Airtel RAG Customer Support Chatbot

Retrieval-Augmented Generation for Telecom Customer Service

LLM + SLM Hybrid

Groq LPU

Brand Voice

Built by Kaustubh Nair | AI Training Program — Week 3, Day 5 Assignment

Project Overview

Use Case

Customer Support Assistant for Airtel

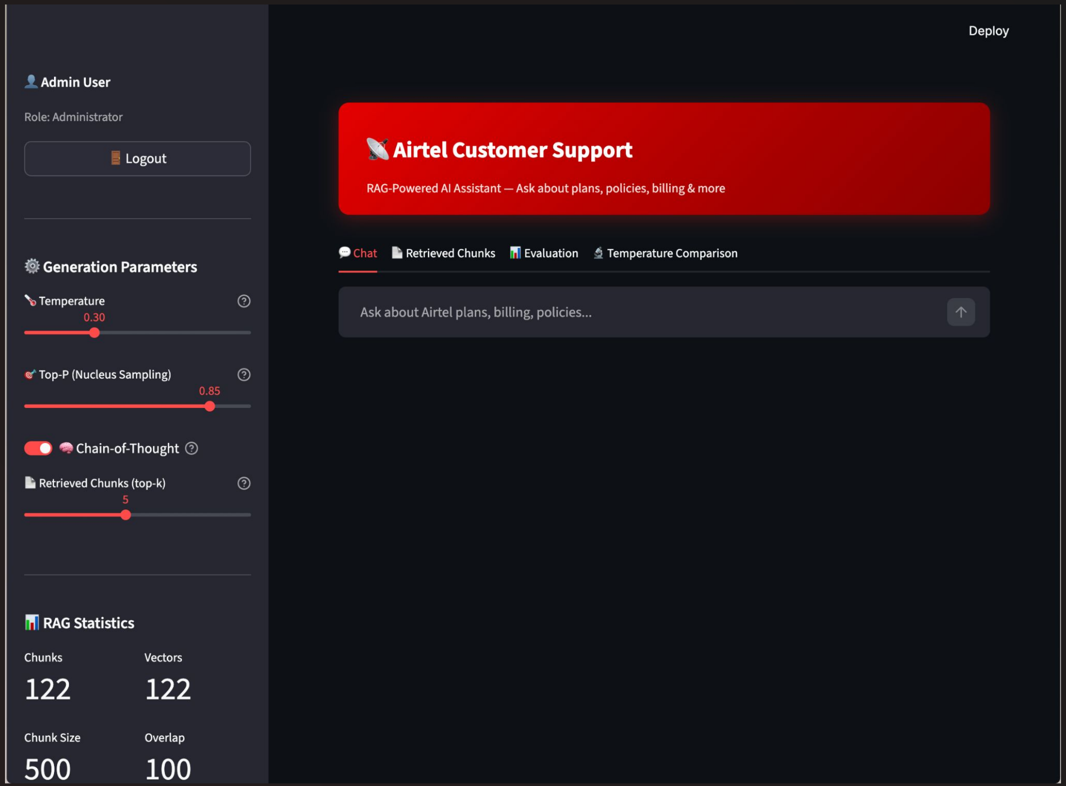
Company

Bharti Airtel Limited

India's Leading Telecom Company

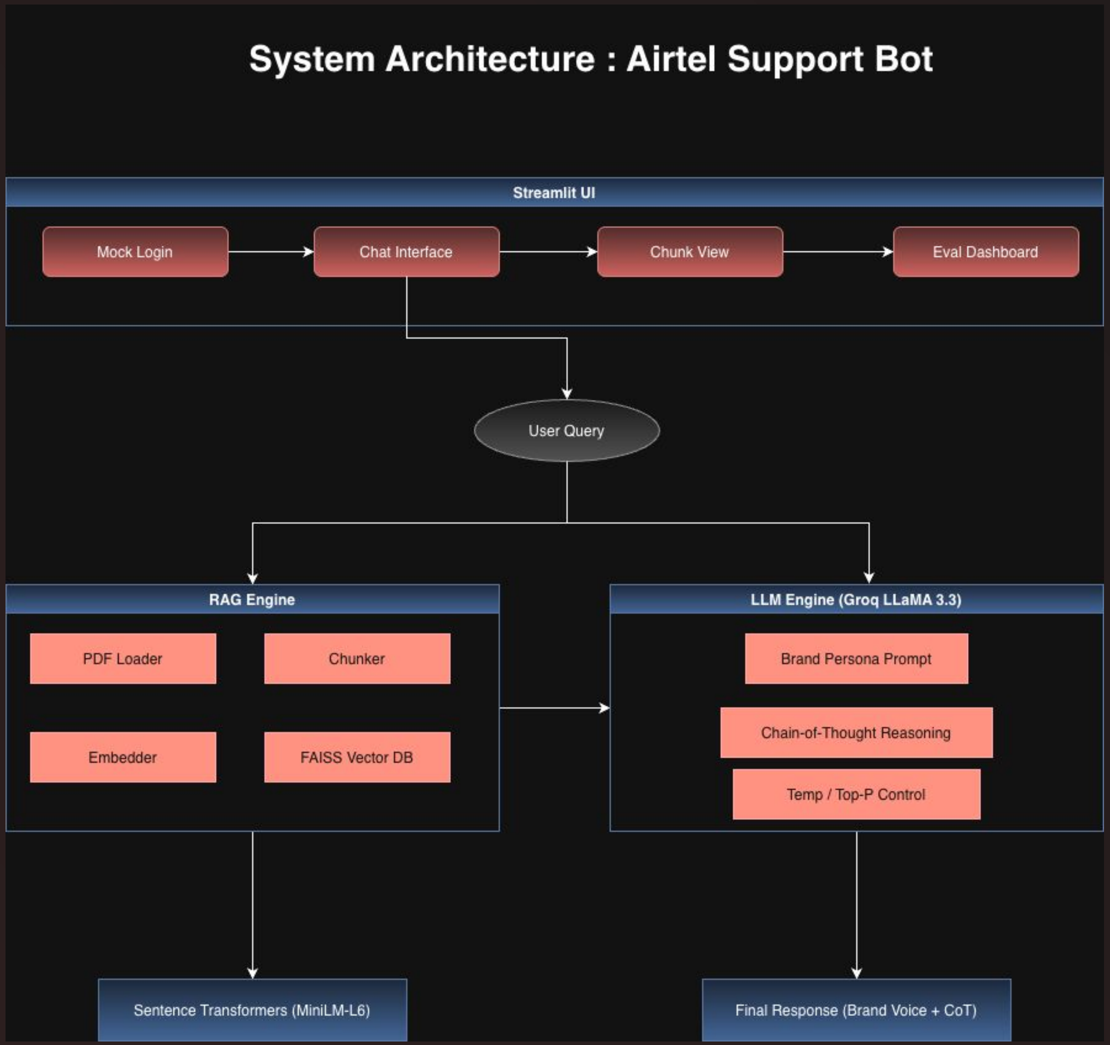
Goal

Build a RAG-based chatbot that answers customer queries about Airtel's **plans, policies, billing, and services** using only verified company documentation



Streamlit-based Chat Interface

System Architecture



STREAMLIT UI

Mock Login → Chat Interface → Chunk View → Eval Dashboard

RAG ENGINE

PDF Loader → Chunker → Embedder → FAISS DB

LLM ENGINE

Groq LLaMA 3.3 → Brand Persona → CoT Reasoning

EMBEDDINGS

sentence-transformers (MiniLM-L6-v2)

Response Generation: Combines retrieved context with brand voice and CoT reasoning

Technology Stack

LLM

Groq (LLaMA 3.3 70B Versatile)

Ultra-fast inference via Groq's LPU, excellent instruction-following

Embeddings

all-MiniLM-L6-v2

Lightweight (80MB), fast, 384-dim. Ideal for semantic search without GPU

Vector DB

FAISS (Facebook AI)

Fast similarity search, no server needed, persistent storage

Chunking

LangChain RecursiveCharacterTextSplitter

500-char chunks with 100-char overlap for optimal retrieval

UI

Streamlit

Rapid prototyping, built-in chat components

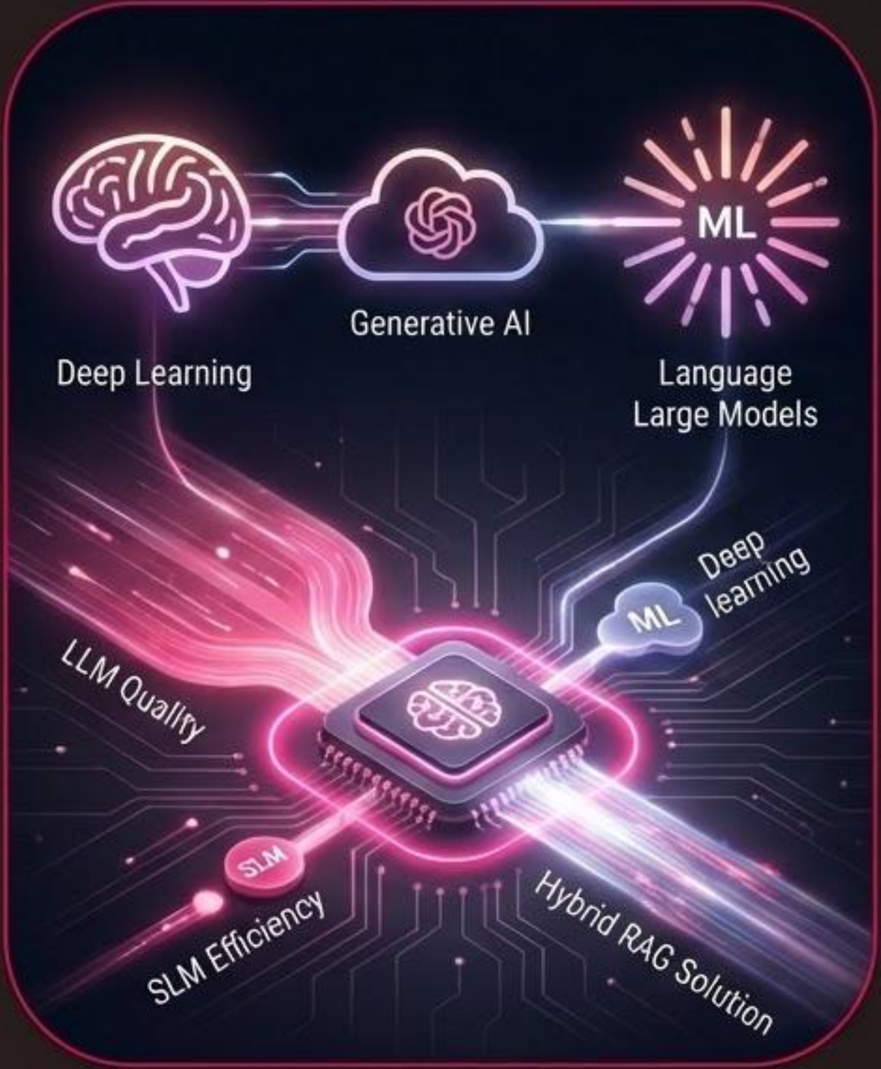
Authentication

Custom Mock Login (SHA-256)

Simple security gate as required

Hybrid approach: Cloud LLM for quality + Local SLM for efficiency

Hybrid Model Selection



LLaMA 3.3

Used For: Response generation

Why:

Superior brand-voice, CoT reasoning

Size:

Cloud API

Latency: 0.5-2s (LPU)

Cost: Free tier available

MiniLM-L6-v2

Used For: Document embeddings

Fast lightweight, no GPU needed

80MB local model

Latency: ~50ms per embedding

Cost: Free (local)

Why Hybrid Approach?

Pure SLM struggles with brand voice adherence, CoT reasoning, multi-turn conversations, and detailed structured responses. **Hybrid gives SLM efficiency + LLM quality**

Best of Both Worlds | Efficient Retrieval

Key Features

RAG Pipeline

PDF loading → Chunking → Embedding → FAISS → Retrieval → Generation

Brand Voice

Strict "Airtel Assist" persona using only provided context

Chain-of-Thought

Model explains retrieval logic before answering

Parameter Controls

Live sliders for Temperature and Top-P generation parameters

Chunks Display

Dedicated tab showing source chunks with relevance scores

Mock Login

Username/password authentication gate with SHA-256 hashing

Evaluation Suite

10-question benchmark with keyword matching & hallucination detection

Multi-turn Chat

Conversation history maintained for context across interactions

End-to-end RAG solution with comprehensive evaluation and real-time parameter tuning

Setup & Installation

1 Clone Repository

```
git clone https://github.com/KaustubhNair-bot/AI_Tr_BOT.git
cd AI_training_BOT/RAG_real_life_use_case_kaustubh
```

2 Virtual Environment

```
python3 -m venv venv
source venv/bin/activate
```

3 Install Dependencies

```
pip install -r requirements.txt
```

4 Set Up API Key

```
cp .env.example .env
```

Add your Groq API key in .env file

5 Run the App

```
streamlit run streamlit_app.py
```

6 Login

`admin/admin123` `agent/agent123` `demo/demo123`

Get your Groq API key at: `https://console.groq.com/keys`

Evaluation & Performance

Evaluation Categories

- Prepaid Plans
- Postpaid Plans
- Porting / MNP
- Intl. Roaming
- Refund Policy
- Broadband
- Customer Support
- Rewards Program
- Fair Usage Policy
- Cancellation

Performance Metrics

Keyword Match Score

Percentage of expected keywords found in response

Hallucination Rate

Percentage of unsupported numeric claims

Generation Parameters Comparison

Factual

Temp: 0.0

Top-P: 0.5

Lowest Hallucination

Balanced

Temp: 0.3

Top-P: 0.85

Low Risk

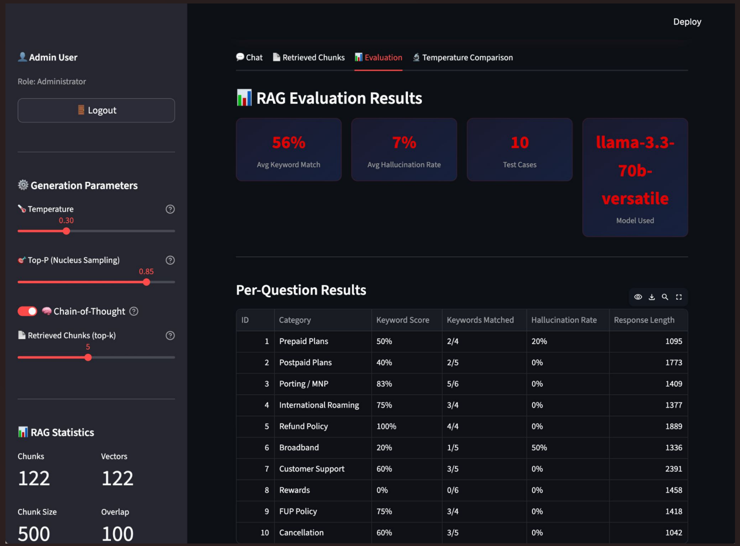
Creative

Temp: 0.8

Top-P: 0.95

Higher Risk

Optimal Settings: Temperature 0.0–0.3 with Top-P 0.5–0.85 provides best balance of factual accuracy and brand-voice adherence



ID	Category	Keyword Score	Keywords Matched	Hallucination Rate	Response Length
1	Prepaid Plans	50%	2/4	20%	1095
2	Postpaid Plans	40%	2/5	0%	1773
3	Porting / MNP	83%	5/6	0%	1409
4	International Roaming	75%	3/4	0%	1377
5	Refund Policy	100%	4/4	0%	1889
6	Broadband	20%	1/5	50%	1336
7	Customer Support	60%	3/5	0%	2391
8	Rewards	0%	0/6	0%	1458
9	FUP Policy	75%	3/4	0%	1418
10	Cancellation	60%	3/5	0%	1042

Conclusion & Key Takeaways

Security Features

- SHA-256 hashed passwords
- Session-based authentication
- API key stored in .env
- Context constraints

Optimal Parameters

Temperature	0.0 – 0.3
Top-P	0.5 – 0.85

Best balance of **factual accuracy** and **brand-voice adherence**

Project Success Factors

- Hybrid LLM + SLM approach
- End-to-end RAG pipeline
- Comprehensive evaluation suite
- Brand voice persona enforcement

Future Potential

- Scalable to other telecom companies
- Enhance with more data sources
- Potential for real-time integration

Project Success

The hybrid RAG approach delivers the perfect balance of efficiency, accuracy, and brand consistency for customer support applications

Built by Kaustubh Nair

AI Training Program