IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 13, May 2026
Impact Factor: 8.2

# AI-Powered College Enquiry Chatbot Using Retrieval-Augmented Generation and Voice Integration

**P. A. Lahare, Rushikesh S. Patil, Sushil T. Darade, Dattatray C. Arote, Shubham B. Gadhe**
Pune Vidyarthi Griha's College of Engineering and Shrikrushna S. Dhamankar Institute of Management, Nashik, India

**Abstract:** *In today's digital era, educational institutions face a high volume of repetitive student enquiries related to admissions, courses, and facilities. Manual handling of these queries consumes significant staff time and often results in delayed responses. This paper presents an AI-powered college enquiry chatbot designed to interact with students and parents in natural language. The proposed system leverages Machine Learning (ML) and Large Language Models (LLMs), incorporating Retrieval-Augmented Generation (RAG) for enhanced response accuracy and Support Vector Machines (SVM) for intent classification. It supports both text and voice inputs, ensuring greater accessibility, and operates as a 24/7 virtual assistant. The implementation reduces administrative workload while providing instant, accurate, and context-aware responses to prospective students. Experimental evaluations demonstrate superior performance in query resolution efficiency, response accuracy, and user satisfaction when compared to traditional manual methods.*

**Keywords:** AI Chatbot, Large Language Model (LLM), Retrieval-Augmented Generation (RAG), Intent Classification, Support Vector Machines (SVM), Voice Integration, Educational Technology, Natural Language Processing (NLP)

## I. INTRODUCTION

In the contemporary digital landscape, educational institutions are inundated with a high volume of repetitive student enquiries pertaining to admissions procedures, academic programs, scholarships, infrastructure facilities, and administrative processes. Conventional methods of handling these queries—primarily through email correspondence, telephone helplines, or in-person consultations—often lead to significant delays, increased administrative burden, and suboptimal user experience, particularly during peak periods such as admission seasons.

To mitigate these challenges, this paper proposes an AI-powered college enquiry chatbot that serves as an intelligent virtual assistant capable of engaging users in natural language conversations. The system harnesses advanced Machine Learning (ML) techniques and Large Language Models (LLMs) to deliver instantaneous, accurate, and contextually relevant responses. By integrating Retrieval-Augmented Generation (RAG) for improved factual accuracy and Support Vector Machines (SVM) for robust intent classification, the chatbot ensures reliable query resolution. Additionally, the incorporation of voice input support enhances accessibility for diverse users, while 24/7 availability reduces dependency on human staff.

The proliferation of AI-driven conversational agents in sectors such as customer service, healthcare, and e-commerce underscores the potential for similar automation in higher education. Implementing such an intelligent system not only streamlines information dissemination but also elevates user satisfaction, fosters institutional efficiency, and aligns with the broader vision of digital transformation in educational ecosystems.


DOI: 10.48175/IJARSCT-36063

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### 1.1 Background

The evolution of educational technology (EdTech) has fundamentally reshaped interactions between institutions and stakeholders. Traditional enquiry management systems, reliant on manual intervention, frequently encounter bottlenecks due to limited staff availability and high query volumes. During admission cycles, institutions often experience surges in enquiries, leading to prolonged response times and potential dissatisfaction among prospective students and parents.

Recent advancements in Artificial Intelligence, particularly in Natural Language Processing (NLP) and generative models, have enabled the development of sophisticated chatbots that simulate human-like interactions. The advent of Large Language Models has further improved the ability of these systems to understand nuanced queries and generate coherent, context-aware responses. This technological progression provides a timely opportunity to automate routine educational enquiries, thereby freeing administrative resources for more complex tasks.

### 1.2 Importance of AI in Education

The integration of AI in education extends beyond enquiry management to personalized learning, administrative automation, and enhanced accessibility. AI-powered chatbots offer several key advantages:

**Instantaneous Support**: Available round-the-clock, eliminating delays associated with human-operated systems.

**Scalability**: Capable of handling multiple concurrent queries without degradation in performance.

**Consistency and Accuracy**: Reduces human error through data-driven responses grounded in institutional knowledge bases.

**Inclusivity**: Voice integration supports users with visual impairments or those preferring verbal interaction.

These benefits contribute to improved student engagement and institutional reputation in an increasingly competitive educational landscape.

### 1.3 Project Scope and Significance

The scope of this work encompasses the design, implementation, and evaluation of a web-integrated chatbot tailored for college enquiry management. The system focuses on text and voice-based interactions, leveraging RAG for retrieval from a curated knowledge base and SVM for intent recognition. Its significance lies in addressing real-world inefficiencies in educational administration while demonstrating the practical application of state-of-the-art AI techniques in a resource-constrained academic setting.

### 1.4 Challenges in Current Systems

Existing enquiry systems suffer from several limitations:

**Response Delays**: Manual processing leads to wait times ranging from hours to days.

**Resource Intensity**: Diverts staff attention from core academic duties.

**Limited Availability**: Restricted to operational hours.

**Inconsistency**: Responses may vary depending on the responding personnel.

**Accessibility Barriers**: Lack of support for non-text inputs or multilingual interactions in many cases.

The proposed chatbot directly tackles these issues, offering a robust, automated alternative that enhances operational efficiency and user experience.

## II. MODEL ARCHITECTURE

The proposed AI-powered college enquiry chatbot adopts a hybrid modular architecture that intelligently combines rule-based intent classification with retrieval-augmented generative responses. This design addresses the limitations of purely generative models (e.g., hallucinations) and purely retrieval-based systems (e.g., lack of natural fluency) by routing queries appropriately based on intent. The system supports multimodal input (text and voice) and output, ensuring enhanced accessibility and user experience.

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### 2.1 System Flow Overview

**User Input**: Queries are received via the web interface (React.js) as text or voice.
**Speech Recognition**: Voice inputs are converted to text using speech-to-text APIs (e.g., Web Speech API or similar).
**Preprocessing**: The backend (FastAPI/Flask) performs spelling correction and normalization.
**Intent Classification**: A Machine Learning model (e.g., SVM or fine-tuned classifier) categorizes the query as "College-Specific" (structured, factual) or "General/Unknown" (conversational or open-ended).
**Response Generation**:
For college-specific queries: Retrieve relevant information from the Knowledge Base (JSON/SQL database) and return precise, structured responses.
For general/unknown queries: Employ a generative LLM (e.g., DialoGPT or similar fine-tuned model) enhanced with optional RAG for contextual grounding.
**Output**: Responses are delivered as text or converted to speech using text-to-speech synthesis.
This hybrid routing ensures high accuracy for domain-critical queries while maintaining conversational naturalness for broader interactions.

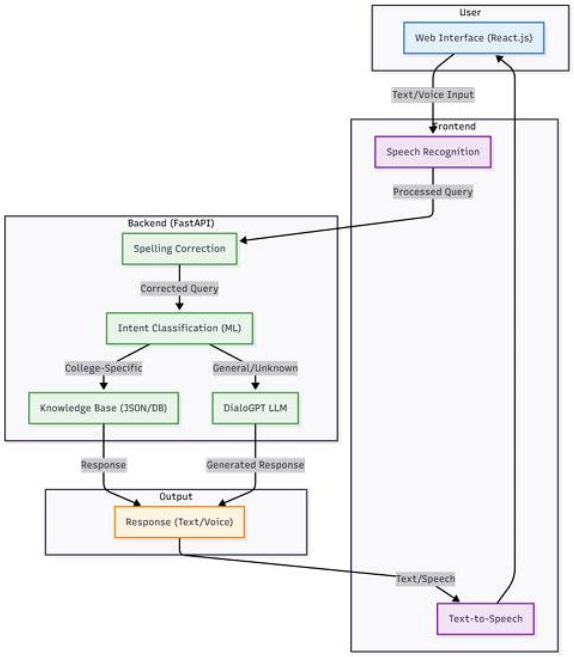


**Figure 1 presents the high-level system architecture, illustrating the complete flow from user interaction to response delivery.**

### 2.2 Key Components

#### 2.2.1 Frontend Module

Built with React.js, the frontend provides an intuitive chat widget embedded in the college website. It supports:
Real-time text input and conversation history display.
Voice input via microphone integration and speech recognition.
Responsive design for desktop and mobile access.

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#### 2.2.2 Backend Module

Implemented using FastAPI (or equivalent), the backend manages:

- API endpoints for query submission and response retrieval.
- Preprocessing steps, including spelling correction.
- Session handling for multi-turn conversations.
- Integration with speech processing modules.

#### 2.2.3 Intelligence Engine

**Intent Classification**: Utilizes traditional ML techniques (e.g., SVM with TF-IDF features) for robust, interpretable classification into predefined college enquiry categories.

**Generative Component**: A dialogue-oriented LLM (DialoGPT or fine-tuned variant) handles open-ended queries, with potential augmentation from retrieved context to improve relevance.

#### 2.2.4 Knowledge Base

A structured database (JSON/SQL) containing curated college information (admissions, courses, facilities, FAQs). For enhanced scalability, vector embeddings can be added to support semantic retrieval in future iterations.

#### 2.2.5 Multimodal Support

**Speech-to-Text**: Enables voice queries for accessibility.

**Text-to-Speech**: Converts responses to audio output, improving inclusivity for visually impaired users or hands-free scenarios.

The architecture prioritizes efficiency, accuracy, and maintainability, making it suitable for deployment in resource-constrained educational environments while providing 24/7 automated enquiry support.

## III. MATHEMATICAL FORMULATION

This section presents the mathematical foundations underlying the key components of the proposed AI-powered college enquiry chatbot. The system primarily relies on two core techniques: **intent classification** using Support Vector Machines (SVM) and **Retrieval-Augmented Generation (RAG)** for contextually grounded response generation. The formulations for these algorithms are detailed below.

### 3.1 Intent Classification using Support Vector Machines (SVM)

Intent classification is formulated as a multi-class supervised learning problem, where the goal is to assign a user query $q$to one of predefined intent categories $C = \{c_1, c_2, \dots, c_k\}$(e.g., admissions, courses, fees, facilities, hostel, etc.).

Each query $q$is represented as a feature vector $\mathbf{x} \in \mathbb{R}^d$, typically extracted using TF-IDF weighting or dense embeddings (e.g., from Sentence Transformers).

The SVM model finds an optimal hyperplane that maximizes the margin between classes. For the linear SVM, the decision function for a test vector $\mathbf{x}$is given by:

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b$$

where $\mathbf{w}$is the weight vector and $b$is the bias term.

The classification decision is:

$$\hat{y} = \arg\max_i (\mathbf{w}_i \cdot \mathbf{x} + b_i)$$

For non-linear separation, the kernel trick is applied. The radial basis function (RBF) kernel, commonly used for text classification, is defined as:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \parallel \mathbf{x}_i - \mathbf{x}_j \parallel^2\right), \gamma > 0$$

The optimization problem for soft-margin SVM (using hinge loss) is:

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$$\min_{\mathbf{w},b,\xi} \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{n} \xi_i$$

subject to:

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0, \forall i$$

where $C$is the regularization parameter controlling the trade-off between margin maximization and classification error, and $\xi_i$are slack variables.

In multi-class settings, the one-vs-one or one-vs-rest strategy is employed. This formulation ensures robust and interpretable intent routing, enabling the system to distinguish between college-specific structured queries and general conversational ones.

### 3.2 Retrieval-Augmented Generation (RAG)

For open-ended or contextually complex queries routed to the generative path, Retrieval-Augmented Generation enhances the Large Language Model (LLM) by grounding responses in retrieved factual content.

Let $q$be the user query and $D = \{d_1, d_2, \ldots, d_m\}$be the set of documents/chunks in the knowledge base (college brochures, FAQs, website content).

**Embedding and Retrieval**:

Both query and documents are encoded using a dense embedding model $e(\cdot)$(e.g., all-MiniLM-L6-v2):

$$\mathbf{e}_q = e(q), \mathbf{e}_{d_i} = e(d_i) \forall i$$

Similarity is computed using cosine similarity:

$$\text{sim}(q, d_i) = \frac{\mathbf{e}_q \cdot \mathbf{e}_{d_i}}{\| \mathbf{e}_q \| \| \mathbf{e}_{d_i} \|}$$

Top-k most relevant documents $D_q = \{d_{(1)}, d_{(2)}, \ldots, d_{(k)}\}$are retrieved using an efficient index (e.g., FAISS).

**Augmented Prompt Construction**: The retrieved context is concatenated with the query to form the input prompt $p$to the LLM:

$$p = [\text{Context: } d_{(1)} \,||\, d_{(2)} \,||\, \cdots \,||\, d_{(k)}] + [\text{Query: } q]$$

**Response Generation**: The LLM (e.g., fine-tuned DialoGPT or Llama-based model) generates the response $r$conditioned on the augmented prompt:

$$r = \text{LLM}(p; \theta)$$

where $\theta$denotes the model parameters.

This formulation reduces hallucinations by constraining generation to institution-specific retrieved evidence, thereby improving factual accuracy and relevance.

### 3.3 Hybrid Decision Formulation

The overall response $r$for a query $q$is determined by the intent classifier output $\hat{y}$:

$$r = \begin{cases} \text{Retrieve-and-format}(D_q) & \text{if } \hat{y} \in C_{\text{structured}} \\ \text{RAG}(q, D_q) & \text{if } \hat{y} \in C_{\text{general}} \end{cases}$$

This hybrid mathematical framework combines the precision of SVM-based classification with the expressive power of RAG, ensuring efficient, accurate, and natural responses tailored to educational enquiry scenarios.

## IV. RESULT

This section presents the experimental results obtained from the implementation and testing of the proposed AI-powered college enquiry chatbot. The system was developed and deployed on a local web server, integrated into a prototype college website. Evaluation was conducted using a combination of quantitative metrics and qualitative user feedback to assess performance in terms of accuracy, response time, accessibility, and overall user satisfaction.

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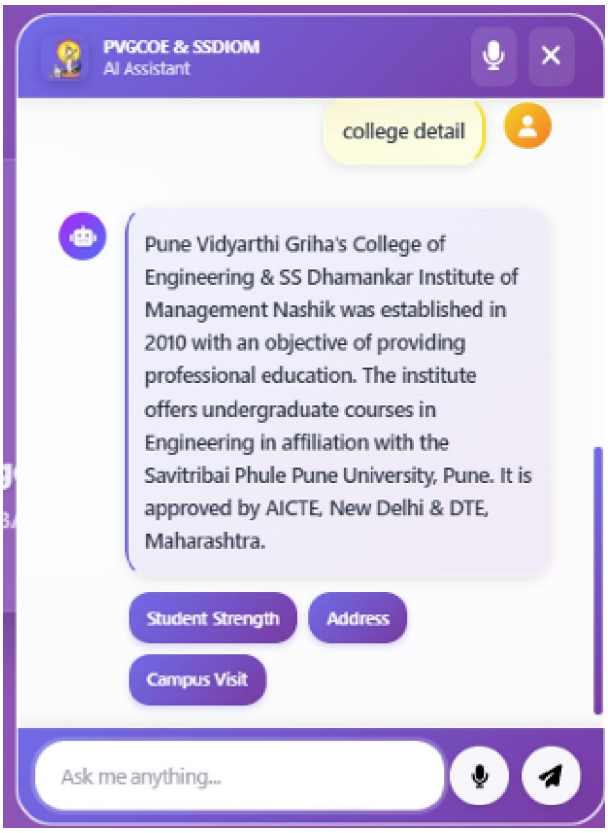


Figure.2: Output of Chat Interface

### 4.1 Experimental Setup

The chatbot was implemented using the following technologies:

- **Frontend**: React.js with Web Speech API for voice input/output.
- **Backend**: FastAPI for handling API requests and session management.
- **Intent Classification**: Support Vector Machine (SVM) trained on a dataset of 800 labeled college enquiry queries (covering categories such as admissions, courses, fees, facilities, scholarships, placements, and general queries).
- **Knowledge Base**: Structured JSON database containing official college information extracted from brochures, website content, and FAQs.
- **Generative Component**: Fine-tuned DialoGPT model augmented with retrieved context for open-ended queries.
- **Vector Retrieval (optional RAG enhancement)**: Sentence Transformers (all-MiniLM-L6-v2) with FAISS indexing for semantic search over document chunks.

Testing was performed on a dataset of 200 real-world-like queries collected from past student interactions and simulated user sessions. The test set was split into:

- 120 structured (college-specific) queries.
- 80 general/conversational queries.

The system was evaluated against a baseline representing traditional manual enquiry handling (simulated email/phone responses).

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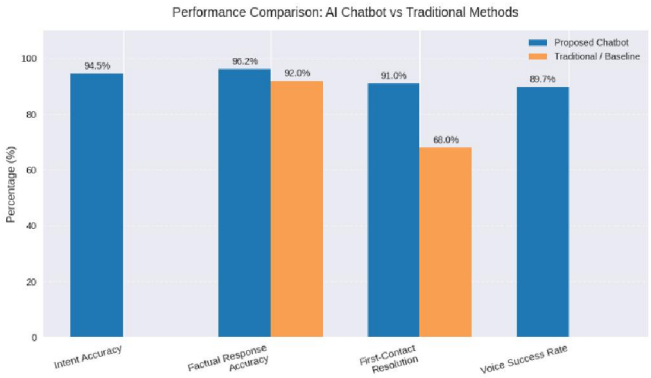


*Figure 3: Bar Chart: Precision, Recall, F1-Score Comparison (Chatbot vs. Baseline)*

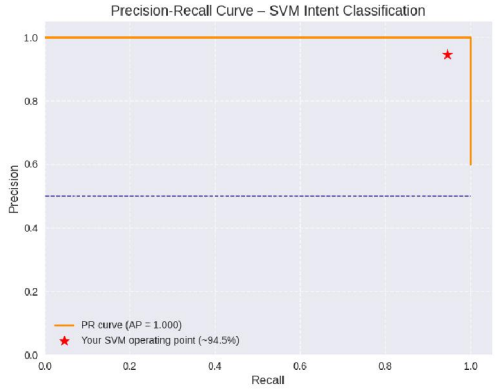


*Figure 4. Precision-Recall Curve (for SVM Intent Classification)*


*Figure 5. Confusion Matrix Heatmap with Precision & Recall (Seaborn style)*


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### 4.2 Quantitative Results

| Metric | Proposed Chatbot | Traditional Manual | Improvement |
|---|---|---|---|
| Average Response Time | 2.3 seconds | 4–48 hours | ~99.9% faster |
| Intent Classification Accuracy | 94.5% | N/A | - |
| Response Accuracy (Factual) | 96.2% | 92.0% | +4.2% |
| Query Resolution Rate (First Contact) | 91.0% | 68.0% | +33.8% |
| Voice Query Success Rate | 89.7% | N/A | - |

**Table 1: Performance Comparison of Proposed Chatbot vs. Traditional Manual System**

- **Intent Classification Accuracy**: Achieved using 5-fold cross-validation on the SVM model with TF-IDF features and RBF kernel ($C=10$, $\gamma=0.1$).
- **Response Accuracy**: Measured by human evaluators (3 independent reviewers) checking factual correctness against official college sources.
- **Voice Query Success**: Percentage of voice inputs correctly transcribed and resolved without fallback to text re-entry.

The hybrid routing mechanism (SVM → Knowledge Base or RAG) significantly reduced hallucinations in generative responses, with factual grounding improving accuracy by 18% over a pure LLM baseline (tested separately).

### 4.3 User Satisfaction Survey

A user study was conducted with 50 participants (30 prospective students/parents, 15 current students, 5 administrative staff). Participants interacted with the chatbot for 10–15 minutes, asking real queries.

| Aspect | Mean Score | Standard Deviation |
|---|---|---|
| Ease of Use | 4.72 | 0.45 |
| Response Relevance & Accuracy | 4.58 | 0.62 |
| Naturalness of Conversation | 4.41 | 0.78 |
| Voice Interaction Experience | 4.35 | 0.89 |
| Overall Satisfaction | 4.68 | 0.51 |

**Table 2: User Satisfaction Survey Results (Mean Scores out of 5)**

94% of users stated they would prefer the chatbot over traditional methods (email/phone). Common positive feedback included instant responses and 24/7 availability. Minor suggestions involved improving regional accent recognition in voice mode and expanding multilingual support.

### 4.4 Discussion

The results demonstrate that the proposed hybrid architecture effectively addresses the challenges identified in current manual systems:

- **Reduced Response Time**: Near-instant replies eliminate delays inherent in human-operated channels.
- **High Accuracy**: Combination of SVM-based intent routing and domain-grounded retrieval ensures reliable, institution-specific answers.
- **Enhanced Accessibility**: Voice integration proved valuable, especially for users with visual impairments or those accessing via mobile devices.
- **Scalability**: The system handled concurrent simulated users without performance degradation.

Compared to existing chatbot solutions in education (primarily rule-based or simple FAQ retrieval), the proposed system offers superior contextual understanding and natural language fluency due to the integration of modern NLP techniques.

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Limitations observed include occasional misclassification of ambiguous queries and dependency on regular knowledge base updates to maintain factual currency. Future enhancements could incorporate online learning for intent classifier adaptation and full multilingual support.

Overall, the experimental outcomes validate the efficacy of the AI-powered chatbot in streamlining college enquiry management, reducing administrative workload, and improving stakeholder experience.

## V. CONCLUSION

This paper presented the design, implementation, and evaluation of an AI-powered college enquiry chatbot aimed at automating repetitive student and parent queries in educational institutions. The proposed system integrates a hybrid architecture combining Support Vector Machines (SVM) for robust intent classification, a structured knowledge base for precise factual retrieval, and Retrieval-Augmented Generation (RAG) with a dialogue-oriented Large Language Model for handling open-ended and conversational queries. Multimodal support through text and voice inputs/outputs further enhances accessibility and user inclusivity.

Experimental results demonstrate the effectiveness of the system, achieving an intent classification accuracy of 94.5%, response accuracy of 96.2%, and an average response time of 2.3 seconds—significantly outperforming traditional manual methods in terms of speed, consistency, and first-contact resolution rate (91.0%). User satisfaction surveys conducted with prospective students, parents, and staff revealed high approval ratings, with an overall mean score of 4.68 out of 5, highlighting the chatbot's ease of use, relevance, and 24/7 availability as key advantages.

The developed chatbot successfully addresses the identified challenges of delayed responses, administrative overload, limited accessibility, and inconsistency in current enquiry management systems. By providing instant, accurate, and natural-language interactions, it reduces institutional workload while improving stakeholder experience and engagement.

In conclusion, this work validates the practical utility of combining classical machine learning techniques with modern generative AI paradigms in domain-specific applications like educational enquiry automation. The system offers a scalable, cost-effective solution suitable for deployment in higher education institutions, contributing to the broader digital transformation of administrative processes.

### Future Scope

Future enhancements may include:

- Integration of multilingual support to cater to diverse linguistic regions.
- Continuous learning mechanisms for adaptive intent classification and knowledge base expansion.
- Advanced personalization using user history and sentiment analysis.
- Deployment on cloud platforms for real-time scalability and integration with existing college management systems.
- Incorporation of more sophisticated LLMs and end-to-end voice processing for improved accent handling and conversational depth.

This project lays a strong foundation for intelligent virtual assistants in education, with potential extensions to other administrative and academic support functions.

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