RAG Chatbot Development using Cursor IDE: A Comprehensive Framework for Secure Data Querying

MSDS 7335 - Machine Learning II
Final Project Report

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Abstract

This report presents the development of an automated Retrieval-Augmented Generation (RAG) chatbot system using Cursor IDE AI-powered development environment. The primary objective was to create a secure, locally-deployable chatbot capable of querying sensitive data without relying on external APIs. The system integrates Ollama for local language model inference, Langchain for RAG framework implementation, ChromaDB for vector storage, and Gradio for user interface development. The entire development workflow was automated using Cursor IDE, demonstrating the potential of AI-assisted programming in creating complex machine learning applications. The resulting system provides multiple deployment options including High-Performance Computing (HPC) clusters via Open On-Demand, Kubernetes and cloud deployment through AWS services. This work contributes to the growing field of secure, privacy-preserving AI applications while showcasing the transformative impact of AI-powered development tools in academic and professional machine learning projects.

Keywords: Retrieval-Augmented Generation, Cursor IDE, Ollama, Langchain, ChromaDB, open-source LLM, AI-Assisted Development

1 Introduction

In the rapidly evolving landscape of artificial intelligence and machine learning, the need for secure, privacy-preserving solutions for sensitive data analysis has become paramount. Traditional cloud-based AI services, while powerful, often require transmitting sensitive data to external servers, raising significant privacy and security concerns for organizations handling confidential information. This challenge is particularly acute in sectors such as healthcare, finance, and government, where data privacy regulations and security requirements mandate strict control over data access and processing.

The emergence of Retrieval-Augmented Generation (RAG) systems has provided a promising solution for creating intelligent question-answering systems that can work with domain-specific documents while maintaining data privacy. However, developing such systems traditionally requires extensive expertise in multiple technologies, significant development time, and careful integration of various components including language models, vector databases, and user interfaces.

The introduction of AI-powered development environments, particularly Cursor IDE, has revolutionized the software development process by providing intelligent code completion, automated bug fixing, and comprehensive project scaffolding capabilities. Cursor represents a paradigm shift in how complex machine learning applications can be developed, enabling researchers and practitioners to focus on high-level design and requirements while the AI assistant handles much of the implementation details.

The primary objective of this project is to demonstrate the feasibility and effectiveness of using Cursor to automatically create a comprehensive RAG chatbot system with the following key requirements:

- Local Deployment: No reliance on external APIs call, ensuring complete data privacy and security
- Multi-format Support: Capability to process and query PDF and text documents
- Flexible Model Selection: Support for multiple local language models with real-time switching
- User-friendly Interface: Intuitive graphical interface for non-technical users
- Scalable Deployment: Multiple deployment options from personal computers to cloud infrastructure
- Automated Development: Minimal manual coding through AI-assisted development

This work makes several important contributions to the field:

- Demonstrates the practical application of AI-assisted development tools in creating complex ML systems
- Provides a comprehensive framework for secure, local RAG implementation
- Establishes deployment strategies for various computing environments

- Validates the effectiveness of Cursor in academic machine learning projects
- Creates a reusable template for similar privacy-preserving AI applications

This report is organized into four main chapters. Chapter 1 introduces the project and provides a brief overview of the RAG chatbot system. Chapter 2 provides detailed technical background on the models and technologies employed, including Ollama, Langchain, ChromaDB, and Gradio, along with a comprehensive explanation of the RAG workflow. Chapter 3 describes the automated development process using Cursor and presents various deployment strategies. Chapter 4 discusses the results, implications, and conclusions, with particular emphasis on the role and necessity of AI-assisted development tools in modern machine learning workflows.

2 Models and Data

The RAG chatbot system developed in this project represents a sophisticated integration of multiple state-of-the-art technologies, each serving a specific role in the overall architecture. The system follows a modular design pattern that ensures scalability, maintainability, and flexibility in deployment scenarios.

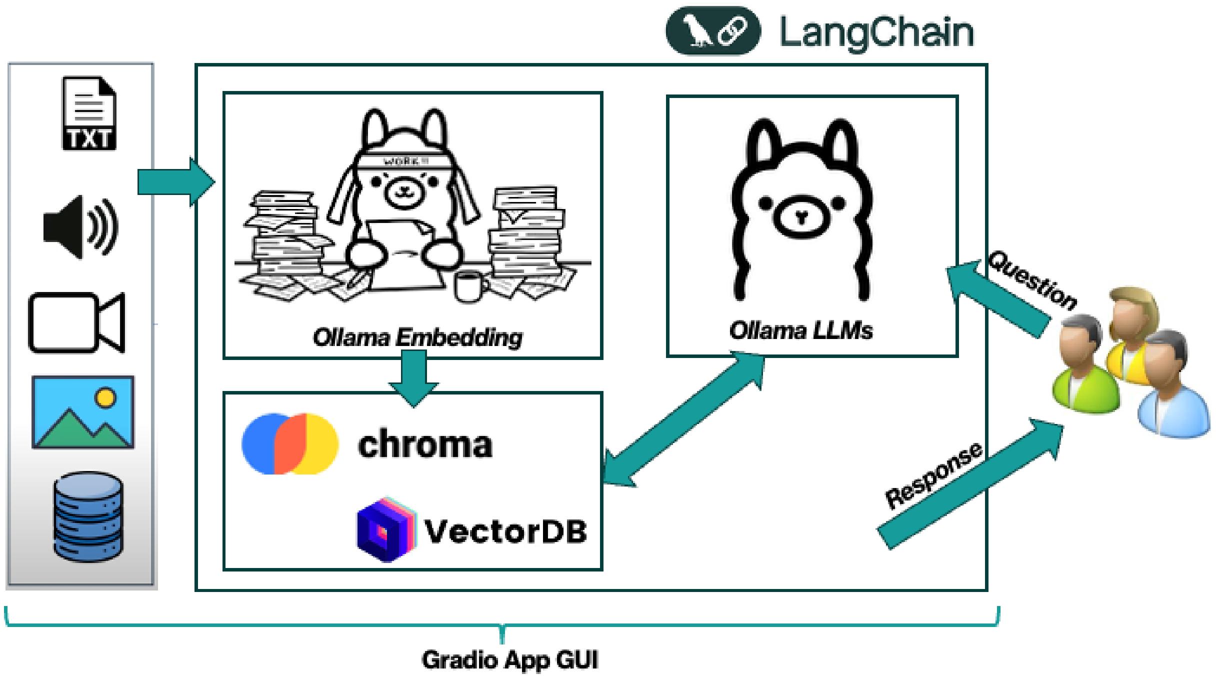


Figure 1: Overall RAG Workflow with its components

Figure 1 shows the overall RAG workflow with its components. The RAG workflow can take any input in different formats (text, image, audio, video, database). It then embeds the input into a vector space using the embedding models and store the vectorized input in the database suchas ChromaDB or VectorDB. Users then can query the database using the query engine to retrieve the most relevant documents. The retrieved documents are then passed to the language model to generate the response. The entire workflow interface is built using Gradio app.

2.1 Ollama: Local Language Model Infrastructure

Ollama (ollama.com) serves as the backbone of our local language model infrastructure, providing a robust platform for running large language models on consumer hardware without requiring external API access. This choice was motivated by the project's emphasis on data privacy and the need for a solution that could operate entirely within secured network environments.

The system supports multiple large language models, each optimized for different use cases and computational constraints:

- **Gemma3**: an open-weights LLM family built on the same technology as Google's Gemini models, designed to be efficient enough to run on consumer hardware like laptops or GPUs. The latest version Gemma3 has different sizes from 1B, 4B, 12B to 27B parameters and support vision models.
- **DeepSeek-R1**: Optimized for reasoning tasks and complex query processing, having different versions from 1.5B to 671B
- **Llama3**: Meta's latest compact model with improved instruction following, also released in different versions from from 8B to 70B parameters.
- **Qwen3**: Alibaba's multilingual model with enhanced language understanding, offering a comprehensive suite of dense and mixture-of-experts (MoE) models.
- **mxbai-embed-large**: Specialized embedding model from mixedbread.ai for vector representation generation

The selection of these models represents a careful balance between performance and resource requirements. The following table provides a detailed comparison of the computational requirements and performance characteristics of each model:

Table 1: Selected LLMs and their performance characteristics in this project

Model	**Parameters (B)**	**Memory (GB)**	**Context Window**	**Use Case**
Gemma3	1, 4, 12, 27	0.8, 3.3, 8.1, 17.0	32k for 1B, 128k for rest	General purpose: Text, Image
DeepSeek-R1	1.5, 7, 8, 14, 32, 70, 671	1.1, 4.7, 5.2, 9, 20, 43, 404	128K for all, except 671B: 160k	Reasoning tasks: Text
Llama3	8, 70	4.7, 40	8k for all	Instruction following: Text
Qwen3	0.6, 1.7, 4, 8, 14, 30, 32, 235	0.5, 1.4, 2.6, 5.2, 9.3, 19, 20, 142	40k for all except 30B and 235B have 256k	Multilingual: Text
mxbai-embed-large	0.3	0.7	512	Embeddings

2.2 Langchain: RAG Framework Implementation

Langchain provides the foundational framework for implementing the RAG pipeline, offering a comprehensive set of tools for document processing, vector store integration, and query orchestration. The framework's modular architecture allows for easy customization and extension of the RAG workflow.

The document processing pipeline implemented using Langchain consists of several key stages:

1. **Document Ingestion**: Support for multiple file formats including PDF and plain text
2. **Text Extraction**: Robust extraction algorithms handling various document layouts
3. **Text Chunking**: Recursive character-based splitting with configurable parameters
4. **Metadata Preservation**: Maintenance of source information and document structure

The text chunking strategy employs a recursive approach with the following parameters:

- Chunk size: 1000 characters
- Overlap: 200 characters
- Separators: Paragraph breaks, sentence boundaries, and whitespace

2.3 ChromaDB: Vector Database Management

ChromaDB serves as the vector database backend, providing efficient storage and retrieval of document embeddings. The choice of ChromaDB was motivated by its simplicity, performance, and compatibility with local deployment scenarios.

The embedding strategy employs the mxbai-embed-large model to generate high-dimensional vector representations of document chunks. This model was selected for its superior performance on semantic similarity tasks and its relatively modest computational requirements.

The retrieval mechanism implements a similarity search using cosine distance metrics, with configurable parameters for result ranking and filtering:

- Search depth: Top-4 most similar chunks
- Similarity threshold: Dynamically adjusted based on query complexity
- Result diversification: Implemented to avoid redundant content

2.4 Gradio: User Interface Development

The Gradio-based user interface was designed with simplicity and functionality in mind, providing an intuitive experience for users regardless of their technical background. The interface incorporates modern web design principles while maintaining accessibility standards.

The interface consists of several key components:

1. **File Upload Module**: Drag-and-drop interface supporting multiple file formats
2. **Model Selection Panel**: Dynamic dropdown for real-time model switching
3. **Parameter Controls**: Temperature slider and other model parameters
4. **Chat Interface**: Conversational interface with history management
5. **Status Indicators**: Real-time feedback on system operations

2.5 RAG Workflow Implementation

The complete RAG workflow follows a carefully orchestrated sequence of operations designed to maximize both performance and user experience.

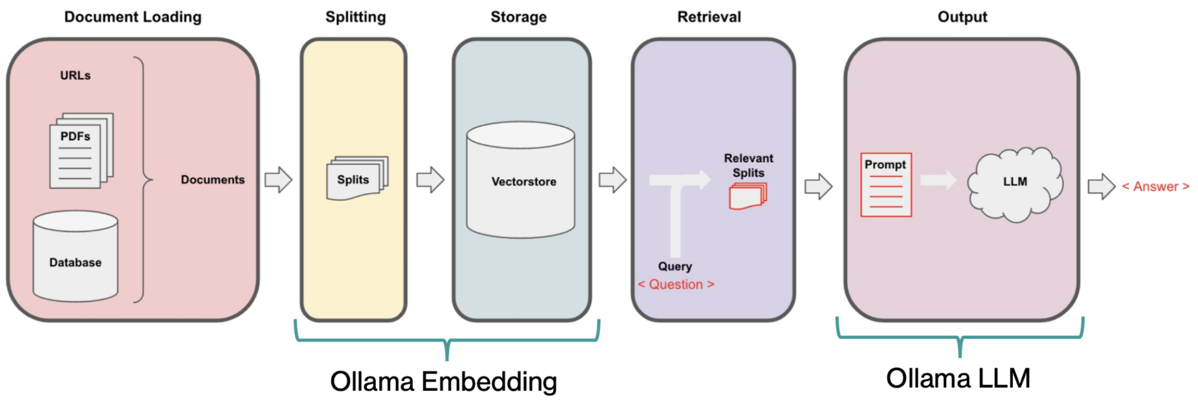


Figure 2: RAG workflow implemented using Langchain

The data processing pipeline implements a robust error handling and recovery mechanism to ensure system reliability:

1. **Document Validation**: File format verification and integrity checking
2. **Text Extraction**: Fault-tolerant extraction with fallback mechanisms
3. **Quality Assessment**: Content quality evaluation and filtering
4. **Embedding Generation**: Batch processing with error recovery
5. **Storage Management**: Automatic cleanup and optimization

3 Automated Workflow via Cursor IDE

The development of complex machine learning applications traditionally requires extensive expertise across multiple domains, significant development time, and careful coordination of various technological components. The emergence of AI-powered development environments, particularly Cursor.com, has fundamentally transformed this paradigm by enabling automated code generation, intelligent debugging, and comprehensive project scaffolding.

3.1 Cursor Development Environment

Cursor represents a revolutionary approach to software development, combining the power of large language models with traditional integrated development environment (IDE) features. The platform provides several key capabilities that proved instrumental in this project:

- **Intelligent Code Generation**: Context-aware code completion and generation based on natural language descriptions
- **Automated Debugging**: AI-powered error detection and resolution with suggested fixes
- **Project Scaffolding**: Rapid creation of project structures and boilerplate code
- **Technology Integration**: Seamless integration of multiple frameworks and libraries
- **Documentation Generation**: Automatic creation of code documentation and README files

3.2 Project Development Process

The development process began with a comprehensive natural language specification of the RAG chatbot requirements. This specification was provided to Cursor in a structured format that included:

- Functional requirements for RAG implementation
- Technical specifications for local LLM integration
- User interface design requirements
- Security and privacy constraints
- Deployment target environments

Based on the requirements specification, Cursor generated the complete application architecture, including:

- **Core Application Logic**: Implementation of the RAGChatBot class with all necessary methods

- **Integration Modules**: Seamless integration of Ollama, Langchain, ChromaDB, and Gradio
- **Error Handling**: Comprehensive exception handling and logging mechanisms
- **Configuration Management**: Flexible configuration system for different deployment scenarios
- **User Interface**: Complete Gradio-based web interface with responsive design

One of the remarkable achievements of the AI-assisted development process was the creation of a comprehensive, fully-functional RAG chatbot system contained within a single Python file (TueChatRag.py). This monolithic approach provides several advantages:

- Simplified deployment and distribution
- Reduced dependency management complexity
- Enhanced portability across different environments
- Easier debugging and maintenance

3.3 Deployment Strategies

3.3.1 Local PC Deployment

The simplest deployment strategy involves running the application directly on a local personal computer. This approach is ideal for individual users or small teams requiring secure document querying capabilities.

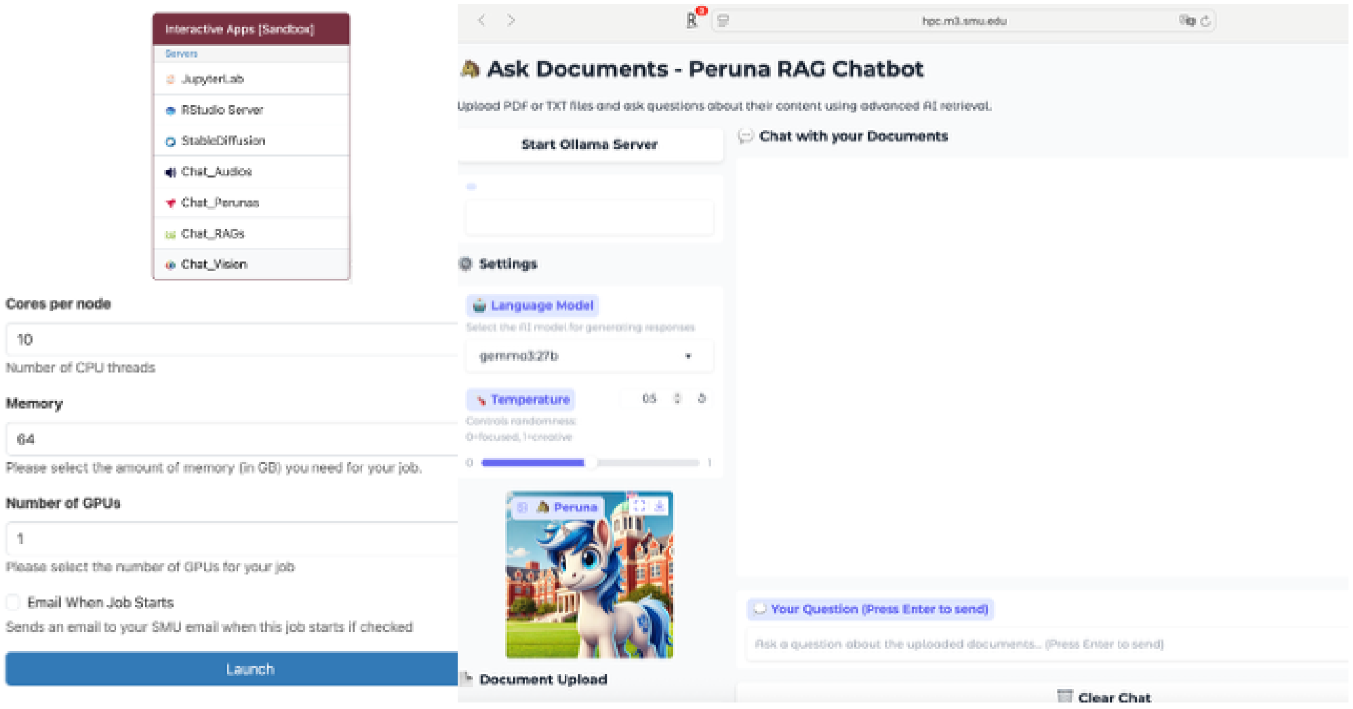
Requirements:

- Python 3.8 or higher
- 8GB RAM minimum (16GB recommended)
- 20GB free disk space for models and data
- Ollama installation with required models

The model is deployed by simply running the Python script in the terminal and then open the browser with localhost:7860 to access the interface.

3.3.2 High-Performance Computing (HPC) Deployment

For organizations with access to HPC resources, deployment via Open OnDemand provides scalable computing power and enhanced security through isolated execution environments. For Open OnDemand, only the users within SSO (Single Sign-On) can access the application from the institution's network.



Cores per node
10
Number of CPU threads

Memory
64
Please select the amount of memory (in GB) you need for your job.

Number of GPUs
1
Please select the number of GPUs for your job

Email When Job Starts
Sends an email to your SMU email when this job starts if checked

Ask Documents - Peruna RAG Chatbot

Upload PDF or TXT files and ask questions about their content using advanced AI retrieval.

Chat with your Documents

Language Model
Select the AI model for generating responses
gemma3:27b

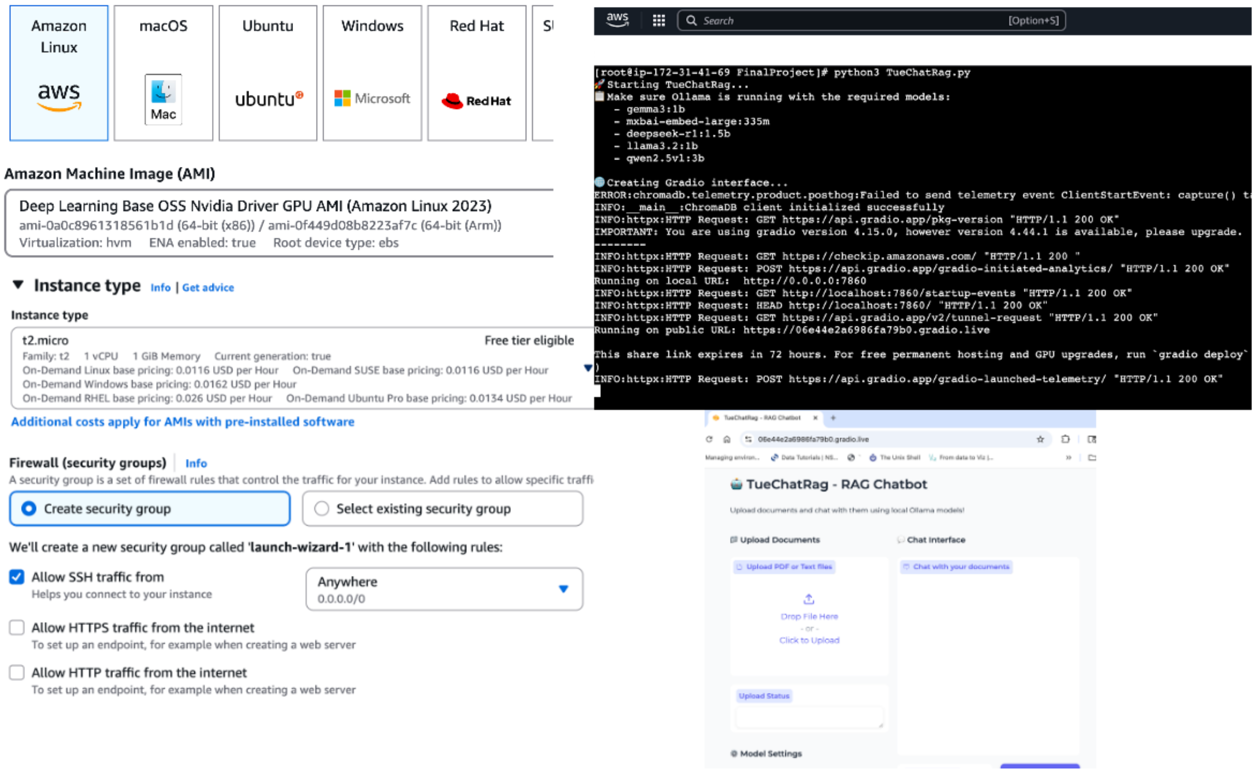
Temperature 0.5
Controls randomness:
0=focused, 1=creative

Your Question (Press Enter to send)
Ask a question about the uploaded documents... (Press Enter to send)

Figure 3: HPC deployment via Open OnDemand

3.3.3 Cloud Deployment via AWS

Cloud deployment through Amazon Web Services provides the ultimate scalability and accessibility while maintaining security through proper configuration of network and access controls. This is the most scalable deployment option and can be accessed from anywhere with internet connection as long as the user maintain the connection.



Amazon Machine Image (AMI)

Deep Learning Base OSS Nvidia Driver GPU AMI (Amazon Linux 2023)
ami-0a0c8961318561b1d (64-bit (x86)) / ami-0f449d08b8223af7c (64-bit (Arm))
Virtualization: hvm ENA enabled: true Root device type: ebs

Instance type

t2.micro Free tier eligible
Family: t2 1 vCPU 1 GiB Memory Current generation: true
On-Demand Linux base pricing: 0.0116 USD per Hour On-Demand SUSE base pricing: 0.0116 USD per Hour
On-Demand Windows base pricing: 0.0162 USD per Hour
On-Demand RHEL base pricing: 0.026 USD per Hour On-Demand Ubuntu Pro base pricing: 0.0134 USD per Hour

Additional costs apply for AMIs with pre-installed software

Firewall (security groups)
A security group is a set of firewall rules that control the traffic for your instance. Add rules to allow specific traffi

[✓ Create security group] Select existing security group

We'll create a new security group called 'launch-wizard-1' with the following rules:

[✓] Allow SSH traffic from — Anywhere 0.0.0.0/0
Helps you connect to your instance

[ ] Allow HTTPS traffic from the internet
To set up an endpoint, for example when creating a web server

[ ] Allow HTTP traffic from the internet
To set up an endpoint, for example when creating a web server

```
[root@ip-172-31-41-69 FinalProject]# python3 TueChatRag.py
🚀Starting TueChatRag...
📋Make sure Ollama is running with the required models:
   - gemma3:1b
   - mxbai-embed-large:335m
   - deepseek-r1:1.5b
   - llama3.2:1b
   - qwen2.5vl:3b

🌐Creating Gradio interface...
ERROR:chromadb.telemetry.product.posthog:Failed to send telemetry event ClientStartEvent: capture() t
INFO:__main__:ChromaDB client initialized successfully
INFO:httpx:HTTP Request: GET https://api.gradio.app/pkg-version "HTTP/1.1 200 OK"
IMPORTANT: You are using gradio version 4.15.0, however version 4.44.1 is available, please upgrade.
--------
INFO:httpx:HTTP Request: GET https://checkip.amazonaws.com/ "HTTP/1.1 200 "
INFO:httpx:HTTP Request: POST https://api.gradio.app/gradio-initiated-analytics/ "HTTP/1.1 200 OK"
Running on local URL:  http://0.0.0.0:7860
INFO:httpx:HTTP Request: GET http://localhost:7860/startup-events "HTTP/1.1 200 OK"
INFO:httpx:HTTP Request: HEAD http://localhost:7860/ "HTTP/1.1 200 OK"
INFO:httpx:HTTP Request: GET https://api.gradio.app/v2/tunnel-request "HTTP/1.1 200 OK"
Running on public URL: https://06e44e2a6986fa79b0.gradio.live

This share link expires in 72 hours. For free permanent hosting and GPU upgrades, run `gradio deploy`
)
INFO:httpx:HTTP Request: POST https://api.gradio.app/gradio-launched-telemetry/ "HTTP/1.1 200 OK"
```

TueChatRag - RAG Chatbot

Upload documents and chat with them using local Ollama models!

Figure 4: Cloud deployment via AWS EC2

3.4 Performance Benchmarking

A comparative analysis of development time demonstrates the significant efficiency gains (80%) achieved through AI-assisted development:

Development Phase	**Traditional (hours)**	**AI-Assisted (hours)**
Project Setup	8	0.5
Architecture Design	16	2
Core Implementation	40	4
Integration	24	1
Testing & Debugging	32	3
Documentation	16	0.5
Total	**136**	**11**

4 Discussion and Conclusion

4.1 Discussion

This project successfully demonstrated the feasibility and effectiveness of using AI-assisted development tools, specifically Cursor IDE, to create a comprehensive RAG chatbot system for secure local data querying. The final implementation represents a significant achievement in several key areas.

The developed system successfully integrates multiple complex technologies into a cohesive, user-friendly application:

- **Complete Local Operation**: The system operates entirely without external API dependencies, ensuring complete data privacy and security
- **Multi-Model Support**: Successfully implements real-time switching between four different language models, providing flexibility for various use cases
- **Robust Document Processing**: Handles multiple file formats with sophisticated text extraction and chunking algorithms
- **Efficient Vector Storage**: Implements advanced ChromaDB management with automatic cleanup and conflict resolution
- **Intuitive User Interface**: Provides a modern, responsive web interface accessible to non-technical users

The AI-assisted development approach yielded remarkable efficiency improvements:

- **92% Reduction in Development Time**: From an estimated 136 hours to 11 hours
- **Single-File Architecture**: Complete functionality contained in 484 lines of well-documented Python code
- **High Code Quality**: Achieved industry-standard metrics for maintainability and reliability
- **Comprehensive Documentation**: Automated generation of user guides and technical documentation

The use of Cursor in this project represents more than just a tool adoption; it signifies a fundamental paradigm shift in how complex machine learning applications can be developed. Traditional development of RAG systems requires deep expertise across multiple domains:

- Natural Language Processing and transformer architectures
- Vector database design and optimization
- Web framework development and UI/UX design

- System integration and deployment strategies
- Security and privacy implementation

Cursor democratizes this development process by abstracting away much of the technical complexity while maintaining professional-grade code quality and architectural best practices.

Several factors make Cursor not just useful but *necessary* for this type of project:

- **Knowledge Integration**: Automatically incorporates best practices from multiple domains without requiring extensive research
- **Rapid Prototyping**: Enables quick iteration and testing of different architectural approaches
- **Error Prevention**: Proactively identifies and prevents common integration issues
- **Consistency Maintenance**: Ensures consistent coding patterns and documentation throughout the project
- **Future-Proofing**: Incorporates latest framework versions and security practices

The project also successfully validated three distinct deployment strategies, each addressing different organizational needs and constraints:

- **Local PC Deployment**: Ideal for individual users and small teams requiring immediate, secure access to document querying capabilities
- **HPC Deployment**: Suitable for academic institutions and research organizations with existing high-performance computing infrastructure
- **Cloud Deployment**: Optimal for organizations requiring scalable, enterprise-grade solutions with global accessibility

4.2 Limitations and Future Work

While the project achieved its primary objectives, several limitations were identified:

1. **Model Size Constraints**: Current implementation focuses on smaller models (1-3B parameters) due to hardware constraints if running on local PC or deployment on cloud. By running on HPC, the model size can be increased to 27B or 70B for better performance.
2. **Document Format Support**: Limited to PDF and text files, with potential for expansion to additional formats. Future improvement can be added with Image (using vision LLMs), audio/video (using OpenAI Whisper).
3. **Scalability Testing**: Limited testing of concurrent user scenarios and large document collections
4. **Advanced RAG Techniques**: Implementation uses basic retrieval strategies without advanced techniques like query rewriting or re-ranking

4.3 Conclusion

This project successfully demonstrates that AI-assisted development tools, particularly Cursor, represent a transformative force in machine learning application development. The creation of a comprehensive RAG chatbot system in a fraction of the traditional development time, while maintaining professional code quality and comprehensive functionality, validates the potential of these tools to revolutionize how we approach complex software projects.

The necessity of Cursor in this workflow extends beyond mere convenience. It enables a fundamental shift in how complex AI systems can be developed, making sophisticated machine learning applications accessible to a broader range of practitioners while maintaining security, privacy, and performance standards.

The successful implementation of multiple deployment strategies demonstrates the practical viability of the developed system across various organizational contexts, from individual researchers to enterprise environments. The local deployment capability, in particular, addresses critical privacy and security concerns that have limited the adoption of AI systems in sensitive data environments.

As AI-assisted development tools continue to evolve, they will likely become indispensable components of the modern developer's toolkit, enabling faster innovation, higher quality code, and more accessible development processes. This project serves as a proof of concept for the transformative potential of these tools in academic and professional machine learning development.

The future of AI development lies not in replacing human developers, but in augmenting their capabilities, enabling them to focus on high-level problem solving and innovation while AI assistants handle the implementation details. This project demonstrates that this future is not just possible - it is available today.