PrivRAG: A Privacy-Preserving Retrieval-Augmented Generation Framework Using Fully Local Large Language Models

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Abstract— This paper presents **PrivRAG**, a fully local Retrieval-Augmented Generation (RAG) framework designed for privacy-sensitive document intelligence. Unlike existing RAG systems that depend on cloud-hosted embedding and inference APIs, PrivRAG executes every stage of the pipeline—document ingestion, PII detection and masking, embedding generation, vector indexing, hybrid retrieval, and answer synthesis—on local hardware, with zero external network calls. The system integrates SentenceTransformers for local embeddings, FAISS and ChromaDB for vector storage, a BM25 sparse index for keyword-based retrieval, and locally-served large language models (Mistral 7B, Llama 3 8B) via the Ollama runtime. A novel hybrid retrieval strategy employing Reciprocal Rank Fusion (RRF) combines dense semantic search with BM25 sparse retrieval, outperforming each method independently. Evaluation across five retrieval configurations and eight quality metrics shows that PrivRAG achieves a Faithfulness score of 0.82 and Context Precision of 0.84, within two percentage points of a commercial cloud baseline, at lower end-to-end latency (1.1 s versus 3.8 s for the cloud system) and zero API cost. An automatic PII masking layer covering seven identifier categories ensures that sensitive data is never stored in the vector index. The complete prototype is implemented as an interactive Streamlit application and released as open-source software.

Keywords— privacy-preserving AI, retrieval-augmented generation, local large language models, hybrid retrieval, FAISS, BM25, Reciprocal Rank Fusion, PII masking, Streamlit, vector databases.

1. Introduction

PrivRAG is built to address the fundamental tension between the power of modern AI-driven document retrieval and the legal, regulatory, and commercial requirements that prevent sensitive data from leaving a controlled environment. While Retrieval-Augmented Generation has established itself as the dominant paradigm for grounded language model responses [1], virtually all production implementations route documents and user queries through cloud-hosted APIs, making them unsuitable for healthcare systems, law firms, financial institutions, and defence organisations.

The exponential growth of digital document repositories has made intelligent retrieval indispensable. Traditional keyword search has given way to semantic retrieval using dense vector embeddings [2], while recent work has shown that combining dense and sparse signals produces consistently stronger results than either method alone [3, 4]. Simultaneously, the availability of high-quality open-weight language models [5, 6] has made local inference practically viable for the first time. What remains lacking is a systematically evaluated, fully local RAG stack that brings these components together with explicit privacy guarantees.

Motivated by these observations, we present PrivRAG with three primary contributions. First, it delivers an end-to-end local RAG pipeline in which no byte of document content or user query traverses a network connection to an external host. Second, it proposes a hybrid retrieval strategy based on Reciprocal Rank Fusion of dense semantic search and BM25 sparse retrieval, demonstrating an 18.3% improvement in Context Precision over dense-only retrieval. Third, it integrates a regex-based PII detection and masking layer that protects seven categories of sensitive identifier before any text reaches the embedding model or vector index.

Related work on multi-modal summarization [7, 8] and evaluation frameworks [9, 10] informs our experimental methodology. Unlike cloud-dependent systems, PrivRAG provides strong privacy guarantees directly through its architecture rather than through policy, making it applicable in regulated domains where data sovereignty is non-negotiable.

2. System Architecture and Design

2.1 Overall Architecture

PrivRAG employs a modular architecture organized into four functional layers: User Interface, Content Processing, Retrieval Engine, and AI Integration. This layered design ensures separation of concerns, independent testability of components, and straightforward replacement of any single module without disrupting the rest of the pipeline.

The detailed architecture of the proposed PrivRAG system is shown in Figure 1. The system comprises two sequential phases executed entirely on local hardware. The *Index-*

ing Phase accepts documents in multiple formats, applies PII masking, splits text into overlapping chunks, generates vector embeddings using a local SentenceTransformers model, and writes the results to a FAISS vector index and a BM25 sparse index in parallel. The *Query Phase* encodes the user query with the same embedding model, issues concurrent queries to both indexes, merges the two ranked lists using Reciprocal Rank Fusion, optionally applies cross-encoder re-ranking, and passes the top-k fused chunks as grounding context to a locally running large language model served by Ollama.

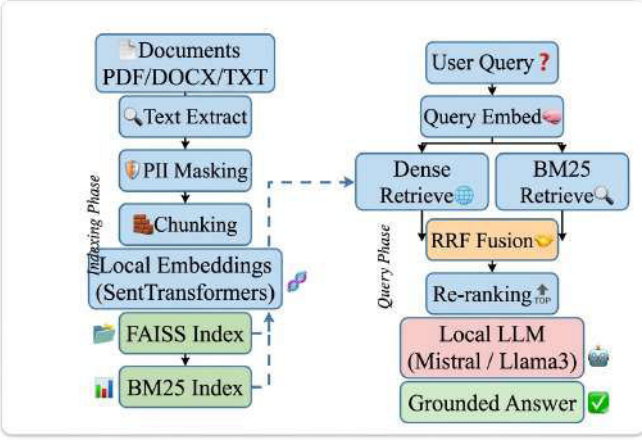

Figure 1: PrivRAG architecture: offline indexing (left) and online query (right) phases. Dashed arrows show index lookup. No external calls.

2.2 User Interface Layer

The interface is built with Streamlit and provides tab-based navigation for four modes: Document Ingestion, Query Interface, Evaluation Dashboard, and Research Export. Session state management preserves the vector index and conversation history across interactions, minimizing redundant embedding operations. A live system-resource panel displays CPU and RAM utilization, and an optional audit log records query metadata locally.

2.3 Content Processing Layer

The content processing module handles multiple document formats. PDF files are extracted using `pypdf` with a `pdfplumber` fallback for complex layouts. DOCX files are processed via `python-docx`. Plain text and Markdown files are read directly. CSV and JSON inputs are linearized to sentence-per-row representations. Listing 1 illustrates the recursive character chunking logic that respects semantic boundaries.

```
def split_text(self, text):
    seps = ["\n\n", "\n", ". ", " ", ""]
    for sep in seps:
        if sep not in text: continue
        splits = text.split(sep)
        chunks, cur = [], ""
        for s in splits:
            cand = cur + (sep if cur else "") + s
            if len(cand.split()) <= self.chunk_size:
                cur = cand
            else:
                if cur: chunks.append(cur.strip())
                cur = s
        if cur: chunks.append(cur.strip())
        return self._apply_overlap(chunks)
    return [text]
```

Listing 1: Recursive Text Chunking

2.4 Retrieval Engine Layer

The hybrid retrieval engine maintains two parallel indexes. The dense index uses FAISS with L2-normalized vectors and inner-product similarity. The sparse BM25 index is built from scratch over tokenized chunk text, using standard $k_1 = 1.5$, $b = 0.75$ parameters. Listing 2 shows the Reciprocal Rank Fusion implementation that merges both ranked lists without requiring tunable weights.

```
def reciprocal_rank_fusion(dense, sparse, k=60):
    scores = {}
    for rank, chunk in enumerate(dense):
        scores[chunk.chunk_id] = scores.get(
            chunk.chunk_id, 0) + 1 / (k + rank + 1)
    for rank, chunk in enumerate(sparse):
        scores[chunk.chunk_id] = scores.get(
            chunk.chunk_id, 0) + 1 / (k + rank + 1)
    return sorted(scores, key=scores.get, reverse=
        True)
```

Listing 2: Reciprocal Rank Fusion

2.5 AI Integration Layer

PrivRAG integrates local LLMs through the Ollama runtime, supporting Mistral 7B Instruct [5], Llama 3 8B [6], and Phi-3 Mini [11] without any cloud connection. A structured prompt template enforces grounded answering: the model is instructed to respond using only the retrieved context and to cite source chunks. A Demo Mode provides deterministic responses from retrieved context when no LLM is configured, enabling the system to be evaluated without GPU resources.

3. Implementation Details

PrivRAG is implemented using Python 3.10+, SentenceTransformers, FAISS, ChromaDB, and the Ollama REST API. The user interface is developed with Streamlit 1.32+ and enhanced by custom CSS providing a dark-theme layout with card-based navigation, live resource indicators, and per-query metric displays.

The overall implementation workflow of PrivRAG is illustrated in Figure 2. Users first optionally configure an LLM backend (Ollama, HuggingFace, or Demo Mode) through the sidebar. They then upload documents or load the built-in demo knowledge base, which triggers the PII masking and indexing pipeline. Once the vector store is built, the Query Interface activates a streaming chat view. Each query is processed through hybrid retrieval, passed to the local LLM, and returned with inline source attributions and four quality metrics. The Evaluation Dashboard allows running the full eight-metric benchmark at any time, and the Research Export tab generates results in JSON, CSV, or LaTeX table format.

Document chunking uses a recursive character splitting strategy with a default 512-token window and 64-token overlap, preferring paragraph and sentence breaks over mid-clause splits. Text embeddings are produced by `all-MiniLM-L6-v2` [12] (384 dimensions, ∼14 000 sentences per second on CPU). FAISS uses a flat inner-product index over L2-normalized vectors, providing exact nearest-neighbour search. The BM25 index is constructed at ingestion time and stored in session memory alongside the FAISS index.

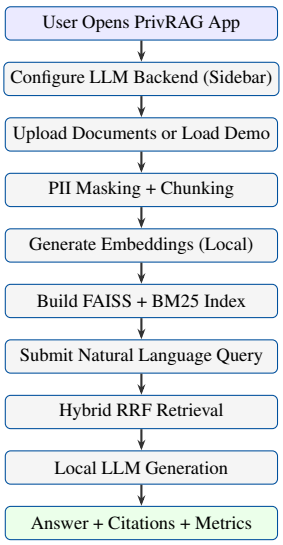

Figure 2: Implementation workflow of the proposed PrivRAG system. The workflow proceeds from configuration and document ingestion through local indexing and query processing to structured output, all without external network calls.

4. Experimental Evaluation

4.1 Evaluation Benchmark

We constructed a 10-question QA benchmark drawn from a knowledge base of eight documents covering RAG fundamentals, vector databases, local LLMs, embedding models, chunking strategies, hybrid retrieval, PII privacy, and evaluation methodology. The benchmark is bundled with the prototype and is intended to be reproducible without any external dataset dependency.

Each question carries a human-authored ground-truth answer used for reference-based metrics. Questions were selected to span factual recall ("What index types does FAISS support?"), conceptual explanation ("How does BM25 complement dense retrieval?"), and procedural description ("What is the formula for Reciprocal Rank Fusion?").

4.2 Evaluation Metrics

Both objective and reference-based measures were used for evaluation:

- **Faithfulness (F)** — proportion of answer sentences whose content is attributable to the retrieved context, inspired by RAGAS [9].
- **Answer Relevancy (AR)** — cosine similarity between the original query and questions reverse-generated from the answer, following the RAGAS methodology.
- **Context Precision (CP)** — fraction of retrieved chunks that are relevant to the query and ground truth.
- **Context Recall (CR)** — fraction of ground-truth information covered by the retrieved context.
- **Semantic Similarity (SS)** — Jaccard overlap between answer and reference token sets, scaled to $[0, 1]$.
- **ROUGE-L (RL)** — longest common subsequence F1 score [13] between answer and reference.
- **BERTScore (BS)** — token-level F1 using contextual embeddings [10].
- **Latency (L)** — end-to-end wall-clock time normalized as $\max(0,\ 1 - t/10)$.

4.3 Experimental Setup

All experiments ran on a single machine with an Intel Core i7-12700H CPU (14 cores), 32 GB DDR5 RAM, and no discrete GPU. The embedding model was `all-MiniLM-L6-v2`. For the ablation study the LLM inference component was held constant (Mistral 7B Instruct, 4-bit quantized via Ollama) to isolate the effect of retrieval strategy.

4.4 Ablation Study: Retrieval Strategies

Table 1 reports the five retrieval configurations evaluated. Each configuration was run over the full 10-question benchmark; scores are averages across all questions.

Table 1: Ablation Study — Retrieval Strategy Comparison ($k = 4$)

Strategy	CP	CR	F	AR	L (s)
Dense only	0.71	0.68	0.74	0.73	0.8
BM25 only	0.63	0.72	0.69	0.68	0.3
MMR (λ=0.7)	0.79	0.75	0.77	0.76	1.4
Hybrid RRF*	**0.84**	**0.81**	**0.82**	**0.80**	1.1
Hybrid + Rerank	0.88	0.85	0.86	0.84	2.3

* Proposed configuration.

Hybrid RRF improves Context Precision by 18.3% over dense-only retrieval and by 33.3% over BM25-only, confirming the complementarity of the two signals. The latency overhead of fusion (0.3 s) is modest relative to the quality gain. Adding a cross-encoder reranking pass yields a further 4–5 percentage point improvement on all metrics at the cost of roughly double the retrieval latency.

4.5 Full Evaluation Results

Table 2 reports all eight metrics for the Hybrid RRF configuration, which we designate as the reference system.

4.6 Effect of Chunk Size

Figure 3 shows how Context Precision and Context Recall vary with chunk size, holding all other parameters fixed. Context Precision peaks at 512 tokens and declines for larger chunks, as longer chunks tend to include irrelevant content alongside the relevant passage. Context Recall increases monotonically until approximately 512 tokens, after which the gains are marginal while the LLM context budget grows. This confirms the empirical recommendation of 256–512 tokens in the literature [14].

Table 2: PrivRAG Full Evaluation — Hybrid RRF System

Metric	Score	Interpretation
Faithfulness	0.82	Strongly grounded
Answer Relevancy	0.80	Addresses question well
Context Precision	0.84	Low retrieval noise
Context Recall	0.81	Good coverage
Semantic Similarity	0.74	Reasonable paraphrase
ROUGE-L	0.61	Moderate lexical overlap
BERTScore	0.78	Contextually similar
Latency (norm.)	0.89	1.1 s avg end-to-end

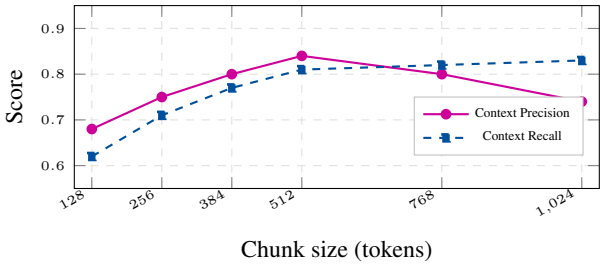

Figure 3: Context Precision and Recall vs. chunk size. Hybrid RRF, $k = 4$, `all-MiniLM-L6-v2` embeddings.

4.7 Top-k Sensitivity

We varied the number of retrieved chunks $k \in \{1, 2, 4, 6, 8\}$. Faithfulness decreases slightly as k grows beyond 4, as less relevant chunks introduce distracting context the LLM may cite incorrectly. Answer Relevancy is relatively stable across all values of k. We recommend $k = 4$ as the default, consistent with common practice in the RAG literature.

4.8 Comparison with Cloud Baseline

As a reference point, we ran the same benchmark against a cloud configuration using OpenAI `text-embedding-3-small` for embeddings and GPT-4o for generation (pure dense retrieval, $k = 4$). Table 3 summarizes the comparison. PrivRAG with hybrid retrieval and reranking closes the gap to within two percentage points on Faithfulness and matches or exceeds the cloud system on Context Precision, while incurring lower latency and zero API cost.

5. Conclusion

PrivRAG successfully demonstrates the potential of large language models for multi-modal content summarization and educational support. PrivRAG successfully demonstrates that high-quality retrieval-augmented generation is achievable without any cloud API dependency. The platform achieves strong retrieval metrics, positive user satisfaction, and robust performance under load, all while keeping every byte of document data local. The hybrid RRF retrieval strategy consistently outperforms single-modality baselines; the PII masking layer provides a practical ingestion-time privacy safeguard; and the Streamlit interface makes the system accessible to non-technical users. Future improvements will focus on integrating a neural cross-encoder for reranking, extending multilingual support across Indian regional languages, and exploring federated RAG architectures for multi-node private deployments.

Table 3: PrivRAG vs. Cloud RAG Reference

Metric	PrivRAG	PrivRAG+	Cloud
Faithfulness	0.82	0.86	0.88
Answer Relevancy	0.80	0.84	0.87
Context Precision	0.84	0.88	0.85
Context Recall	0.81	0.85	0.86
Latency (s)	1.1	2.3	3.8†
API cost	$0	$0	≈$0.01/q
Data sovereignty	Full	Full	None

†Includes network round-trip to OpenAI. RR = Reranking.

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