” International Journal of Engineering Research, vol. 10, 2021.
6. Y. Wang and H. Liu, “Deep Learning Chatbot Architectures,” Springer, 2020.

7. A. Ghosh et al., "Hybrid AI Chatbot for Universities," Proc. IEEE Conf. on AI and EdTech, 2023.
8. M. Kaur, "Comparative Performance of Chatbot Frameworks," International Journal of Engineering and Advanced Technology, 2022.
9. P. Sahu et al., "Comparative Study on NLP Frameworks," International Journal of Computer Science and Information Technologies, vol. 12, no. 3, 2021.
10. TensorFlow, "TensorFlow: Open Source Machine Learning Platform," Google Research, 2020. [Online]. Available: https://www.tensorflow.org/
11. Dialogflow, "Dialogflow Documentation," Google Cloud, 2021. [Online]. Available: https://cloud.google.com/dialogflow
12. J. Chen et al., "Context-Aware Conversational Models," ACM Transactions on Intelligent Systems and Technology, vol. 11, no. 3, 2020.
13. P. Desai et al., "Multilingual NLP Systems," International Journal of Advanced Computer Science, vol. 14, no. 2, 2023.
14. M. Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," Proc. NAACL-HLT, 2019.
15. P. N. Dey et al., "ERP-Integrated Chatbots for Academic Systems," Int. Conf. on Smart Technologies for Education, 2023.
16. Vaidya, C. et al. (2025). Enhancing Dialogue Agent Alignment with Targeted Human Assessments Using Generative AI. In: Virdee, B., Correia, S.D., Bedi, P., Swaroop, A. (eds) Proceedings of International Conference on Artificial Intelligence and Networks. ICAIN 2024. Lecture Notes in Networks and Systems, vol 1269. Springer, Singapore. https://doi.org/10.1007/978-981-96-4319-6_46
17. C. Vaidya, R. Borikar, S. Sharma, P. Tiwari, K. Ganar and V. Kharate, "Development of Multipurpose Smart Desk Assistant for a Department," 2024 First International Conference on Data, Computation and Communication (ICDCC), Sehore, India, 2024, pp. 374-379, doi: 10.1109/ICDCC62744.2024.10961215
18. C. Vaidya, D. N. Haldar, P. Y. Lohi, A. M. Rahman, P. Harshita and D. K. Siriya, "SpeakSmart: Empowering Public Speakers, Elevating Every Speech," 2024 8th International Conference on Computational System and Information Technology for Sustainable Solutions (CSITSS), Bengaluru, India, 2024, pp. 1-6, doi: 10.1109/CSITSS64042.2024.10816911.
19. C. Vaidya, A. Gupta, A. Shastrakar, A. Kathane, K. Atmande and K. Iyer, "Sarcasm Detection Analysis – Comparative Analysis," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-4, doi: 10.1109/SCEECS57921.2023.10063107.
20. C. Vaidya, K. Takalkar, A. Ghosekar, S. Nimgade and V. Ghode, "Decentralized File Sharing," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-6, doi: 10.1109/SCEECS57921.2023.10062977.