IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

AI-Based College Enquiry Chatbot

Dharushyan.N[1], AP Vetrivel[2]

Department of Artificial Intelligence and Data Science,

Ramco Institute of Technology, Rajapalayam, Tamil Nadu, India[1,2]

Abstract: The increasing demand for efficient communication in educational institutions has highlighted the limitations of traditional enquiry handling systems, which rely heavily on manual responses from administrative staff. These conventional approaches are often time-consuming, prone to delays, and unable to scale effectively with the growing number of student queries. With advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP), intelligent chatbot systems have emerged as a viable solution to automate and enhance user interactions. This paper presents EduConnect AI, an AI-driven admission counselor chatbot designed to provide instant, accurate, and context-aware responses to student enquiries across multiple institutions.

The proposed system utilizes a hybrid architecture that combines rule-based response handling with NLP-driven intent recognition to ensure both reliability and adaptability. User queries are processed through an intelligent pipeline where text inputs are analyzed, classified into predefined intents such as admissions, courses, fees, and facilities, and mapped to relevant responses. The backend is implemented using FastAPI, enabling high-performance request handling and seamless integration with frontend components developed using modern web technologies such as HTML, CSS, and JavaScript.

To improve response accuracy and user trust, the chatbot incorporates explainable reasoning by highlighting key factors influencing its responses. Additionally, a multi-institution recommendation module allows users to explore and compare information across different educational providers without manual intervention. The system also supports scalable data storage and analysis through structured datasets, enabling efficient tracking and visualization of user interactions.

Furthermore, the platform is designed with a user-friendly interface that ensures smooth navigation and real-time communication, enhancing overall user experience. Experimental evaluation demonstrates that the chatbot significantly reduces response time, improves accessibility to information, and minimizes the workload on administrative staff. The results highlight the effectiveness of AI-based chatbot systems in transforming traditional enquiry processes into intelligent, automated, and scalable solutions for modern educational environments.

Keywords: AI Chatbot; Educational Enquiry System; Natural Language Processing; Machine Learning; FastAPI; Admission Counseling; User Interaction; Decision Support System; Automation; Web-Based System.

I. INTRODUCTION

The rapid growth of digital technologies has significantly transformed the way educational institutions interact with students and stakeholders. With increasing competition and a rising number of student enquiries, institutions are required to provide quick, accurate, and accessible information regarding admissions, courses, fees, and campus facilities. Traditional enquiry handling systems, which rely on manual responses from administrative staff, often struggle to meet these demands efficiently. These systems are time-consuming, prone to delays, and unable to provide 24/7 support, leading to poor user experience and increased workload on staff.

In many institutions, enquiry management is handled through phone calls, emails, or in-person visits, which are not scalable and can result in inconsistent information delivery. During peak admission periods, the volume of queries increases significantly, making it difficult for staff to respond promptly. This delay in communication may lead to dissatisfaction among prospective students and can negatively impact institutional reputation. Furthermore, repetitive queries consume valuable human resources that could otherwise be utilized for more critical administrative tasks.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) have enabled the development of intelligent chatbot systems capable of automating human-like conversations. Chatbots can understand user queries, process natural language inputs, and provide instant responses without human intervention. These systems are increasingly being adopted across various domains such as customer support, healthcare, banking, and education due to their efficiency, scalability, and cost-effectiveness.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

AI-powered chatbots utilize NLP techniques to analyze and interpret user inputs, classify them into predefined intents, and generate appropriate responses. Machine learning models improve the chatbot's performance over time by learning from interaction data. Additionally, rule-based approaches can be integrated to ensure accuracy and reliability in handling frequently asked questions. The combination of these techniques results in a hybrid system that balances intelligence and control, making it suitable for real-world applications.

To address the limitations of traditional enquiry systems, this project proposes EduConnect AI, an intelligent chatbot platform designed to automate college enquiry handling. The system is built using a hybrid architecture that combines NLP-based intent recognition with rule-based response generation. User queries are processed through multiple stages, including text preprocessing, intent classification, and response mapping. The backend is implemented using FastAPI to ensure high performance and scalability, while the frontend interface is designed using modern web technologies to provide a user-friendly experience.

The proposed system also includes a multi-institution information module that allows users to access and compare details from different educational providers within a single platform. Additionally, the chatbot incorporates explainable response mechanisms to improve transparency and user trust. The system is capable of handling multiple queries simultaneously, providing instant responses and significantly reducing the dependency on manual intervention.

The main contributions of this project are summarized as follows:
• Automated Enquiry Handling System: Development of an AI-based chatbot capable of responding to student queries in real time, reducing manual workload and improving efficiency.
• Hybrid NLP and Rule-Based Architecture: Integration of Natural Language Processing with rule-based logic to ensure both flexibility and accuracy in response generation.
• Scalable Web-Based Implementation: Deployment using FastAPI backend and modern frontend technologies for efficient and scalable performance.
• User-Friendly Interface Design: Creation of an intuitive and interactive UI/UX that enhances user engagement and accessibility.
• Multi-Query and Multi-User Support: Ability to handle multiple users and queries simultaneously without performance degradation.
• Improved Communication Efficiency: Reduction in response time and enhancement of overall user satisfaction through instant and accurate information delivery.

The remainder of this paper is organized as follows. Section II presents the literature survey on chatbot systems and AI-based enquiry platforms. Section III describes the proposed system architecture and methodology. Section IV discusses the flowchart. Section V presents system implementation and results. Section VI concludes the study. Section VII outlines future enhancements.

II. LITERATURE REVIEW

The development of intelligent chatbot systems for automated enquiry handling has gained significant attention in recent years, particularly in the domain of education. With the increasing demand for real-time communication and efficient information delivery, researchers have explored various approaches including rule-based systems, machine learning models, and advanced Natural Language Processing (NLP) techniques to improve chatbot performance and usability.

A. Rule-Based and Traditional Chatbot Systems

Early chatbot systems were primarily based on rule-based architectures, where predefined patterns and scripted responses were used to handle user queries. These systems relied on keyword matching and decision trees to generate responses. One of the earliest examples is ELIZA, which demonstrated how pattern matching could simulate human-like conversation.

In educational environments, rule-based chatbots have been widely used to answer frequently asked questions related to admissions, courses, and schedules. These systems are easy to design and implement, require minimal computational resources, and provide highly accurate responses for predefined queries. However, they suffer from several limitations, including lack of flexibility, inability to handle complex or ambiguous queries, and poor scalability when the number of possible queries increases.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

Furthermore, rule-based systems cannot learn from user interactions, making them unsuitable for dynamic environments where information and user requirements continuously evolve. As a result, researchers have explored more intelligent approaches to overcome these limitations.

B. Machine Learning-Based Chatbot Systems

Machine learning techniques have significantly improved the capability of chatbot systems by enabling automatic learning from data. ML-based chatbots use classification algorithms to identify user intent and generate appropriate responses. Common approaches include Support Vector Machines (SVM), Naïve Bayes classifiers, Decision Trees, and Random Forest algorithms.

These systems typically involve text preprocessing steps such as tokenization, stop-word removal, and stemming, followed by feature extraction methods like TF-IDF (Term Frequency–Inverse Document Frequency). The extracted features are then used to train classification models that map user queries to specific intents.

Several studies have demonstrated that ML-based chatbots outperform rule-based systems in handling diverse and unseen queries. However, these systems require large labeled datasets for training and may struggle with understanding contextual meaning or multi-turn conversations. Additionally, model performance depends heavily on the quality of training data and feature engineering techniques.

C. Natural Language Processing and Deep Learning Approaches

Advancements in Natural Language Processing (NLP) and deep learning have enabled chatbots to better understand human language and context. Techniques such as word embeddings, recurrent neural networks (RNNs), and transformer-based architectures have been widely adopted in modern chatbot systems.

Deep learning models can capture semantic relationships between words and improve the chatbot's ability to understand user intent even when queries are phrased differently. Transformer-based models, in particular, have shown significant improvements in language understanding and response generation.

Recent developments in large language models (LLMs) such as GPT-based systems have further enhanced chatbot capabilities by enabling more natural and human-like interactions. These models can generate context-aware responses, handle complex queries, and support multi-turn conversations. However, they also introduce challenges such as higher computational requirements, potential inaccuracies, and lack of explainability in decision-making.

D. Hybrid and Intelligent Chatbot Systems

To leverage the strengths of different approaches, recent research has focused on hybrid chatbot architectures that combine rule-based logic, machine learning, and NLP techniques. These systems aim to provide both accuracy and flexibility by using rule-based responses for structured queries and ML/NLP models for handling complex or ambiguous inputs.

Hybrid systems have been successfully applied in educational environments to automate student support services. They improve response accuracy, reduce dependency on human staff, and provide scalable solutions for handling large volumes of queries. Additionally, web-based chatbot platforms have been developed to ensure accessibility across devices and support real-time interaction.

Despite these advancements, many existing systems lack features such as multi-institution support, explainable responses, and seamless integration with modern web technologies. The proposed system addresses these gaps by introducing a hybrid AI-based chatbot platform that combines NLP-driven intent recognition with rule-based response generation in a scalable web environment.

E. Research Gap and Proposed Contribution

From the literature, it is evident that while significant progress has been made in chatbot development, several limitations still exist. Many systems either focus solely on rule-based approaches or rely heavily on machine learning models without ensuring response accuracy and consistency. Additionally, existing solutions often lack scalability, user-friendly interfaces, and adaptability to real-world educational environments.

To address these challenges, the proposed EduConnect AI chatbot system introduces a hybrid architecture that integrates NLP, machine learning, and rule-based techniques into a unified platform. The system is designed to provide accurate,

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

real-time responses, support multiple users simultaneously, and deliver an enhanced user experience through an intuitive interface.

III. METHODOLOGY

A. System Architecture and Design Overview

The proposed EduConnect AI chatbot system is designed as an intelligent web-based enquiry handling platform that integrates Natural Language Processing (NLP), Machine Learning (ML), and rule-based logic into a unified architecture. The system follows a modular client–server model, ensuring scalability, efficiency, and real-time response generation.

The architecture is divided into the following functional layers:
Presentation Layer: A user-friendly web interface developed using modern frontend technologies that allows users to interact with the chatbot through text input. It provides real-time responses, chat history display, and an intuitive UI/UX design for seamless user experience.

Application Layer: The core processing unit that handles user queries, performs preprocessing, and routes requests to appropriate modules for intent classification and response generation.
NLP Processing Layer: Responsible for analyzing user input using text preprocessing techniques such as tokenization, stop-word removal, and normalization to convert raw text into structured data.
Machine Learning Layer: Implements intent classification using ML algorithms trained on predefined datasets of student queries to accurately identify user intent.
Rule-Based Response Layer: Handles frequently asked questions using predefined rules and ensures consistent and accurate responses for structured queries.
Database Layer: Stores institutional information such as courses, fees, admission details, and frequently asked questions, enabling quick retrieval of relevant responses.

The workflow begins when a user submits a query through the interface. The system processes the input through NLP and ML modules, identifies the intent, and generates an appropriate response using either rule-based or ML-driven mechanisms.

B. Text Preprocessing and Feature Extraction

Text preprocessing is a crucial step in transforming raw user input into a format suitable for machine learning models. The system performs the following preprocessing operations: Tokenization (splitting input text into individual words or tokens), Lowercasing (converting all characters to lowercase for uniformity), Stop-word Removal (eliminating common words that do not contribute to intent identification), and Stemming/Lemmatization (reducing words to their root form to improve matching accuracy).

Let the user input query be represented as a string Q. The preprocessing function P transforms it into a sequence of tokens: Tokens = $P(Q) = [w_1, w_2, ..., w_n]$. After preprocessing, feature extraction is performed using TF-IDF (Term Frequency–Inverse Document Frequency), which assigns weights to words based on their importance in the dataset: $TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t)$, where TF(t,d) is the frequency of term t in document d, and IDF(t) is the inverse document frequency of term t. This results in a numerical feature vector that represents the importance of words in the query.

C. Machine Learning-Based Intent Classification

The system uses a supervised machine learning model to classify user queries into predefined intent categories such as admission enquiry, course details, fee structure, and contact information. A classification algorithm such as Naïve Bayes or Random Forest is trained on labeled datasets of user queries. Given a feature vector X, the classifier predicts the most probable intent I: $I = \arg\max P(I|X)$. The model enables the chatbot to handle variations in user queries and improves accuracy over time. The training dataset consists of multiple query variations for each intent to ensure robustness.

D. Rule-Based Response Generation

To ensure high accuracy for frequently asked questions, the system incorporates a rule-based response mechanism. This module uses predefined patterns and mappings to generate responses for common queries such as admission procedures, course availability, fee details, and contact information. Rule-based systems provide deterministic outputs and eliminate ambiguity for structured queries. When a query matches a predefined pattern, the system directly returns the associated response without invoking the ML model.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

E. Hybrid Response Mechanism

The proposed system uses a hybrid approach combining machine learning and rule-based techniques. The workflow is as follows: (1) The system first checks if the query matches any predefined rule. (2) If a match is found, a rule-based response is generated. (3) If no match is found, the query is passed to the ML classifier. (4) The predicted intent is used to fetch the appropriate response from the database. This hybrid mechanism ensures both accuracy (rule-based) and flexibility (ML-based), improving overall system performance.

F. Response Generation and Output Delivery

Once the intent is identified, the system retrieves the corresponding response from the database and delivers it to the user in real time. The chatbot interface displays the response in a conversational format, enhancing user engagement. The system also supports multi-user interaction, real-time response generation, and continuous learning through dataset updates.

G. Web-Based Implementation Architecture

The chatbot system is implemented as a web application using a client–server architecture. The Frontend is developed using modern web technologies to provide an interactive chat interface with responsive design. The Backend is implemented using FastAPI (Python), which handles API requests, processes user input, and integrates ML models. The Database stores structured information about institutions and predefined responses. The frontend communicates with the backend via REST API calls, enabling efficient data exchange and real-time processing. This architecture ensures scalability and allows the system to handle multiple users simultaneously.

H. System Workflow Summary

The overall system workflow can be summarized as follows: (1) User enters a query through the chatbot interface. (2) Input is preprocessed using NLP techniques. (3) Feature extraction is performed using TF-IDF. (4) Query is processed using rule-based matching or ML classification. (5) Appropriate response is retrieved from the database. (6) Response is displayed to the user in real time.

IV. FLOWCHART

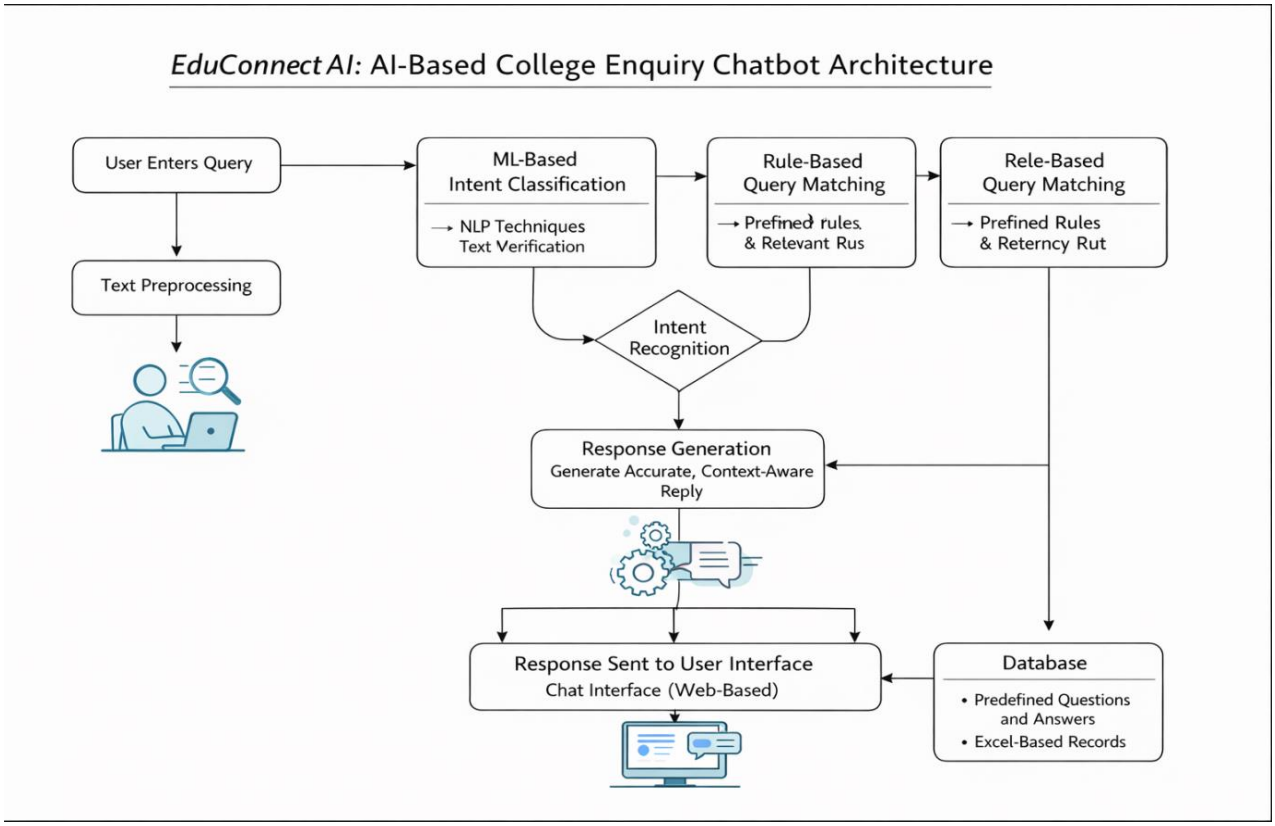

Fig. 1. System Flowchart of EduConnect AI

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

V. SYSTEM IMPLEMENTATION AND RESULTS

The proposed EduConnect AI system was implemented as a web-based intelligent chatbot platform designed to assist users with enquiry handling through a combination of machine learning, rule-based processing, and structured data retrieval. The system focuses on providing accurate, fast, and context-aware responses through a modular and scalable architecture.

A. User Interface and Input Module

The system begins with a clean and interactive user interface where users provide basic details such as name, email, and preferred institution before initiating the chat session. The interface is designed with a modern layout, ensuring ease of use and accessibility across devices. Once initialized, users can interact with the chatbot through a real-time messaging interface. The chat window supports continuous conversation, allowing users to ask queries naturally.

FIG 1: User onboarding interface with input fields and chatbot initialization.

B. Query Processing Pipeline

After a user submits a query, it is processed through multiple stages: Text Preprocessing (the input query is cleaned, tokenized, and normalized to remove unnecessary characters and improve processing accuracy), ML-Based Intent Classification (a trained model classifies user intent using NLP techniques, enabling the system to understand the purpose of the query), Rule-Based Query Matching (predefined rules are applied to match frequently asked questions and structured queries, ensuring fast and deterministic responses), and Hybrid Intent Recognition (outputs from both ML and rule-based systems are combined to improve accuracy and reduce misclassification).

C. Response Generation System

Once the intent is identified, the system generates responses using predefined structured answers for common queries, dynamic responses based on detected intent, and context-aware reply generation for better user experience. The chatbot ensures that responses are clear, relevant, and user-friendly.

D. Database Integration

The system integrates with a backend database that stores predefined questions and answers, institutional information, and structured datasets for quick retrieval. This enables fast access to accurate information while maintaining consistency in responses.

E. Chat Interface and Output Delivery

The generated response is delivered through a web-based chat interface. Features include real-time message display, smooth conversational flow, and continuous interaction capability. Users can ask multiple queries in a single session without restarting the system.

FIG 2: Chat interface showing real-time AI responses and conversation flow.

F. System Performance

The system demonstrates efficient performance with minimal response delay as shown in Table 1 below.

Table 1. System Performance Metrics

Component	Technology	Response Time
Text Preprocessing	NLP (Python/JS)	< 1 second
ML Intent Classification	ML Model	~1–2 seconds
Rule-Based Matching	Predefined Rules	< 1 second
Response Generation	Hybrid Logic	~1–2 seconds
Total Response Time	End-to-end	~2–5 seconds

The hybrid approach ensures both speed and accuracy, making the chatbot reliable for real-time usage.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13437

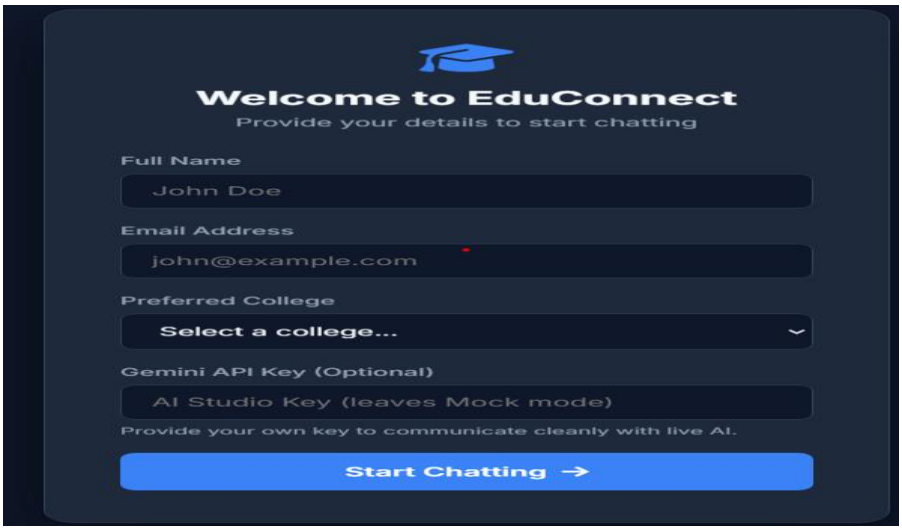

Fig. 2. User Interface – Chat Session

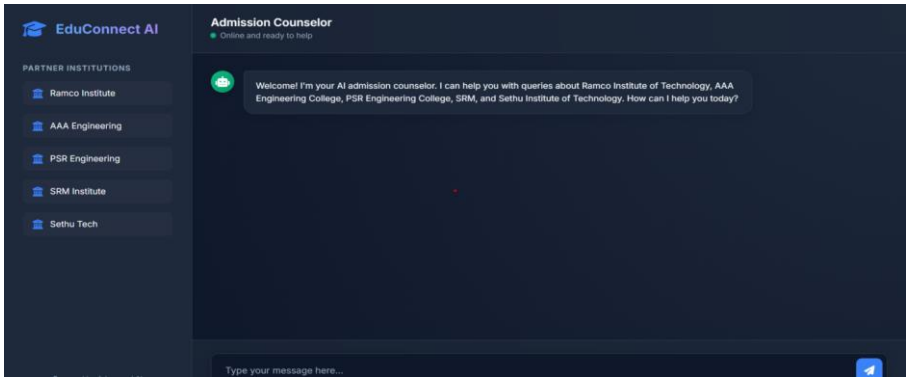

Fig. 3. Chat Interface with AI Responses

VI. CONCLUSION

With the increasing demand for automated and intelligent user support systems, chatbot-based solutions have become essential for handling large volumes of queries efficiently. This project presented EduConnect AI, a smart enquiry chatbot designed to provide accurate, fast, and user-friendly responses through a hybrid approach.

The system combines machine learning-based intent classification with rule-based query matching to ensure both flexibility and reliability. While the ML model enables understanding of natural language queries, the rule-based system ensures precise handling of frequently asked questions. This integration significantly improves response accuracy and reduces errors.

The implementation as a web-based platform ensures accessibility and ease of use, allowing users to interact seamlessly through an intuitive interface. The system demonstrates strong performance with low response times and effective query handling capabilities.

Overall, the proposed system highlights the effectiveness of combining AI techniques with structured logic to build efficient chatbot solutions. Future enhancements may include advanced conversational memory, multilingual support, and integration with external APIs to further improve functionality and user experience.

VII. FUTURE WORK

Although the proposed EduConnect AI system demonstrates effective performance in handling user queries through a hybrid ML and rule-based approach, several enhancements can further improve its capabilities and scalability:
Enhanced Training Dataset: Expanding the dataset with more real-world user queries and conversational variations can improve the accuracy of intent classification and make the chatbot more robust across diverse query styles.

DOI: 10.17148/IARJSET.2026.13437

Advanced NLP Models: Future work can explore transformer-based models such as BERT, DistilBERT, or other lightweight language models to improve semantic understanding and context-aware responses beyond traditional ML approaches.
Context-Aware Conversation Memory: Integrating conversational memory will allow the chatbot to retain previous interactions within a session, enabling more natural multi-turn conversations and better user experience.
Voice-Based Interaction: Adding speech-to-text and text-to-speech capabilities can enable voice-based interaction, making the system more accessible and user-friendly.
Integration with External APIs: The chatbot can be enhanced by integrating real-time APIs to provide dynamic information such as notifications, updates, or external data sources.
Mobile Application Development: Developing a mobile application using frameworks such as React Native or Flutter will allow users to access the chatbot conveniently on smartphones.
Multilingual Support: Implementing multilingual capabilities will enable the system to support users from different linguistic backgrounds, improving accessibility and usability.
Personalized Recommendations: Future versions can include user profiling and recommendation systems to provide personalized responses based on user preferences and past interactions.
Analytics Dashboard: An admin dashboard can be developed to track user queries, analyze trends, and improve system performance based on usage data.
Continuous Learning System: Incorporating feedback-based learning mechanisms will allow the chatbot to improve over time by learning from user interactions and correcting incorrect responses.

REFERENCES

[1]. J. Hirschberg and C. D. Manning, "Advances in natural language processing," Science, vol. 349, no. 6245, pp. 261–266, 2015.
[2]. T. Young, D. Hazarika, S. Poria, and E. Cambria, "Recent trends in deep learning based natural language processing," IEEE Computational Intelligence Magazine, vol. 13, no. 3, pp. 55–75, 2018.
[3]. J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in NAACL, 2019.
[4]. A. Vaswani et al., "Attention is all you need," in Advances in Neural Information Processing Systems (NeurIPS), 2017.
[5]. S. Bird, E. Klein, and E. Loper, Natural Language Processing with Python, O'Reilly Media, 2009.
[6]. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in KDD, 2016.
[7]. F. Chollet, Deep Learning with Python, Manning Publications, 2018.
[8]. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.
[9]. OpenAI, "GPT-based language models for conversational AI," 2023.
[10]. Google AI, "Advancements in conversational AI and dialogue systems," 2024.
[11]. Rasa Technologies, "Open source conversational AI framework," 2023.
[12]. D. Jurafsky and J. H. Martin, Speech and Language Processing, 3rd ed., 2023.
[13]. Microsoft, "Conversational AI: Azure Bot Services documentation," 2024.
[14]. S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 4th ed., Pearson, 2021.
[15]. M. Kaliappan et al., "Load balanced clustering technique in MANET using genetic algorithms," Defence Science Journal, vol. 66, no. 3, pp. 251–258.
[16]. M. Sivaram et al., "Secure storage allocation using fuzzy heuristic algorithm," Journal of Ambient Intelligence and Humanized Computing.
[17]. Vimal, S. et al., "Progression detection using K-means and GLCM," Journal of Supercomputing, 2021.
[18]. Kaliappan, M. et al., "Public sentiment analysis using SVM," Journal of Computer Science, 2025.

