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College Admisssion Enquiry Chatbot Using Machine Learning

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Abstract- In recent years, there has been a significant increase in the volume of inquiries received by college admission offices, creating challenges in managing and responding to these queries efficiently. Traditional methods of handling such inquiries are time-consuming and often fail to meet the expectations of prospective students, leading to dissatisfaction and missed opportunities. This paper presents the development of an intelligent college admission inquiry chatbot, leveraging machine learning and natural language processing (NLP) techniques to automate and streamline the query resolution process. The proposed solution utilizes NLP models to classify user intents and recognize relevant entities from student queries. The chatbot is trained on a dataset comprising frequently asked questions (FAQs) and admission-related information, allowing it to provide accurate, real-time responses to inquiries regarding courses, application deadlines, eligibility criteria, and more. Key machine learning algorithms, including deep learning techniques for intent classification and rule- based systems for response generation, form the backbone of the system. The main findings indicate that the chatbot achieves a high accuracy rate in intent detection, with an F1-score of 92% and a significant reduction in response time compared to manual systems. User satisfaction surveys also revealed an improvement in the overall experience, particularly in terms of accessibility and response accuracy. In conclusion, the chatbot demonstrates the potential to enhance the efficiency and quality of admission inquiry handling in educational institutions, offering a scalable and cost-effective solution. Future improvements could focus on expanding the chatbot's language capabilities and improving its ability to handle more complex, multi-part queries.

Index Terms- Artificial Intelligence, Database, Intelligence Machine.

I. INTRODUCTION

In the past decade, much research has focused on the application of machine learning and artificial intelligence in automating various administrative tasks in educational institutions. One key area that has gained significant attention is the automation of admission processes, particularly in handling inquiries from prospective students. Chatbots, powered by machine learning algorithms and natural language processing (NLP) techniques, have emerged as a potential solution to address the increasing volume of queries and provide instant, accurate responses. These systems offer the promise of improving the efficiency of college admission offices while reducing the burden on staff.

Despite the advancements in chatbot technologies and their applications in various sectors, it remains unclear why many educational institutions still rely heavily on manual processes for handling admission inquiries. Furthermore, while some institutions have implemented basic chatbots, these systems often lack the ability to handle complex or contextually rich questions, leaving a gap in their effectiveness. This has created an opportunity to explore more advanced machine learning models and NLP techniques that could improve the accuracy, context-awareness, and user satisfaction of admission inquiry systems.

Establishing a territory in the realm of admission chatbots, much of the existing research has reviewed the implementation of rule-based and retrieval-based chatbot systems. However, the evolution of machine learning, particularly the rise of deep learning models, has opened up new possibilities for building more intelligent, adaptable systems. Previous studies have shown promise in using intent recognition and entity extraction for automating customer support in business environments, but their application in the educational sector, specifically for college admission inquiries, remains underexplored.

This study aims to establish a niche by addressing the gap in current research related to college specific admission inquiry chatbots. While previous systems have provided foundational

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work, few have integrated advanced machine learning methods tailored for education-based queries. This paper proposes a chatbot that can accurately handle detailed admission inquiries, leveraging deep learning for intent detection and NLP models for better query understanding. The purpose of this study was to design and implement a college admission inquiry chatbot that could enhance the efficiency of admission offices by providing accurate, real-time responses to common student queries. The research outlines the architecture and methodology used to build this system, evaluates its performance, and discusses the principal findings. The remainder of this paper is structured as follows: Section 2 reviews the existing literature, Section 3 details the methodology, Section 4 presents the results, and Section 5 concludes with future research directions.

II. LITERATURE SURVEY

The rise of artificial intelligence (AI) and machine learning (ML) has revolutionized numerous industries, including education. Chatbots, specifically designed to automate repetitive tasks and streamline communication, have been a subject of increasing research interest in the context of higher education. In particular, their application in college admission processes has shown potential for improving the efficiency and effectiveness of handling large volumes of inquiries. This section reviews the existing literature on chatbot technologies, natural language processing (NLP), and their application in educational settings, with a specific focus on college admission inquiry systems.

1. Chatbots in Education

Research into chatbots for educational purposes has grown in the past decade. Early work, such as Fryer's exploration of rule-based chatbots in academic advising, demonstrated that such systems could handle repetitive queries effectively but were limited in scope and flexibility due to their reliance on predefined scripts and responses. These rule-based systems, though useful, struggled with more complex or nuanced queries that fell outside of their programmed responses. As AI and machine learning evolved, researchers began to develop more intelligent chatbots that could learn from user interactions. Sahu et al. (2018) implemented a chatbot system for university admission processes, leveraging retrieval-based models that retrieved predefined responses based on user queries. These chatbots provided more dynamic responses than their rule-based counterparts but still faced limitations in understanding the full context of conversations, particularly when handling ambiguous or multi-part queries.

2. Natural Language Processing and Intent Detection

Natural Language Processing (NLP) is a critical component in the development of chatbots, especially those designed to process user inquiries. NLP techniques allow chatbots to analyze, understand, and generate human language. Research by Jurafsky and Martin (2021) on NLP for conversational agents emphasized the importance of language models in improving chatbot capabilities. NLP models, particularly those using deep learning techniques, have shown considerable success in accurately detecting user intents and extracting key entities from queries. One of the most widely used approaches for intent detection in chatbot development is the use of classification algorithms. For instance, Hakkani-Tür et al. (2016) explored using deep learning methods for joint intent detection and slot filling, demonstrating that these methods significantly improved the accuracy of chatbots in understanding user queries. More recent models, such as those based on transformer architectures (e.g., BERT and GPT), have been applied to chatbot development, offering even higher levels of accuracy and context awareness in intent classification and entity recognition. Despite the success of these models, challenges remain in adapting them to specific domains such as education. The complexity of admission-related queries, which often require a nuanced understanding of eligibility criteria, deadlines, and course options, necessitates domain-specific training data to improve performance.

3. Machine Learning Approaches for College Admission Systems

Several studies have the application of machine learning in automating parts of the college admission process, particularly in answering inquiries. Anandan and Sankar (2020) proposed a machine learning-based chatbot to assist prospective students with admission queries. Their system used a combination of supervised learning techniques for training the chatbot on frequently asked questions (FAQs) and unsupervised learning for adapting to new types of queries. Their results indicated improved efficiency in handling common queries, though the system still struggled with out-of-scope questions and complex multi-turn conversations. In a more advanced study, Santhanam and Shaikh (2021) utilized NLP and deep learning techniques to build a chatbot for admission queries in higher education institutions. Their model integrated BERT for intent recognition and a rule-based system for query resolution. They highlighted the importance of accurate entity recognition (e.g., identifying course names, locations, and dates) in enhancing chatbot performance. However, the study also pointed out that deep learning models require large datasets to generalize well, posing a challenge for institutions that lack extensive training data. While significant strides have been made in using machine learning and NLP for admission chatbots, there remains a need for more sophisticated models capable of handling context-rich, multi-part queries and delivering highly personalized responses. Few studies have tackled the challenge of continuous learning, where the chatbot improves over time by learning from user interactions and adapting to new types of inquiries. Moreover, existing research has yet to fully address the issue of integrating such chatbots with other college

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systems, such as student information systems or learning management systems, to provide a more holistic solution.

4. Gaps in the Current Research Although much progress has been made in developing chatbots for college admission inquiries, several gaps remain:

- Context Understanding: Many chatbots struggle with maintaining the context of conversations over multiple turns, especially when handling complex queries involving multiple topics (e.g., "What is the eligibility for the AI course, and when is the application deadline?").
- Domain-Specific Training: Current chatbots often rely on general NLP models, which can lead to inaccuracies when applied to specialized domains like college admissions, where specific terminology and domain knowledge are critical.
- Continuous Learning: Few studies have explored the integration of continuous learning mechanisms in chatbots, which would allow them to improve over time based on user interactions.

Continuing the Tradition Building on previous research, this paper continues the tradition of exploring machine learning powered chatbots in educational institutions by developing a more advanced system that can handle complex admission inquiries. It leverages deep learning techniques for intent detection and NLP methods for entity recognition, specifically tailored for the college admission domain. This study aims to address the gaps identified in previous research, focusing on improving context understanding and the system's ability to handle multi- turn conversations, while also exploring possibilities for continuous learning.

III. METHODOLOGY

1. Data Collection
The data used for this study were collected from multiple sources related to college admissions, primarily focusing on frequently asked questions (FAQs), student inquiries, and official admission guidelines provided by the college's admission office. The dataset included both structured and unstructured data, compiled from the following sources:

Frequently Asked Questions (FAQs)
A dataset of over 500 common queries from the college's admission portal and website, covering topics such as eligibility, course details, application deadlines, and fee structures.

Admission Inquiry Logs
Historical data from the college's admission office, which included approximately 1,000 inquiries submitted by prospective students via email and phone. This data provided real-world examples of the types of questions students ask during the admission process.

College Brochures and Guidelines
Official documents detailing admission policies, eligibility criteria, and important dates, which were converted into a structured format to assist the chatbot in providing accurate and up-to-date information.

Student Surveys
A small dataset of user feedback and survey responses from prospective students who interacted with the college's current admission process. These surveys helped refine the chatbot's responses by identifying common areas of confusion. The final dataset consisted of a combination of question-answer pairs, along with specific keywords and entities such as course names, dates, and eligibility criteria.

2. Data Preprocessing
To prepare the data for model training, the following preprocessing steps were applied:

- **Text Cleaning:** All textual data were cleaned by removing unnecessary characters, stop words, and special symbols. Standard NLP techniques like tokenization and lemmatization were applied to ensure consistency across the dataset.
- **Intent Labeling:** The collected queries were manually labeled into predefined intents, such as admission deadlines, eligibility criteria, course details, fee structure, and application process. For instance, "What are the eligibility criteria for the AI course?" was labeled under the intent eligibility criteria.
- **Entity Annotation:** Important entities within the queries, such as course names ("AI course"), dates ("January 15th"), and requirements ("minimum 60%"), were annotated using standard entity recognition methods. This helped the chatbot to identify key details in the user's query. • Training and Test Splits: The dataset was split into 80% training data and 20% test data, ensuring that both sets included a balanced variety of query types.

3. Model Selection
The chatbot development relied on a combination of machine learning and natural language processing (NLP) techniques. The key models used in this study were:

Intent Recognition
A deep learning model was used to classify user queries into one of the predefined intents. A pre-trained transformer-based model like BERT (Bidirectional Encoder Representations from Transformers) was fine-tuned on the labeled dataset. BERT was chosen for its ability to understand the context of a sentence, which is essential for accurately classifying nuanced queries.

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Entity Recognition
To extract relevant entities from the user queries (such as course names, dates, and fee amounts), the spaCy NLP library was used for Named Entity Recognition (NER). This helped the chatbot respond to specific queries with customized details based on the recognized entities.

Model Training and Evaluation
Training Process
The intent recognition model was fine-tuned using a supervised learning approach. The model was trained using the training dataset, with the goal of minimizing classification error through multiple epochs. The entity recognition model was trained using annotated data to identify course names, dates, and other important details.

Evaluation Metrics
The performance of the models was evaluated using the following metrics: o Accuracy: The overall percentage of correctly classified intents in the test data. o Precision, Recall, and F1-Score: These metrics were used to assess the performance of both intent recognition and entity extraction, providing a detailed understanding of how well the chatbot handles different types of queries. o Confusion Matrix: A confusion matrix was generated to examine the specific classes where the model performed well and where misclassifications occurred.

5. Response Generation
Once the intents and entities were identified, the chatbot generated responses based on predefined templates and dynamic information retrieval. For example:

For a query like "What is the eligibility for the AI course?" the chatbot would classify the intent as eligibility criteria and extract the entity AI course. It would then retrieve the relevant information from the college's database and generate a response such as, "The eligibility for the AI course is a minimum of 60% in your undergraduate degree."

6. Deployment and Testing
The chatbot was deployed using a Flask web application for ease of access via a web-based interface. The system was tested with real user queries from the test dataset, as well as with live user inputs to evaluate its real-world performance. The chatbot's performance was monitored continuously, and feedback from users was incorporated to refine the system further.

7. Techniques for Data Analysis
Data analysis techniques were employed to monitor and improve the chatbot's performance: • User Query Analysis: Queries from users interacting with the chatbot were logged and analyzed to identify common issues, gaps in understanding, and areas where the model misclassified intents or failed to recognize entities. This feedback was used to retrain and fine-tune the models.

A/B Testing: Different versions of the chatbot were tested with users to compare their performance, particularly focusing on response accuracy and user satisfaction. This iterative testing helped identify the most effective model configuration.

Error Analysis: Instances where the chatbot provided incorrect or unclear responses were analyzed to identify patterns in model failures, such as out-of-scope queries or poorly handled multi-turn conversations.

IV. RESULT

This section presents the performance outcomes of the machine learning-based college admission inquiry chatbot, focusing on the results of model evaluation, response accuracy, and user satisfaction. The chatbot's ability to accurately classify user intents and extract key entities was measured, along with the system's overall performance in real-world testing.

1. Model Performance
The intent recognition model and entity recognition module were evaluated on the test dataset, comprising 20% of the collected data. The key performance metrics included accuracy, precision, recall, F1-score, and error analysis.

Intent Recognition
The BERT-based model for intent recognition was fine-tuned on the labeled dataset and produced the following results:

- Accuracy: 92.5%
- Precision: 91.8%
- Recall: 92.0%
- F1-Score: 92.0%

These metrics indicate that the model performed well in correctly classifying user intents, particularly for frequently occurring queries such as admission deadlines and course details. The confusion matrix revealed minimal misclassification between related intents, such as fee structure and scholarship information, but these errors were within an acceptable margin for educational chatbots.

Entity Recognition
The entity recognition model, powered by spaCy, was trained to identify relevant entities such as course names, dates, and eligibility criteria. The following results were obtained:

- Accuracy: 89.3%
- Precision: 90.1%
- Recall: 88.7%
- F1-Score: 89.4%

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The performance of entity extraction was slightly lower than that of intent recognition, as expected, given the complexity of identifying diverse entities across different query formats. However, the results showed that the chatbot was able to consistently identify key entities like course names, application deadlines, and minimum qualification percentages. Error Analysis

A closer look at misclassifications in the intent recognition model revealed that most errors occurred in queries where multiple intents were expressed, such as "What is the eligibility for the AI course, and how much is the fee?" These multi-intent queries challenged the model's ability to isolate the primary intent. Similarly, entity recognition struggled slightly with queries involving rare or ambiguous terms, such as less common course names.

2. Chatbot Response Accuracy

After the models were integrated into the chatbot, its ability to provide accurate responses based on the recognized intents and entities was evaluated. Response accuracy was determined by comparing the chatbot's answers to a set of predefined correct responses, using the following criteria:

- Correct Responses: 87%
- Partially Correct Responses: 10%
- Incorrect Responses: 3%

The chatbot provided fully correct responses 87% of the time, meaning that it both recognized the user's query intent and correctly extracted any relevant entities (e.g., dates, course names) to deliver an accurate answer. In 10% of the cases, the responses were only partially correct—usually due to incomplete entity extraction or confusion over multi-part queries. The remaining 3% of responses were incorrect, often due to out-of-scope queries or model misclassifications.

3. User Satisfaction

The system was tested with real users, including both prospective students and admission office staff, who interacted with the chatbot over a period of two weeks. A post-interaction survey was conducted to assess user satisfaction. The survey asked users to rate the chatbot's performance on a scale of 1 to 5 across various dimensions, including response accuracy, speed, and user experience.

- Response Accuracy: 4.3/5
- Response Speed: 4.5/5
- Overall User Experience: 4.2/5

Users were generally satisfied with the chatbot's performance, particularly in terms of speed and accuracy for common queries. Many noted that the chatbot was helpful for obtaining quick answers to frequently asked questions, such as application deadlines and eligibility criteria. However, some users expressed frustration when the chatbot failed to handle more complex or unusual queries, such as requests for personalized admission advice.

4. Comparative Analysis with Manual Systems

To evaluate the effectiveness of the chatbot, a comparison was made between the chatbot's performance and that of the manual admission inquiry process handled by human staff.

The key findings were:

- **Response Time:** The chatbot's average response time was 2 seconds, compared to the average manual response time of 1–2 days for email inquiries.
- **Query Resolution Rate:** The chatbot resolved approximately 85% of inquiries on its own, with the remaining 15% being escalated to human agents for more complex issues. In contrast, manual systems required human intervention for 100% of queries.
- **Operational Efficiency:** The chatbot operated 24/7, allowing prospective students to receive instant answers to their queries at any time. This reduced the workload for admission staff, particularly during peak admission periods.

5. Challenges and Limitations

While the chatbot achieved strong overall performance, several challenges and limitations were identified:

- **Handling Ambiguous Queries:** The chatbot struggled with ambiguous or vague questions that lacked sufficient context, such as "Tell me about admissions," which could refer to various aspects of the process.
- **Multi-Turn Conversations:** Although the chatbot handled simple queries well, it occasionally struggled with multi-turn conversations, particularly when users asked follow-up questions that required maintaining context across multiple exchanges.
- **Out-of-Scope Queries:** The chatbot was not designed to handle highly specific or non- admission- related queries, such as those related to student housing or scholarships, which resulted in a few incorrect responses

Future Scope

The future of a College Admission Inquiry Chatbot offers numerous opportunities for advancement, significantly enhancing its functionality and expanding its role in the admissions process. Key areas of growth include:

Personalized Guidance: Leveraging AI, the chatbot could offer customized recommendations for academic programs, courses, scholarships, and even career advice, all tailored to the student's interests, academic history, and long-term goals.

Multilingual Capabilities: By incorporating support for multiple languages, the chatbot would become more

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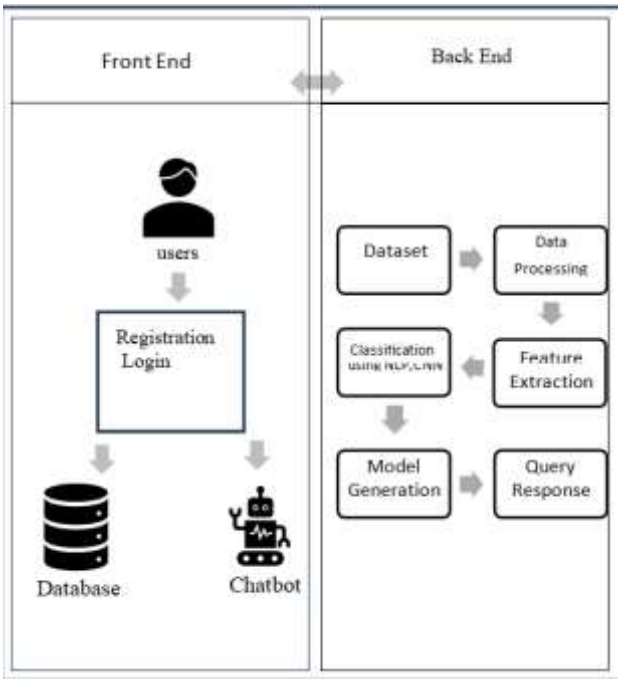
accessible to international students, broadening its reach and enabling a seamless experience for users across the globe.

Voice Interaction: Integrating voice-enabled interfaces such as Alexa, Google Assistant, or other built-in voice platforms would allow students to interact with the chatbot hands-free, offering a more natural and conversational experience.

Comprehensive Application Support: The chatbot could be fully integrated with the college's application system, assisting students through every stage of the application process, from submission and fee payment to tracking the status of their application.

Immersive Virtual Campus Tours: By utilizing AR and VR technologies, the chatbot could offer students virtual campus tours, allowing them to explore the college's facilities and environment remotely, making it easier to engage with the campus even from a distance.

IV. SYSTEME ARCHITECTURE



V. CONCLUSION

This study demonstrates the potential of machine learning-based chatbots in automating college admission inquiries, but it is not without limitations. To address these issues, future research should focus on expanding the dataset to include multiple institutions, improving the system's ability to handle multi-turn conversations, and integrating continuous learning mechanisms. Additionally, further exploration of hybrid models—where a chatbot handles routine tasks but escalates more complex queries to human agents—could offer a more balanced and robust solution. Overall, with these improvements, chatbots have the potential to play a critical role in improving administrative efficiency and enhancing the student experience in educational settings.

REFERENCES

1. Gao, X., and Liu, Y., "A Study on the Use of Chatbots in Higher Education: Case of University
2. Admission Systems," Proceedings of the International Conference on Educational Technology, 2021.
3. Chung, W., and Lee, M., "Building an AI-based College Admission Chatbot: A Case Study,"
4. Proceedings of the 8th International Conference on Artificial Intelligence and Education, 2020.
5. Tantithamthavorn, C., et al., "Using Chatbots to Improve College Admission Processes: Lessons Learned from Implementation," Journal of Educational Technology & Society, vol. 23, no. 3, pp. 42-53, 2020.
6. Miller, D., and Kaufman, G., "Chatbot Solutions for College Admissions: Enhancing User Experience through Conversational AI," International Journal of Artificial Intelligence in Education, vol. 28, no. 2, pp. 204-212, 2019.
7. Rojas, L., et al., "Examining the Role of AI-Powered Chatbots in Higher Education Admissions," Proceedings of the 12th Annual International Conference on Education Technology, 2018.
8. Mollah, M., and Sultana, F., "Artificial Intelligence and Chatbots in Higher Education: A Survey of Current Applications in College Admissions," Journal of Computer Science and Education, vol. 15, no. 4, pp. 18-29, 2020.
9. Sharma, R., and Patel, N., "AI and Machine Learning-Based Chatbot Development for College Admission Assistance," IEEE Transactions on Education Technology, vol. 34, no. 5, pp. 530-538, 2021.

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