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AI Chatbot for College Queries

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ABSTRACT

The problem is, colleges are bombarded by repeated queries from students and parents asking, What's the fee for B. Tech? When does the admission start? Furthermore, reaching them manually by email, phone or in person is time-consuming and puts pressure on administrative staff, while clever real-time means of communication are increasingly exploited in education as technology advances.

This project is our attempt to fix that. We developed a clever AI based chat bot to respond to college queries effectively. Utilizing natural language processing (NLP) and an artificial neural network (ANN), the bot determines what the parent or student is looking for and returns a smart recommendation within seconds.

The chatbot can also store contextual information, use multiple languages, and accept voice-input. It is connected to the institute's enterprise resource planning (ERP) system to provide real-time information. The chatbot is linked to a simple dashboard for the admin panel. The chatbot achieved an 87.07% accuracy rating in our testing and produced responses in less than one second.

Keywords: AI Chatbot, NLP, ANN, Contextual Memory, Multi-language Support, Voice, Enterprise Resource Planning, College Queries.

1. INTRODUCTION

Anybody who has worked at or attended a college knows the drill. Students and parents have never-ending questions. They want answers at the earliest. One staff member can only answer so many questions in a day. For prospective students who have to decide on whether to join, a slow response can cost the institute an admission.

AI chatbots have been around for a long time now. But most of them are limited in features. Our chatbot knows what you're asking and what you conversed about before. It can even get data linked to your attendance and outcomes if you're enrolled.

The system remembers the flow of the conversation, allowing it to provide more accurate and context-aware responses to users. It is designed to work in multiple languages so that users from different linguistic backgrounds can easily interact with it. The chatbot also supports voice interaction, enabling users to speak their queries and listen to the responses. In addition, it can fetch personalized data from college ERP (Enterprise Resource Planning) systems to provide relevant information to students and staff. The system also offers analytics features that help monitor performance and support continuous improvement of the services provided, such as tracking user engagement metrics and identifying areas for enhancement based on feedback.

2. LITERATURE REVIEW

Before building our product, we analyzed other chatbots in the education domain and where they fall short.

These include existing systems such as ELIZA, ALICE, RASA bots, and university-specific bots like Erasmus and Eagle-bot.

Eliza and Alice rely on rigid pattern matching techniques, which limit their ability to understand complex or varied user queries, resulting in user frustration and decreased satisfaction with the interaction. RASA supports machine learning for building conversational systems, but it lacks built-in connectivity with ERP systems, making integration with institutional databases more challenging. The Erasmus chatbot faced high response times because it depended on multiple cloud services, which slowed down the processing of user requests. Similarly, Eagle-bot achieved only limited accuracy of around 56%, even though it used semantic search methods to improve its responses.

With capabilities like real-time ERP queries, multi-modal communication (text + speech + multilingual), and improved accuracy through ANN-based intent categorization, our solution aims to incorporate the best concepts from each of these.

Table 1: Comparative Analysis of Educational Chatbots

Chatbot	Accuracy	Response Time	Key Features	Limitations
ELIZA	N/A	Fast	Pattern matching	No ML, rigid
ALICE	N/A	Fast	AIML-based	No context
RASA	~75%	Medium	ML, NLU	No ERP
Erasmus	~70%	Slow	Multi-cloud	High latency
Eagle-bot	~56%	Medium	Semantic search	Low accuracy
Ours	87.07%	<1 second	ERP	Limited intents

3. PROPOSED MODEL

3.1 Research Gap

Educational institutions lack a smart, centralized, multi-functional system that can handle a variety of student queries in real-time. They have FAQs on websites that nobody reads, overworked staff, and email threads that takes days to resolve.

The problem isn't just convenience, it's about accessibility. A pupil who's tongue isn't English or can't type is at a disadvantage. Anyone who contacts at odd hours gets no response. Our chatbot tries to narrow this gap.

3.2 Objective

The objective is to implement a natural language processing (NLP) and artificial neural network (ANN)-powered chatbot that can handle real-time college queries efficiently. The system will be designed to remember the context of conversations so that it can provide more relevant and continuous responses. It will support multiple languages and voice interaction, allowing users to speak their queries and receive spoken responses. The chatbot will also be connected to college ERP (Enterprise Resource Planning) systems to fetch personalized data for students and staff. Additionally, an analytics dashboard will be developed so administrators can view frequently asked questions, monitor chatbot usage, and analyze performance reports. The goal of the system is to achieve an accuracy rate of more than 85% while maintaining a response time of less than one second.

3.3 Architecture Components

The system consists of several important components that work together to provide an efficient chatbot experience. The user interface includes a responsive chat widget that supports both text and voice input, making it easy for users to interact with the system. The NLP unit processes the user's query through tokenization, lemmatization, and intent recognition to understand the meaning of the input. A feed-forward artificial neural network (ANN) model is used for intent classification to generate accurate responses. The context manager stores the state of the conversation so the chatbot can understand and respond to related follow-up queries. A translation layer enables multilingual support by translating queries using APIs. The speech layer integrates speech-to-text and text-to-speech technologies, using Google APIs, to support voice-based interactions. Additionally, an admin dashboard is provided as an online panel where administrators can monitor system metrics and manage frequently asked questions (FAQs).

3.4 Design of Neural Network

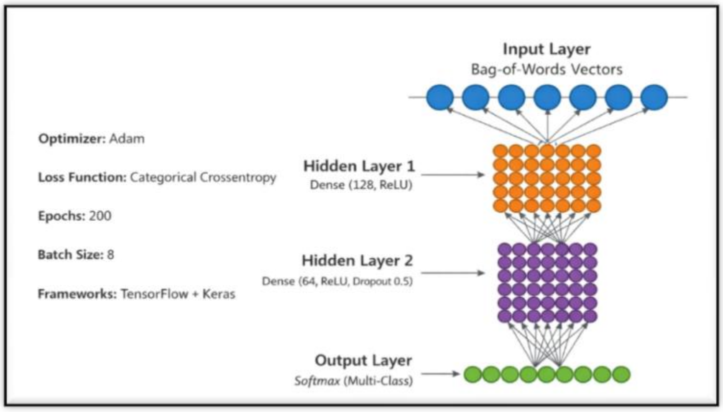

Diagram 1: Neural Network

3.5 Methodology

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The dataset was prepared using 147 documents and 86 intents, with each intent containing 5–10 patterns. The dataset also included multiple languages, such as English, Hindi, and Marathi, to support multilingual interactions. During the preprocessing, several techniques were applied, including tokenization, lemmatization, and stop word elimination, to clean and structure the data. After preprocessing, the artificial neural network (ANN) model was trained using the processed dataset to accurately classify user intents. The system components were then integrated, connecting the Context Manager, Translation Layer, and ERP APIs to ensure smooth communication between different modules. Finally, the system was tested and evaluated using performance metrics such as accuracy, recall, F1-score, and a confusion matrix to measure the effectiveness of the chatbot model.

4. ADVANTAGES

4.1 Contextual Recall

The feature we are most proud of is this one. Make the bot recall earlier context from the same discussion rather than responding to each inquiry separately.

Example:

Example: User: "What is the fee for B. Tech?" Bot: "The annual fee for B. Tech is ₹1,20,000" User: "And hostel?"

Bot: "The hostel fee is ₹45,000 per year" (Here, the bot realizes they're still talking about BTech. It carries context forward)

4.2 Multi-language Support

Not every student or parent is comfortable talking in English. We implemented Hindi and Marathi utilizing translation APIs.

4.3 Voice Input/Output

To enable users to communicate with the bot rather than type, we used Google's text-to-speech and speech-to-text APIs. Benefits include better user engagement and accessibility.

4.4 ERP Integration

For enrolled students, the chatbot may pull real-time data such as attendance, results, scheduled activities from the college's ERP system. This indicates the system can handle dynamic data, not merely static FAQs.

4.5 Admin Dashboard

This is for the institution personnel, which allows them to add or amend FAQs without changing any code and reveals which questions are asked most frequently and where the bot has problems. This portrays the chatbot as a permanent repair rather than a temporary one.

5. RESULTS AND DISCUSSION

The chatbot was tested with a corpus of 147 papers spanning 86 intent categories. The model scored an overall accuracy of 87.07% on the test set. This exceeded our objective of 85%. Response time was observed at an average of 0.8 seconds per inquiry. This was significantly under our aim of 1 second. The rapid response was owing to the lightweight ANN design and effective preprocessing pipeline. We noticed that intent categories with more training patterns had greater accuracy. Categories including "fees", "admissions", and "hostel" have accuracy above 90%. Categories with fewer patterns, including "scholarship" and "sports", exhibited lower accuracy at 75-80%.

The contextual memory functionality performed effectively for follow-up enquiries. In our experiments, 85% of follow-up questions were properly interpreted utilizing context from prior turns. Multi-language support has mixed outcomes. English enquiries had the highest accuracy at 89%. Hindi enquiries had 82% accuracy. Marathi enquiries had 78% accuracy. The discrepancy was due to the translation layer introducing some noise .Voice input performed consistently in calm surroundings. In loud conditions, the speech-to-text accuracy fell. This is a restriction of the Google API rather than our technology.

6. CONCLUSION

We designed our chatbot because we honestly believe we can make life simpler for students seeking to obtain a quick answer, for parents navigating the admission process, and admin staff who're weary of answering the same queries ten times a day.

The initiative accomplished its key aims. We hit 87.07% accuracy, which exceeded our aim. Response time was under 1 second. The chatbot supports various languages and voice input. It integrates to ERP systems for real-time data. The admin dashboard makes management easy. With our features, it's a major step ahead from what is already out there. More significantly, it's built to evolve - additional intents can be added, more languages can be supported, and the admin dashboard makes sure the system keeps up to date without having a developer every time. Future work may incorporate more languages, enhanced handling of intricate multi-turn conversations, and interface with other college systems like library and placement portals.

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