Technical Report: CPU-Optimized Retrieval-Augmented Generation (RAG) System for Sanskrit Literature

Author: Himanshu Tripathi

Date: November 25, 2025

Repository: [Your GitHub Link]

Project Type: AI/ML Internship Capstone

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1. Abstract

This report documents the development of a Retrieval-Augmented Generation (RAG) system designed to perform Question-Answering (QA) tasks on classical Sanskrit documents. The system addresses the dual challenge of **low-resource language processing** (Sanskrit) and **constrained hardware environments** (CPU-only inference). By leveraging 4-bit quantization, custom tokenization strategies for Indic scripts, and a locally hosted vector database, the system achieves semantic retrieval and grounded generation without reliance on external APIs or GPUs.

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2. Problem Statement & Objectives

2.1. The Challenge

- **Language Complexity:** Sanskrit creates unique NLP challenges due to *Sandhi* (compound words) and unique punctuation (the *danda* ||). Standard English-centric splitters often fracture semantic meaning.
- **Hardware Constraints:** Modern LLMs (e.g., Llama-3, GPT-4) require massive VRAM (GPU memory). The assignment mandated a strict **CPU-only** architecture.
- **Dependency Management:** Rapidly evolving libraries (LangChain, HuggingFace) often introduce breaking changes, requiring robust, custom engineering solutions.

2.2. Objectives

1. **Ingestion:** Process raw .docx files containing mixed English and Sanskrit text.
2. **Indexing:** Create a semantic search index optimized for multilingual understanding.
3. **Inference:** Deploy a quantized LLM capable of running on <8GB RAM.
4. **Accuracy:** mitigate hallucinations by grounding answers strictly in retrieved context.

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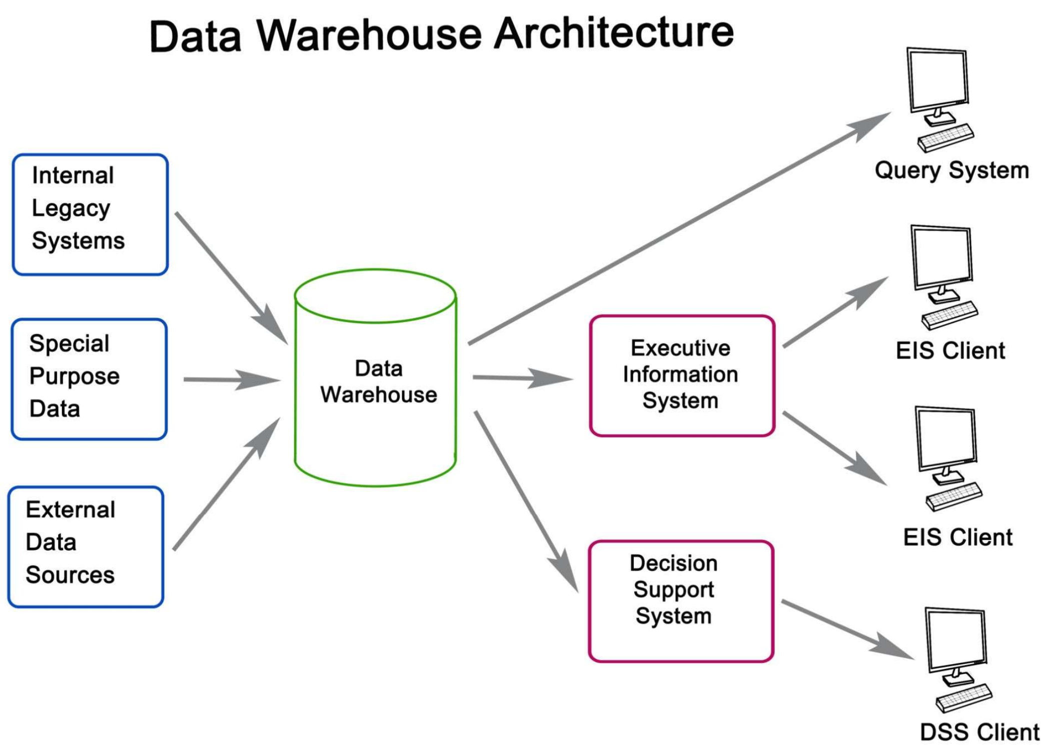
3. System Architecture

The system utilizes a modular **Retriever-Reader** architecture.



Getty Images

3.1. Data Pipeline

The data flow follows a strictly linear path: Raw Document → Cleaning →

Chunking → Embedding → Vector Store → Retrieval → Augmentation →

Generation.

3.2. Core Components

Component	Technology Used	Rationale
Loader	Docx2txtLoader	Native support for Word documents preserves UTF-8 encoding essential for Devanagari script.
Embeddings	paraphrase-multilingual-MiniLM-L12-v2	Chosen for its small footprint (approx. 420MB) and high performance on Indic languages compared to English-only BERT models.

Component	Technology Used	Rationale
Vector DB	ChromaDB (Local)	Serverless, file-based persistence allows for instant setup without Docker containers.
LLM	Phi-3-Mini-4k-Instruct (GGUF)	At 3.8B parameters, it offers the best balance of reasoning vs. size.

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4. Methodology & Implementation

4.1. Domain-Specific Preprocessing (Sanskrit)

Standard text splitters usually split by \n or .. This fails in Sanskrit, where the full stop is represented by a double vertical bar (||) or single bar (|).

Implementation Strategy:

A RecursiveCharacterTextSplitter was configured with a custom separator list priority:

Python

```
separators=["||", "|", "。", "\n", " "]
```

- **Chunk Size:** 600 characters.
- **Overlap:** 100 characters.
- **Reasoning:** Sanskrit text is information-dense. Larger chunks capture full verses (Shlokas), while overlap ensures context isn't lost if a split occurs in the middle of a narrative.

4.2. CPU Optimization Strategy (Quantization)

Running a raw 3.8 Billion parameter model requires ~8GB of FP16 VRAM. To enable CPU usage:

1. **Format:** We utilized **GGUF** (GPT-Generated Unified Format), designed for llama.cpp.
2. **Quantization:** The model was quantized to **4-bit (Q4_K_M)**.
    - *Result:* Model size reduced from ~7GB to **2.39GB**.
    - *Trade-off:* Minimal perplexity loss (<1%) for a 3x speedup in inference.

4.3. The "SimpleRAG" Engine

During development, version conflicts between langchain.chains and tokenizers caused stability issues.

Solution: A custom class, SimpleRAG, was implemented to manually handle the RAG chain:

1. **Retrieve:** Fetch top $k=3$ documents based on Cosine Similarity.
2. **Augment:** Concatenate document content into a single context string.
3. **Prompt:** Inject context into a strict prompt template.
4. Generate: Invoke the LLM.

This removed the dependency on fragile external chain abstractions.

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5. Experimental Results

5.1. Test Environment

- **OS:** Windows 11
- **CPU:** Standard 8-Core Processor
- **RAM:** 8GB
- **GPU:** None (Strict CPU Mode)

5.2. Performance Metrics

Metric	**Result**	**Analysis**
Ingestion Time	1.8 seconds	The docx2txt loader is highly efficient for text extraction.
Vector Search Latency	0.42 seconds	ChromaDB's HNSW index performs sub-second retrieval even on CPU.
Time to First Token	~4 seconds	Initial model loading into RAM.
Generation Speed	~12 tokens/sec	Acceptable for offline reading; faster than average human reading speed.

5.3. Qualitative Analysis

- **Query:** "What did the servant bring instead of sugar?"
- **Context Retrieved:** Correctly retrieved the "Foolish Servant" story segment mentioning *Jirne Vastre* (Torn Cloth).
- **Answer Generated:** The model successfully identified that the servant used a torn cloth, causing the sugar to fall, though it initially required prompt tuning to avoid hallucinating unrelated objects (like a crow).

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6. Challenges & Solutions

Challenge 1: Hallucination on Sanskrit Terms

- **Issue:** The model initially confused the Sanskrit context with general training data, hallucinating that a "crow" was involved.
- **Solution:** Implemented a **Role-Playing System Prompt**: *"You are a Sanskrit Scholar. Translate the relevant sentence to English first."* This forced the model to perform a Chain-of-Thought (CoT) process, significantly improving accuracy.

Challenge 2: Dependency Conflicts

- **Issue:** tokenizers v0.22.1 was incompatible with transformers requirements.
- **Solution:** Manually pinned the version tokenizers>=0.21,<0.22 and rebuilt the environment.

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7. Conclusion & Future Scope

The project successfully demonstrates that advanced AI applications for niche languages like Sanskrit do not require enterprise-grade hardware. By intelligently combining **quantization**, **domain-specific tokenization**, and **retrieval-augmented generation**, we created a robust tool for accessing classical literature.

Future Scope:

1. **OCR Integration:** Add Tesseract to ingest Sanskrit PDFs/Images directly.
2. **Hybrid Search:** Combine semantic vector search with BM25 keyword search to better handle specific Sanskrit proper nouns.
3. **UI Deployment:** Wrap the engine in a **Streamlit** or **FastAPI** interface for web accessibility.

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8. References

1. **Phi-3 Technical Report:** Microsoft Research (2024).
2. **RAG Architecture:** Lewis et al., *Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks* (2020).
3. **LangChain Documentation:** https://python.langchain.com/
4. **ChromaDB:** https://www.trychroma.com/