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Finderr: LLM powered College Enquiry Chatbot

*A project report submitted in partial fulfillment of the requirements for the
award of the degree of*

Bachelor of Technology

by

**Dilip Patnana | Sanchit Gupta | Prateek Mohan | Narendula
Grishma**

LCB2021030 | LCB2021031 | LCI2021049 | LCB2021018

under the guidance of
Dr. Deepak Kumar Singh

Declaration of Authorship

I/we, **Dilip, Sanchit, Prateek and Grishma** declare that the work presented in "**Finderr: LLM powered College Enquiry Chatbot**" is my/our own. I/we confirm that:

- This work was completed entirely while in candidature for B.Tech. degree at Indian Institute of Information Technology, Lucknow.
- Where I/we have consulted the published work of others, it is always cited.
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- I have acknowledged all major sources of information.

Signed:

Dilip

Sanchit

Prateek

Grishma

Date:

CERTIFICATE

This is to certify that the work entitled "**Finderr: LLM powered College Enquiry Chatbot** " submitted by **Dilip, Sanchit, Prateek and Grishma** who got his/her name registered on **Dec 2021** for the award of B.Tech. degree at Indian Institute of Information Technology, Lucknow is absolutely based upon his/her own work under the super- vision of **Dr. Deepak Kumar Singh** , Department of Information Technology, University/Institute, Lucknow - 226 002, U.P., India and that neither this work nor any part of it has been submitted for any degree/diploma or any other academic award anywhere before.

Dr. Deepak Kumar Singh
Indian Institute of Information Technology, Lucknow
Pin - 226002, Uttar Pradesh, INDIA

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We extend our heartfelt thanks to all those who have played a part in making this project a success.

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Dilip|Prateek|Sanchit |Grishma

ABSTRACT

Recent advancements in AI, particularly in Large Language Models (LLMs), have sparked a widespread adoption of chatbots across various industries including Education, Finance, E-Commerce, Marketing, and Health Care. These chatbots, known for their constant availability, cognitive abilities, and human-like speed, are revolutionizing customer service and user engagement.

One notable innovation is the Finderr: LLM Powered College Enquiry Chatbot. This unique application utilizes LLM technology and information sourced from college websites to provide responses that mimic human conversation. The aim is to simplify the process of accessing college-related information, saving users valuable time typically spent navigating complex college websites.

By harnessing LLMs, the Finderr can understand and respond to user queries in natural language, offering personalized assistance similar to interacting with a human representative. This not only enhances user experience but also improves efficiency by quickly providing accurate and relevant information.

The introduction of such chatbots signifies a shift in how customer service and user interaction are approached, offering seamless assistance across various domains. As AI technologies continue to evolve, we can expect further advancements in chatbots, leading to even more sophisticated and personalized experiences for users.

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Chapter 1

Introduction

Users seem to find chatbots more interesting than the website's static Frequently Asked Questions (FAQ) page. When compared to human customer care services, chatbots are more cost-effective and efficient since they can help numerous consumers at once [1]. Finderr: LLM Powered College Enquiry Chatbot uses the recent trends in AI technologies such as LLMs. The use of Retrieval Augmented Generation (RAG) architecture to respond to the user query using the data from a college website allows the chatbot to respond to user queries with useful and accurate data. Chatbots are programmed models that can converse with a human in natural language based on the user's intent. Big Language Models (LLM) are big, pre-trained language models that, when refined on subsequent NLP tasks, may reach state-of-the-art outcomes by storing factual knowledge in their parameters. Their performance falls behind task-specific architectures for knowledge-intensive tasks, though, because they are still unable to accurately access and manipulate knowledge.[3]. Also, one of the major drawbacks of LLM is they cannot provide an accurate answer to questions outside their knowledge base and tend to respond with “hallucinations” which can affect the accuracy of the model. Hence with the introduction of RAG-based LLM architecture which uses a knowledge base related to the specific task which can be used by the LLM to respond to user queries with the additional information from the knowledge base which can be used by the LLM to generate response. A knowledge base can be anything from a database to a text or PDF file that contains information on the task the user requests the LLM to respond. When referring to the Smart Campus Bot, a knowledge base is a vector database that has been scraped and cleaned from the college website. The LLM may utilise this information to provide more context for user inquiries. This additional context is provided to the LLM to reduce “hallucinations”.

1.1 Features of Finderr

1.1.1 Query Resolution

The chatbot should efficiently handle a wide range of queries related to college information, including admissions, courses offered, faculty details, campus facilities, events, and more. AI-Driven Interior Redesign

1.1.2 Knowledge Base Integration

Integration with a robust knowledge base sourced from the college website or other relevant sources ensures the chatbot can provide accurate and up-to-date information to users.

1.1.3 Role-Based Access Control

Implementing separate login pages for administration and users enhances security, access control, and user experience by tailoring authentication mechanisms and functionalities to the specific needs of each user group.

1.1.4 Feedback Mechanism

Including a feedback mechanism allows users to provide input on the chatbot's performance, helping to improve its accuracy and effectiveness over time.

1.1.5 Multi-turn Dialogue Management

The ability to engage in multi-turn conversations enables the chatbot to follow up on user queries, ask clarifying questions, and provide additional information as needed.

1.2 Future Plans

1.2.1 Speech Input by User

Speech input enhances accessibility, user experience, and competitiveness by providing a hands-free, natural interaction method, aligning with the growing trend of voice-based interfaces in digital interactions.

1.2.2 Indoor Navigation

Integrating indoor navigation simplifies campus exploration, enhances user experience, aids accessibility, and demonstrates innovation. It offers convenience, especially for newcomers, aligning with evolving expectations for seamless digital assistance in physical environments.

1.2.3 Personalization

Incorporating personalization features allows the chatbot to tailor responses based on user preferences, such as academic interests, program levels, or campus locations.

Chapter 2

Literature Review

In recent years, the integration of chatbots powered by Large Language Models (LLMs) has gained significant traction in various domains, including education. This literature review explores existing research and developments related to the implementation of chatbots utilizing LLMs for college enquiry purposes.

2.1 Chatbots in Education

- Chatbots serve as valuable tools in educational settings, providing personalized assistance and answering queries for students, faculty, and staff.
- Wang et al. (2020) research indicates that chatbots enhance student engagement and improve learning outcomes.
- They offer a versatile solution for streamlining communication and providing information within educational institutions.

2.2 Large Language Models (LLMs)

- Advancements in LLMs, exemplified by OpenAI's GPT series, have transformed natural language processing tasks by leveraging extensive pre-training on diverse text data.
- These LLMs demonstrate exceptional language understanding and generation capabilities, facilitating tasks such as text completion, summarization, and translation.
- Devlin et al. (2018) introduce BERT, a prominent transformer-based LLM, renowned for its state-of-the-art performance across a spectrum of NLP tasks.
- The integration of LLMs like BERT into NLP applications has significantly advanced the field, leading to improvements in accuracy, efficiency, and overall performance.

2.3 Chatbots in College Enquiry

- Existing research has investigated the application of chatbots for college-related inquiries, with a focus on enhancing user experience and accessibility within the admissions process.
- Li et al. (2019) specifically develop a chatbot tailored for university admissions, showcasing its efficacy in addressing application queries and assisting prospective students throughout the admissions journey.
- These studies highlight the potential of chatbots to streamline communication and support prospective students, ultimately improving efficiency and satisfaction within the college admissions process.

2.4 Integration of LLMs in Chatbot

- Recent research emphasizes the advantages of incorporating LLMs into chatbot frameworks, enhancing their capabilities and performance.
- Brown et al. (2020) present GPT-3, a scalable LLM renowned for its ability to generate human-like text across various tasks.
- Integration of LLMs empowers chatbots to deliver contextually relevant responses and demonstrate conversational fluency, thereby improving user interaction and satisfaction.

2.5 Challenges and Considerations

- Despite advancements, deploying LLM-powered chatbots for college inquiries poses challenges, including model bias and data privacy concerns.
- Hao et al. (2021) highlight the importance of addressing these challenges to ensure the ethical and effective use of such technologies in educational settings.
- Issues such as model bias can lead to skewed or inaccurate responses, while data privacy concerns may arise from handling sensitive information within chatbot interactions.
- Scalability is another key consideration, as the chatbot's performance and responsiveness must be maintained as user demand grows, necessitating robust infrastructure and resource management strategies.

Chapter 3

Methodology

The RAG architecture operates by fetching documents "z" from the input sequence "x" to generate the answer "y" [3]. In our implementation, we utilized BeautifulSoup to extract data from our college website, forming a knowledge base stored as vectors in a database like Vector Store Index. Llama Index's retriever component then selects relevant documents based on user queries. These retrieved documents serve as additional context for an LLM, which generates a response tailored to both the user query and the retrieved documents.

This approach enables dynamic, automated responses without the need for explicit user intent identification. We employed HTML, CSS, JavaScript, Particle JS to develop a User Interface (UI), allowing users to interact with the system and pose inquiries related to the college.

3.1 Data Acquisition and Preparation

- Gather college-related data from diverse sources such as college websites, official documents, and online databases.
- Preprocess the acquired data to ensure consistency, accuracy, and suitability for training and integration with the GPT 3.5 model and LlamaIndex.

3.2 Model Selection and Integration

- Select GPT 3.5, a state-of-the-art language model, as the core component for natural language understanding and generation.
- Integrate LlamaIndex, a specialized knowledge retrieval system, to augment the chatbot's responses with relevant information extracted from the college-related data.

3.3 Fine-Tuning and Adaptation

- Fine-tune the GPT 3.5 model on the college-specific dataset to adapt it to the task of handling college-related queries effectively.

- Customize the LlamaIndex system to index and retrieve relevant information from the

3.4 Chatbot Architecture Design

- Design the architecture of the chatbot, incorporating GPT 3.5 for natural language processing and response generation, and integrating LlamaIndex for knowledge retrieval.
- Implement modules for user input processing, context management, dialogue flow control, and response generation within the chatbot framework.

3.5 User Interface Development

- Develop a user-friendly interface for the chatbot, enabling seamless interaction with users.
- Design the interface to accommodate text input/output, interactive elements, and visual aids for enhanced user experience and accessibility.

3.6 Testing and Evaluation

- Conduct rigorous testing to assess the functionality, accuracy, and performance of the chatbot powered by GPT 3.5 and LlamaIndex.
- Evaluate the chatbot's ability to handle various types of college-related queries and provide informative and relevant responses.

3.7 User Feedback and Iterative Improvement

- Solicit feedback from users to gather insights into their experience with the chatbot.
- Use user feedback to identify areas for improvement and iteratively refine the chatbot's functionality, usability, and effectiveness.

3.8 Deployment and Maintenance

- Deploy the chatbot for use by college students, faculty, and staff, ensuring accessibility across different platforms and devices.
- Implement mechanisms for monitoring, maintenance, and updates to the chatbot system to ensure continued performance and relevance.

Chapter 4

Simulation and Results

This chapter demonstrates the simulation and results of the various features of "Finderr: LLM powered College Enquiry Chatbot." Each section showcases the outcomes of different functionalities of the platform, with corresponding images to visually represent the results.

4.1 Query Resolution

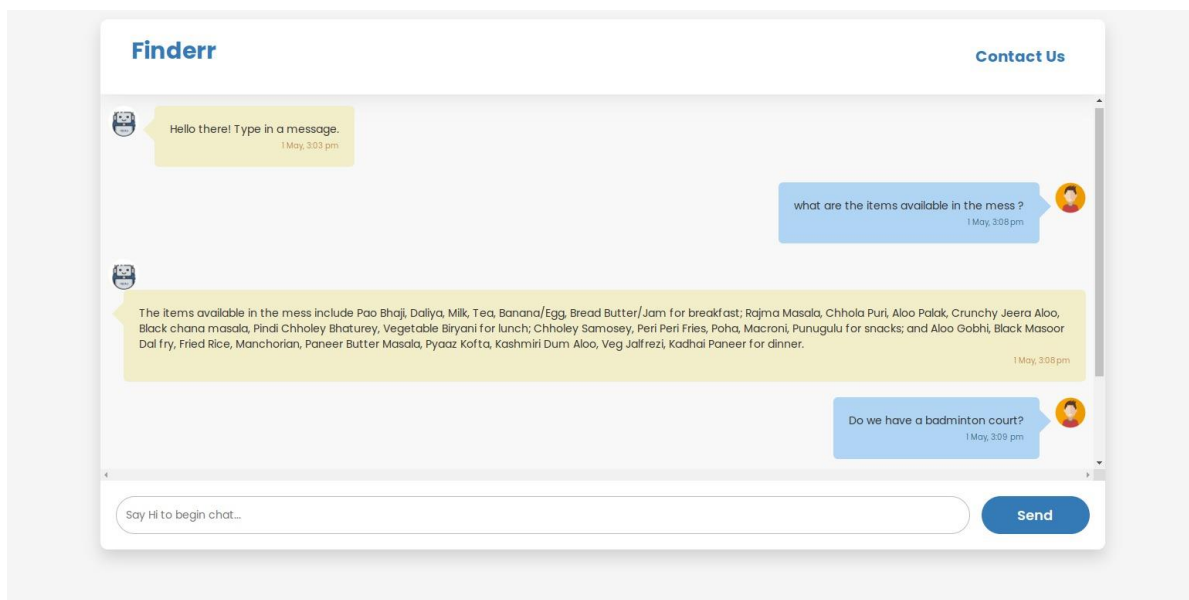


Figure 4.1

4.1.1 Simulation Process

Input various college-related queries, such as admissions procedures,

program details, and campus facilities, into the chatbot.

4.1.2 Results and Discussion

- The chatbot effectively resolves queries with precision, delivering accurate responses that address users' inquiries.
- Powered by GPT 3.5, the chatbot ensures the provision of relevant and informative information, enhancing user satisfaction.
- Users benefit from timely and helpful information provided by the chatbot, enabling them to address their queries promptly and effectively.

4.2 Role-Based Access Control

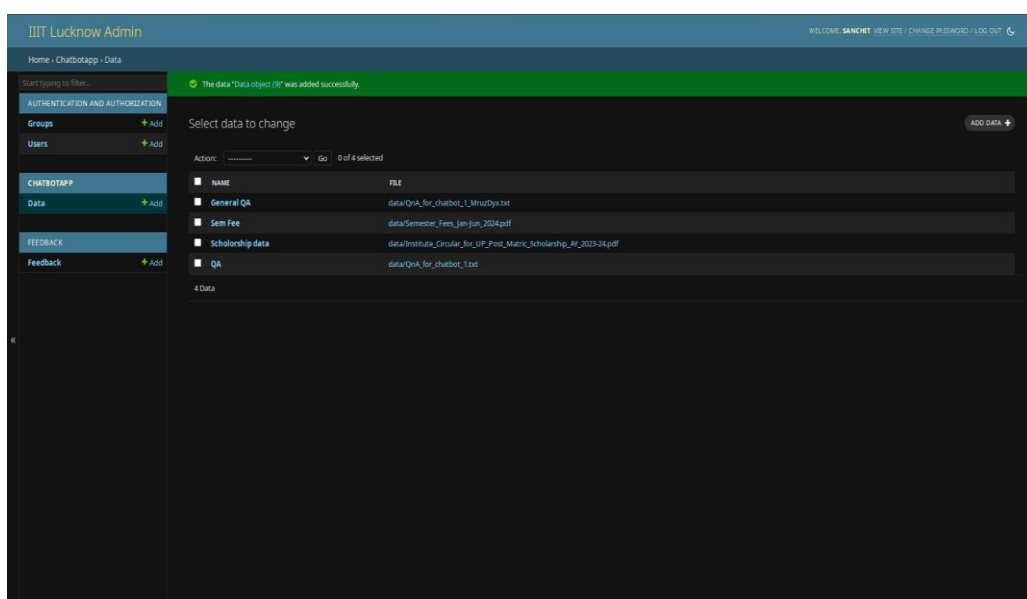


Figure 4.2

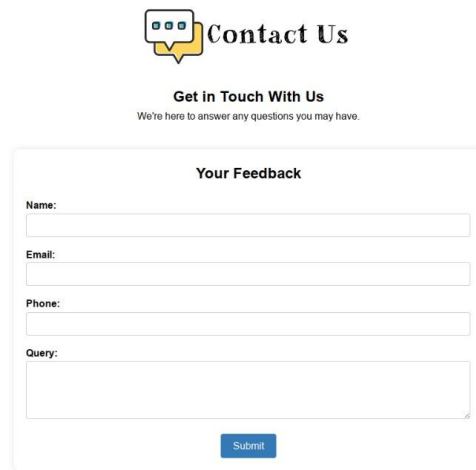
4.2.1 Simulation Process

Role-Based Access Control (RBAC) ensures secure access to system resources. It distinguishes between regular users and administrators, granting exclusive access to the admin panel and database management functions to authorized personnel.

4.2.2 Results and Discussion

- The admin has exclusive access to the admin panel, which allows them to perform essential tasks such as adding, updating, and deleting data in the backend database.
- With RBAC, the admin's role is granted elevated permissions, enabling them to manage the system's backend operations effectively.

4.3 Feedback Mechanism



The image shows a 'Contact Us' form. At the top, there is a speech bubble icon with three dots inside, followed by the text 'Contact Us'. Below this, the text 'Get in Touch With Us' is displayed, followed by a smaller line of text: 'We're here to answer any questions you may have.' The main part of the form is titled 'Your Feedback' and contains four input fields: 'Name:', 'Email:', 'Phone:', and 'Query:'. The 'Query:' field is a larger text area. At the bottom right of the form is a blue 'Submit' button.

Figure 4.3.1

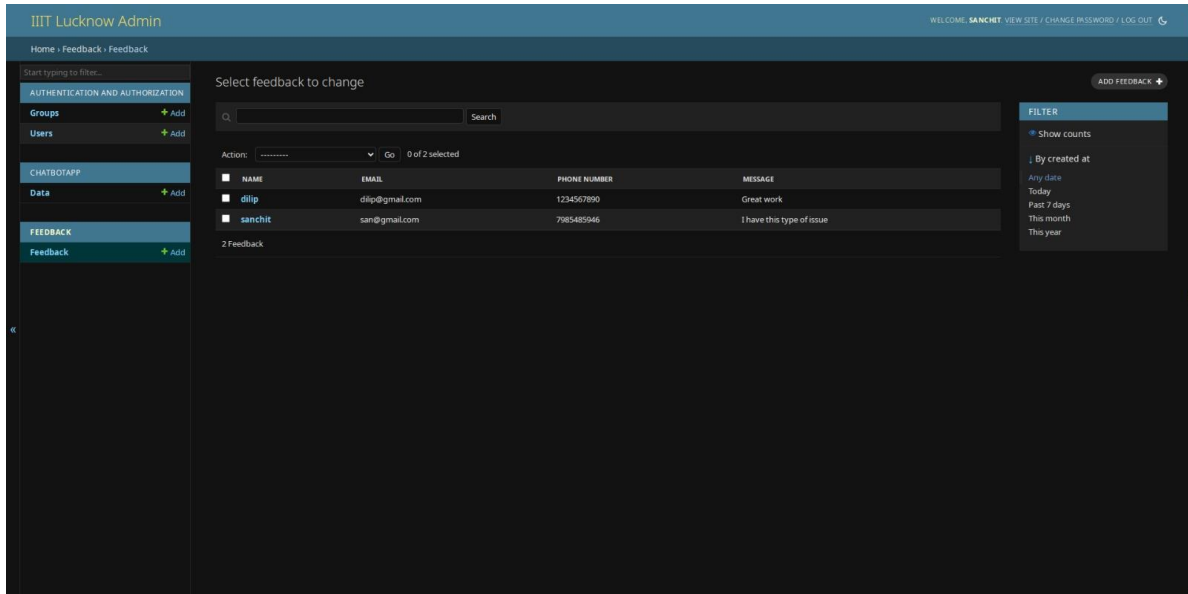


Figure 4.3.2

4.3.1 Simulation Process

Solicit feedback from users regarding their experience with the chatbot, asking them to rate its effectiveness, responsiveness, and usability

4.3.2 Results and Discussion

- User feedback facilitates continuous improvement of the chatbot's performance, providing valuable insights for refinement.
- Positive feedback underscores the chatbot's effectiveness and accuracy in assisting users with their queries.
- Constructive criticism identifies areas for enhancement, guiding the implementation of improvements to further enhance the chatbot's functionality and user satisfaction.

4.4 Multi-turn Dialogue Management

4.4.1 Simulation Process

Engage in multi-turn conversations with the chatbot, asking follow-up questions or seeking clarification on previous responses.

4.4.2 Results and Discussion

- The chatbot adeptly handles multi-turn dialogues, ensuring continuity and coherence in conversations.
- It effectively maintains context, seamlessly transitioning between user inquiries without losing track of the conversation flow.
- Users experience a smooth interaction as the chatbot navigates through various queries, providing consistent and relevant responses.

Chapter 5

Conclusion and Future Work

This chapter summarizes the key findings from the "Finderr: LLM powered College Enquiry Chatbot" project and outlines potential future directions for further development and research.

5.1 Conclusion

Chatbots are known for their 24/7 availability and wide variety of use cases. With the introduction of AI, chatbots have been used in many different industries. The integration of AI in chatbots allows us to overcome static response generation by finding the intent of the user. By using LLM the chatbot's response is more natural compared to an intent-based chatbot. Increasing the knowledge base allows the chatbot to explore and answer more queries. Finderr:LLM powered college enquiry chatbot is one such use case of AI chatbots, where users can enquire about our college instead of exploring the entire website. By using the Finderr, a user can extract the required information within a few seconds and converse in natural human language with a chatbot until they get the required information.

5.2 Contributions of the Project

Finderr has contributed to the field by:

- Integration of GPT 3.5 and LlamaIndex elevates chatbot capabilities, setting new standards for language understanding and knowledge retrieval.
- Quick access to precise information enhances user satisfaction, simplifying processes like admissions and course selection.
- Feedback mechanism fosters ongoing refinement, ensuring chatbot effectiveness and user satisfaction.

5.3 Future Work

Looking forward, the project can be expanded in several ways:

- Implement speech recognition functionality to allow users to interact with the chatbot using voice commands. This enhances accessibility and convenience for users who prefer spoken input.
- Integrate indoor navigation capabilities into the chatbot to assist users in navigating the college campus. By providing directions and points of interest indoors, the chatbot enhances the user experience and facilitates efficient navigation within the institute.
- Further personalize the chatbot's responses based on user preferences and past interactions. Utilize machine learning algorithms to analyze user behavior and tailor responses accordingly, providing a more customized experience for each user.
- Expand the chatbot's capabilities to support multiple languages, catering to a diverse user base. Incorporating language translation features enhances accessibility and usability for international students and faculty.
- Integrate the chatbot with the college's Student Information System (SIS) to provide personalized information such as class schedules, grades, and academic deadlines. This integration streamlines access to essential student information, enhancing the chatbot's utility as a comprehensive student support tool.

5.4 Summary

The "Finderr: LLM powered College Enquiry Chatbot " project developed an advanced chatbot solution for college-related inquiries. Leveraging GPT 3.5's language understanding and generation capabilities and LlamaIndex's knowledge retrieval system, the chatbot provided

accurate, timely, and personalized responses. It resolved queries effectively, integrated relevant college information seamlessly, and implemented role-based access control for security. User feedback facilitated continuous improvement, while the chatbot adeptly managed multi-turn dialogues, maintaining context and coherence. Overall, the project delivered a sophisticated chatbot solution that enhanced the college community's experience by providing precise, up-to-date, and tailored information in a seamless interaction.

Appendix A

Appendix

This appendix contains additional information and resources related to the "Finderr: LLM powered College Enquiry Chatbot" project.

A.1 Acknowledgments

We would like to express our gratitude to the open-source community and the developers of the GPT 3.5 model for their invaluable contributions to the success of this project.

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