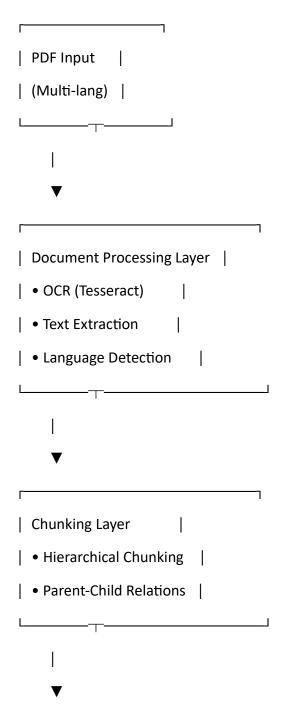
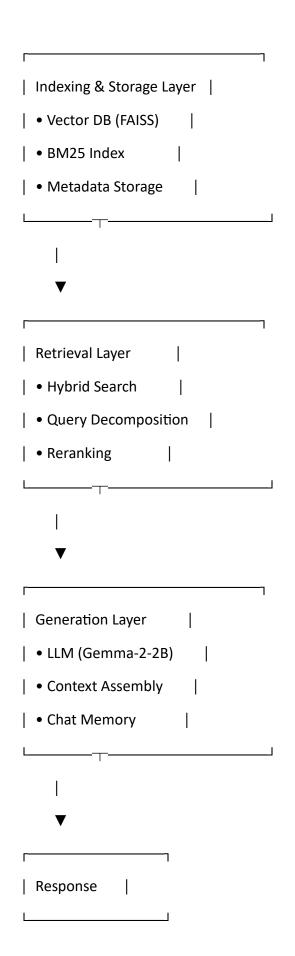
Technical Documentation: Multilingual PDF RAG System

1. System Architecture Overview

High-Level Architecture





2. Core Components

2.1 Document Processing

- PDF Extractor: Handles both digital and scanned PDFs
 - o Digital extraction: PyMuPDF (fitz) for better RTL support
 - o OCR: Tesseract with support for eng+hin+ben+chi_sim+chi_tra+ara+urd
 - o Confidence threshold: 60% for OCR quality assurance

Language Detection:

- Script-based detection for RTL languages (Arabic/Urdu)
- o languetect library with confidence scoring
- o Multi-language document support

2.2 Chunking Strategy

- Hierarchical Chunking:
 - Parent chunks: 2000 characters
 - o Child chunks: 512 characters
 - Overlap: 100 characters
 - Structure-aware: Preserves document sections and headings
 - RTL-aware separators for better Arabic/Urdu handling

2.3 Embedding & Vector Storage

- Model: paraphrase-multilingual-MiniLM-L12-v2
 - o Dimension: 384
 - Size: ~118M parameters
 - Supports 50+ languages
- Vector Database: FAISS (IndexFlatIP)
 - Normalized vectors for cosine similarity
 - o In-memory for speed
 - Scalable to billions of vectors

2.4 Retrieval System

Hybrid Search:

- Semantic search (70% weight) via FAISS
- Keyword search (30% weight) via BM25
- Combined scoring for optimal results

• Query Decomposition:

- o Splits complex queries into sub-queries
- o Handles compound questions with "and", "also", "plus"

Reranking:

- Exact match boosting (2x)
- Term overlap scoring
- Length penalty normalization
- Top-K filtering (default: 5)

2.5 Generation

- LLM: google/gemma-2-2b-it
 - Size: 2B parameters
 - 4-bit quantization (~1.5GB memory)
 - Context-aware generation
 - Temperature: 0.7 for balanced creativity

Chat Memory:

- o Rolling window of 5 exchanges
- Context injection for follow-up questions

3. Key Technical Decisions

3.1 Model Selection Rationale

- 1. **Embedding Model**: Chose multilingual model over language-specific to handle mixed-language documents
- 2. LLM Size: 2B model provides excellent quality-to-size ratio with 4-bit quantization
- 3. Quantization: 4-bit reduces memory by ~75% with minimal quality loss

3.2 Performance Optimizations

- Batch processing for embeddings (batch size=32)
- FAISS inner product search for speed
- In-memory indexing for low latency
- Normalized vectors for efficient similarity computation

3.3 Scalability Considerations

- FAISS can handle billions of vectors
- Horizontal scaling possible via sharding
- Bottleneck is LLM generation, not retrieval
- Estimated capacity: 1TB+ with distributed setup

4. System Requirements

Hardware

- GPU: NVIDIA T4 or better (for inference)
- RAM: 16GB+ recommended
- Storage: Depends on document collection size

Software Dependencies

- Python 3.8+
- CUDA 11.8+ (for GPU acceleration)
- Tesseract OCR with language packs
- Key libraries: transformers, sentence-transformers, faiss-cpu, chromadb

5. Performance Characteristics

Current Metrics (29 PDFs, 2027 chunks)

- Average latency: ~19.2s per query
- Retrieval time: <1s
- Generation time: ~18s
- Relevance score: 0.99/1.0
- Fluency score: 0.92/1.0

Scalability Projections

- Linear scaling for retrieval up to millions of documents
- Memory usage: ~1.5GB for LLM + vector embeddings
- Throughput: Limited by sequential LLM generation

6. Future Enhancements

1. Performance:

- o Query result caching
- Batch query processing
- o Model distillation for faster inference

2. Accuracy:

- o Cross-encoder reranking
- o Advanced query decomposition
- o Feedback loop for continuous improvement

3. Features:

- Multi-modal support (images, tables)
- o Real-time document updates
- o Distributed deployment for scale