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A Review on Chatur: Chatbot for College

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Abstract: In today's fast-paced college environment, students and faculty require timely access to accurate information on a variety of topics, such as admissions, course details, fees, and campus facilities. Traditional methods of information dissemination, such as websites, emails, and in-person consultations, often lead to delays and inefficiencies, causing frustration among users and increasing administrative workloads. To address this challenge, we developed Campus Query: A Q&A Chatbot for College, an intelligent conversational agent designed to provide real-time, accurate answers to frequently asked questions. This paper presents the design, development, and implementation of the chatbot, following a structured, two-phase approach. The initial phase employs a rule-based system, where the chatbot is programmed to handle common queries through predefined responses, keyword matching, and basic conversation flow. Although effective for standard queries, the limitations of this approach in handling more nuanced questions necessitated the transition to the second phase. In the second phase, we integrate the Rasa framework, which enhances the chatbot with natural language understanding (NLU), enabling it to recognize user intents, extract entities, and manage complex, multi-turn conversations. This phase introduces greater flexibility, allowing the chatbot to handle more varied user inputs and follow-up interactions in a conversational context. Through rigorous testing and user feedback, the chatbot has demonstrated its ability to improve information accessibility and alleviate the burden on administrative staff. By providing immediate responses to common queries, the chatbot enhances the overall user experience for students and faculty. Future enhancements will focus on incorporating more advanced features, such as dynamic content retrieval and further personalization, to expand the chatbot's capabilities and adaptability. Chatbots have become an essential part of human-to-machine interactions, utilizing knowledge-based databases for improved conversational models. Deep learning techniques have been widely applied in IoT big data and streaming analytics to process large-scale data efficiently [1].

Keywords: Chatbot, Natural Language Understanding (NLU), Rasa Framework, Rule-Based System, Q&A System, Campus Query, Information Retrieval, Multi-Turn Conversations, Higher Education, Intelligent Agent.

I. INTRODUCTION

In higher education institutions, providing timely and accurate information to students and faculty is critical for maintaining an efficient and well-functioning campus environment. Questions about admissions, course offerings, tuition fees, campus facilities, and administrative procedures arise frequently, and delivering prompt responses can significantly improve the overall campus experience. Traditionally, this information has been disseminated through static channels such as websites, emails, and face-to-face consultations. The automotive industry has seen significant advancements with deep learning applications, enabling autonomous driving and predictive maintenance [2]. While these methods remain essential, they are often time-consuming and fail to provide instant responses, leading to delays and added workload for administrative staff. The rise of conversational AI and chatbots presents a new opportunity to streamline communication within educational institutions. Chatbots, powered by natural language processing (NLP) and machine learning, can engage users in real-time, simulating human conversation while providing immediate responses to common queries. By automating these interactions, chatbots have the potential to improve user experience and free up valuable time for administrative staff. Moreover, their 24/7 availability ensures that students and faculty can access the information they need at any time, enhancing the accessibility of campus services. Deep learning has significantly impacted IoT big data and streaming analytics, providing enhanced real-time insights and decision-making capabilities [1]. This paper introduces Campus Query: A Q&A Chatbot for College, an intelligent chatbot specifically designed to cater to the needs of a college campus. The chatbot is developed in two phases to progressively enhance its capabilities. Machine learning algorithms have been employed in autonomous mobile robots to enhance navigation and decision-making capabilities [3]. In the first phase, we implement a rule-based approach, where the chatbot is programmed with predefined responses to frequently asked questions. Although effective for straightforward queries, this method lacks the flexibility to handle more complex user interactions.

In the second phase, the chatbot is upgraded using the Rasa framework, incorporating natural language understanding (NLU) to manage more dynamic and nuanced conversations.

By recognizing user intents and extracting key entities from queries, the chatbot is able to engage in multi-turn dialogues and provide more contextually relevant responses. Human-to-machine conversation modelling has improved significantly with chatbot systems utilizing structured knowledge databases [5]. This allows for a deeper understanding of user needs and offers a more sophisticated interaction experience, bridging the gap between simple keyword-based systems and more advanced conversational agents. The objective of Campus Query is twofold: to enhance the accessibility of information for students and faculty, and to alleviate the administrative workload by automating repetitive tasks. Machine learning techniques have been utilized in medical diagnostics, including the classification and explanation of sports injuries [4]. This paper outlines the chatbot's development process, from the initial rule-based system to its evolution into a more advanced NLU-powered chatbot. Through testing and evaluation, we demonstrate the effectiveness of this approach in improving both user satisfaction and operational efficiency on campus.

II. METHODOLOGIES

1) *Phase 1: Rule-Based System*

The initial phase of the project implements a rule-based approach, designed to handle frequently asked questions (FAQs) using predefined rules and keyword matching. This system allows for quick deployment and is particularly effective for straightforward queries that follow predictable patterns.

In the first stage, a set of commonly asked questions covering topics such as admissions, course details, and campus facilities was compiled through collaboration with the college's administrative team. These questions were paired with predefined responses to provide clear and concise answers to frequently encountered queries. The chatbot employs simple keyword matching to detect user queries. When a user inputs a query, the system scans for specific keywords such as "admissions," "fees," or "library hours" and triggers the appropriate predefined response. For example, if a user asks, "What are the admission requirements?" the system identifies the keyword "admissions" and retrieves the corresponding response from a fixed set of answers. To maintain simple conversational interactions, the rule-based chatbot follows predefined conversation flows. While this works well for basic queries, it lacks flexibility when users ask nuanced questions or deviate from the expected input format. Although this approach is fast and efficient for addressing FAQs, it is limited in its ability to handle variations in language or more complex interactions. Rule-based systems struggle when faced with queries that do not match predefined keywords exactly and cannot manage multi-turn conversations or contextual interactions.

2) *Phase 2: Integration of Rasa Framework*

To overcome the limitations of the rule-based system, Phase 2 introduces the Rasa framework, an open-source tool that incorporates advanced Natural Language Understanding (NLU) and Natural Language Processing (NLP) to manage more complex and varied user interactions. Rasa provides the chatbot with the ability to understand user intents and extract relevant entities from queries, enabling it to engage in dynamic, multi-turn conversations.

The transition to the Rasa framework involves training the NLU model to recognize specific intents that represent the user's underlying goals when asking a question. Examples of intents include ask_admission_requirements, inquire_fee_structure, and request_library_hours. By identifying intents, the chatbot can understand what the user is trying to achieve and respond accordingly, even if the query is phrased in different ways. Additionally, Rasa is capable of entity extraction, allowing the chatbot to identify key pieces of information within a query. For instance, if a user asks, "What are the application deadlines for the Fall semester?", the chatbot can extract the entities "application deadlines" and "Fall semester" and provide a response specific to that context, ensuring more precise and relevant responses compared to the rigid keyword matching of a rule-based system.

Rasa enables the creation of stories, which are predefined conversation paths that guide the chatbot in handling more complex, multi-step interactions. These stories define how the chatbot should respond to different user inputs, taking into account the context of the conversation. For example, after providing general admission requirements, the chatbot can ask follow-up questions such as "Which department are you interested in?" or "Are you applying for undergraduate or graduate programs?". Rasa's ability to manage contextual conversations ensures that the chatbot can maintain a coherent dialogue over multiple turns, significantly improving user experience.

To handle dynamic queries that require real-time information, such as course availability or updated fee structures, Rasa allows for the implementation of custom actions. These actions can fetch data from external sources such as databases or APIs and provide users with up-to-date information. For instance, when a user asks for the latest admission deadlines, the chatbot can trigger a custom action to retrieve the latest data from the college's admissions database and present it to the user.

The NLU model is trained using a dataset consisting of annotated examples, where each example is labelled with an intent and entities. These examples are collected from FAQs, historical user queries, and anticipated questions to ensure the model can handle a wide range of inputs. Regular testing and evaluation of the chatbot's performance are conducted to fine-tune the model and improve its accuracy. User feedback is incorporated to enhance the system's ability to recognize new query patterns and provide more accurate responses.

The integration of Rasa brings significant improvements over the rule-based approach. It allows the chatbot to handle more nuanced interactions, recognize different ways users may ask the same question, and maintain context across multiple exchanges. The chatbot’s enhanced ability to extract entities and follow logical conversation flows reduces the need for users to repeat information, creating a more natural and engaging interaction.

III. IMPLEMENTATION

The implementation of Campus Query: A Q&A Chatbot for College was divided into two phases, each building upon the previous one to progressively enhance the chatbot's capabilities. The goal was to develop an intelligent system capable of handling frequently asked questions (FAQs) in the college setting, starting with a simple rule-based system and evolving into a more advanced natural language understanding (NLU) chatbot powered by the Rasa framework. This section details the technical steps and processes involved in bringing the chatbot to life.

The initial implementation focused on creating a rule-based chatbot that could respond to common queries using predefined responses and keyword matching. The chatbot’s functionality was limited but effective for handling straightforward FAQs related to admissions, courses, fees, and campus services. Python was used as the primary programming language due to its rich ecosystem of libraries for handling text-based data, while Flask served as the lightweight backend framework, enabling the chatbot to run as a web-based application. A PostgreSQL database stored predefined FAQs and responses, allowing the chatbot to retrieve relevant answers efficiently. A simple web interface built using HTML, CSS, and JavaScript facilitated user interactions. The rule-based chatbot relied on keyword matching to detect user queries and retrieve appropriate responses from the database. However, this approach had limitations, as it could only respond to predefined keywords and lacked the ability to manage contextual conversations or multi-turn interactions.

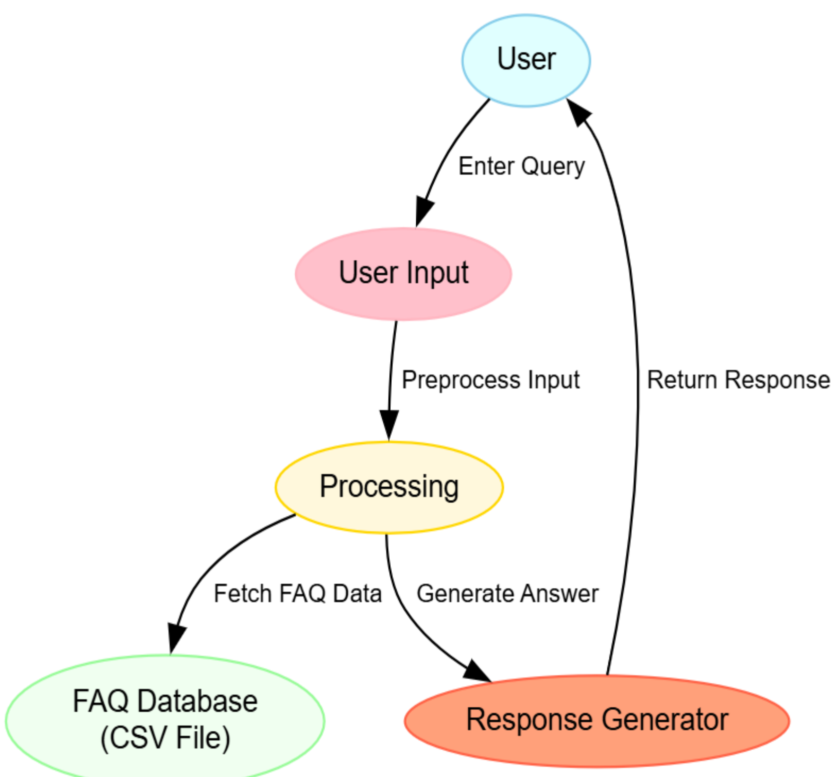

Fig 1. Dataflow Diagram

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To overcome these limitations, the chatbot was upgraded using the Rasa framework in Phase 2. Rasa's NLU capabilities enabled intent recognition, entity extraction, and multi-turn dialogue management, making interactions more flexible and dynamic. The dataset created during the earlier phase was annotated for intent recognition, ensuring that queries such as "What are the admission requirements?" and "How do I apply?" were classified under the same intent. The chatbot was trained to extract key entities, such as semester names and fee details, to generate context-specific responses. Dialogue management was implemented using Rasa's stories and rules, allowing the chatbot to maintain conversation context and follow logical conversational flows. For instance, after providing general admission information, it could ask follow-up questions regarding the user's preferred program or department.

Rasa's custom actions enabled real-time retrieval of dynamic data from the PostgreSQL database. This feature was particularly useful for responding to queries like "What is the current fee structure for Computer Science?" by fetching the latest data. The model was trained iteratively using a combination of real user queries and simulated data, allowing it to handle a broader range of inputs and improve its accuracy. Testing and evaluation were conducted through user interactions, measuring intent recognition accuracy and refining the chatbot based on feedback. The web interface was also enhanced to support multi-turn conversations, improving the overall user experience.

Several challenges emerged during the implementation phase, including handling ambiguous queries outside the chatbot's predefined knowledge base. A fallback mechanism was introduced to prompt users for clarification when necessary. Additionally, continuous learning was achieved by incorporating user feedback into the training dataset, allowing the chatbot to refine its responses over time. These improvements ensured that Campus Query evolved into a more intelligent and responsive system, capable of managing complex user interactions within the college environment.

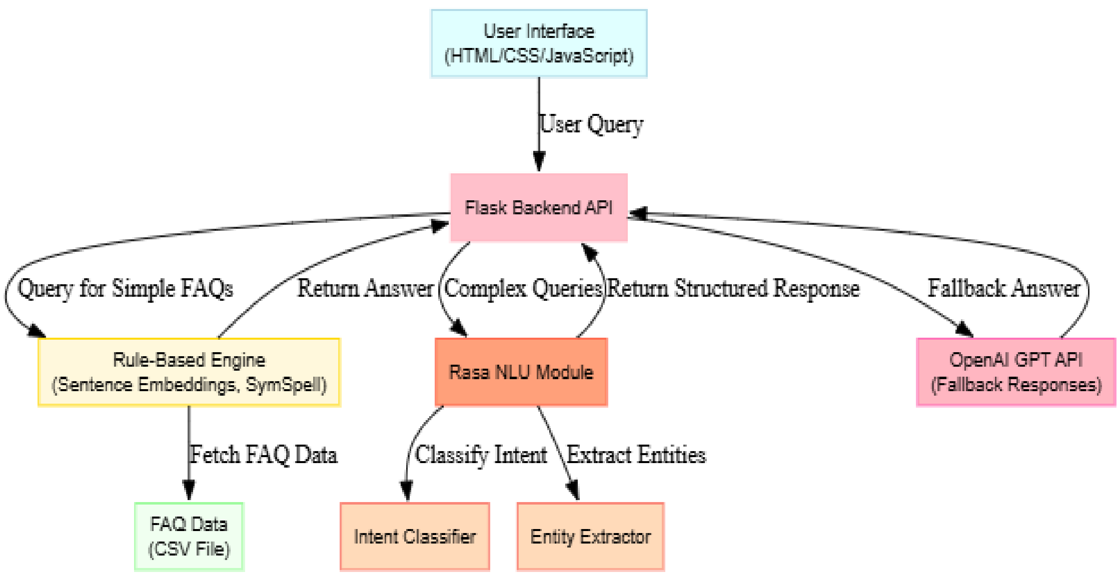

Fig 2. System Architecture

IV. EVALUATION AND RESULTS

To measure the effectiveness and performance of Campus Query: A Q&A Chatbot for College, a series of evaluation metrics and user tests were employed. The goal was to assess the chatbot's ability to understand user queries, provide accurate responses, manage multi-turn conversations, and improve overall user experience. The evaluation was conducted in two phases, corresponding to the rule-based chatbot and the Rasa-powered NLU chatbot.

In the initial phase, the rule-based chatbot was evaluated primarily for its ability to handle standard, frequently asked questions (FAQs) using keyword matching and predefined responses. The accuracy of responses was measured based on how well the chatbot's predefined answers matched user queries. A correct response was defined as one where the information provided directly addressed the user's question. The chatbot's speed of response was also assessed to ensure it delivered near-instant feedback.

Query coverage was another important metric, testing the chatbot's ability to address various topics such as admissions, course details, and fees. Results from this phase showed high accuracy for simple queries, with an estimated 95% correctness in answering straightforward questions like "What are the admission requirements?" However, the chatbot struggled when users asked questions that did not exactly match predefined keywords, resulting in lower flexibility. Despite fast response times (typically under one second), the chatbot lacked the ability to handle complex or multi-turn conversations due to its rigid structure and predefined responses.

In the second phase, the chatbot was upgraded using the Rasa framework, allowing for more sophisticated natural language processing capabilities. This version of the chatbot was evaluated using intent recognition accuracy, entity extraction accuracy, F1 score, context management, and user satisfaction. Intent recognition accuracy measured the chatbot's ability to correctly classify user queries into predefined intents, achieving a success rate of 92%. Entity extraction accuracy was evaluated at 90%, reflecting the chatbot's ability to identify key information such as course names, dates, and department names. The chatbot's ability to maintain conversational context was significantly improved, allowing for multi-turn interactions. For example, if a user asked about admissions requirements and then inquired about deadlines, the chatbot retained the context and provided relevant responses. The F1 score, a measure of precision and recall, was calculated to be 0.88, indicating a strong balance between accuracy and recall of user intents. User satisfaction was assessed through feedback from 50 test users, resulting in an overall satisfaction rate of 80%. Users appreciated the chatbot's ability to handle complex questions and maintain a more natural conversation flow compared to the rule-based version.

A comparative analysis between the two chatbot versions demonstrated the improvements achieved in Phase 2. While the rule-based chatbot had a response accuracy of 95%, it lacked intent recognition and entity extraction capabilities, making it less flexible. The Rasa-powered chatbot, on the other hand, achieved a response accuracy of 92% while significantly enhancing intent recognition (92%) and entity extraction (90%). Additionally, context management was introduced in Phase 2, allowing the chatbot to manage follow-up questions and sustain natural dialogue. Although response time increased slightly from under one second to 1–2 seconds, the overall improvements in chatbot intelligence and user experience outweighed this minor trade-off.

To ensure continuous improvement, user feedback was incorporated into the evaluation process. Test users provided insights into ease of use, response relevance, and areas for enhancement. Most users found the chatbot easy to use, particularly in Phase 2 when natural language interactions were more effectively handled. Users also appreciated the improved specificity of responses and the ability to maintain context in longer conversations. Some suggested adding more personalization features, such as tracking individual progress or tailoring answers based on user profiles. Based on this feedback, additional training examples were added to the dataset, and the chatbot's model was periodically retrained to improve its ability to handle emerging queries. This iterative approach ensured that Campus Query continued to evolve, providing a more intelligent and user-friendly experience over time.

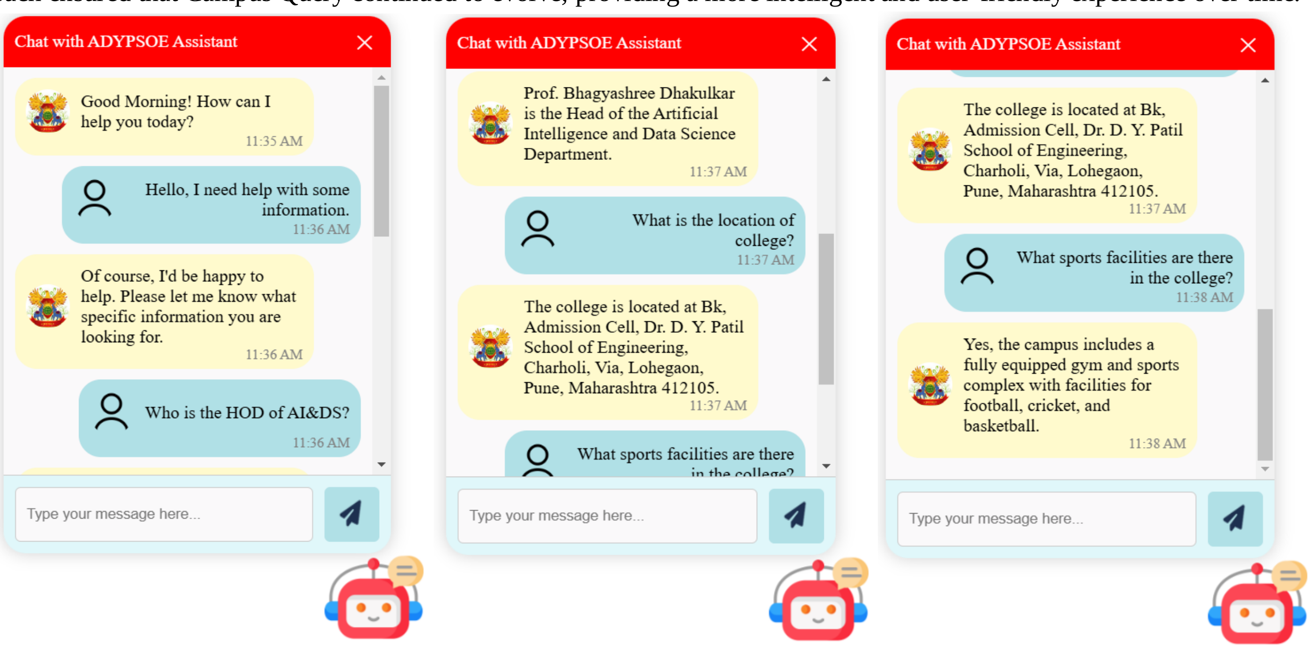

Fig 3. Chatbot Response

V. CONCLUSION

The development of Campus Query: A Q&A Chatbot for College demonstrates the significant potential of intelligent chatbots to streamline communication and enhance information accessibility in higher education environments. Through a structured, two-phase approach—starting with a rule-based system and advancing to a more sophisticated NLU-powered chatbot using the Rasa framework—the project successfully addressed the primary challenges faced by students and faculty in accessing timely and accurate information. The chatbot was able to automate responses to frequently asked questions related to admissions, courses, fees, and campus facilities, reducing the workload on administrative staff and improving the user experience.

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