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Dense Meets Sparse: A Hybrid RAG Architecture for Context-Aware Language Generation

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Abstract: Large language models'(LLM) accuracy is enhanced through Retrieval-Augmented Generation (RAG) by leveraging external knowledge retrieval to generate context-dependent responses. A hybrid RAG system combining sparse and dense retrieval techniques improves document retrieval functionality and response generation speed. Document Chunking is achieved by breaking content into smaller, related chunks using specific chunk and overlap sizes, with partitioned segments embedded via the all-MiniLM model and stored in a pgvector database. Query embeddings follows similar process, enabling retrieval through OpenSearch for sparse keyword searches and dense vector searches for semantic matching, with collective scoring maximizing document relevance for generated response. The system selects appropriate document parts based on user queries and predefined prompts, which are then further processed by an LLM that bases its answers strictly on retrieved context, reducing hallucinations and maintaining factual accuracy. Thus proposed model takes care of two major flaws of existing systems which are suffering from hallucinations and non maintenance of factual information. Hybrid retrieval methods, effective chunking strategies, and prompt engineering significantly improve retrieval accuracy and response reliability. A Python interface using FastAPI structures the RAG system into a microservices architecture, where retrieval and response generation stages are integrated with a MERN-based chatbot interface operating as separate microservices. Real-time deployment, automation, and scalability are facilitated by AWS EC2 servers, Docker orchestration, and Jenkins-managed CI/CD pipelines, ensuring smooth and efficient system operation at scale.

Keywords: Retrieval-Augmented Generation (RAG), Hybrid RAG, Document Chunking, all-MiniLM Embeddings, pgvector, LLM Response Generation, OpenSearch, FastAPI Interface, CI/CD pipeline

1. INTRODUCTION

A. *Need for the Proposed Work*

The rapid advancement of accessible digital information has significantly increased the demand and necessity for intelligent systems that can not only access but also integrate knowledge in a contextual, coherent, and reliable manner to address a broad spectrum of NLP queries. Such systems are expected to ensure and capable enough to demonstrate competence, precision, and consistency by avoiding irrelevant or out-of-context responses. Large Language Models (LLMs) such as GPT-4 have shown remarkable capability in handling diverse NLP tasks with efficiency and fluency. However, similar to other advanced LLMs, GPT-4 also exhibits limitations, particularly the issue of hallucination—the tendency to generate fabricated or inaccurate information. This challenge becomes especially critical in domains requiring high sensitivity and factual correctness, such as healthcare, finance, and legal consulting [1], [2].

To mitigate this problem, Retrieval-Augmented Generation (RAG) models have been proposed in this paper. These models enhance the reliability of LLMs by leveraging external knowledge sources to ground the responses, thereby combining the strengths of retrieval-based approaches with generative capabilities [3]. By anchoring outputs to verified information repositories, RAG frameworks substantially reduce hallucination while improving contextual alignment. Nevertheless, recent research has highlighted persisting inefficiencies within hybrid retrieval systems [4]. Specifically, current RAG models often struggle to achieve an optimal balance among retrieval accuracy, computational cost, processing efficiency, and scalability. This limitation becomes particularly pronounced in applications demanding real-time or near real-time performance, where maintaining both accuracy and efficiency is highly needed.

B. *Existing Work and Identified Gaps*

Traditional sparse retrieval methods, such as BM25 and TF-IDF, have long been the foundation of information

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retrieval systems. These methods are efficient enough in keyword-based matching, effectively identifying documents that contain explicit or specific query terms. However, they are inherently limited in their capability to capture deeper semantic relationships, often failing when queries rely on contextual meaning, paraphrasing, or synonyms[5]. In contrast, dense retrieval approaches, which uses transformer-based embeddings to decode semantic similarity, demonstrate superior performance in capturing nuanced relationships between queries and documents. Yet, this improvement in semantic understanding comes at a significant cost-dense retrieval is computationally intensive, requiring substantial storage, memory, and inference power, which makes it less practical for large-scale or latency-sensitive applications [6].

To address these shortcomings, hybrid retrieval strategies have emerged as a middle ground, combining the strengths of sparse keyword-based retrieval with dense semantic retrieval. While promising, such approaches face persistent challenges in terms of ranking efficiency and system latency [7]. For instance, [8] highlights inefficiencies in passage selection strategies within hybrid pipelines, where the retrieval process can be slowed down by suboptimal filtering or ranking mechanisms. Similarly, [9] underscores the trade-offs between retrieval granularity and computational overhead, showing that finer-grained retrieval often improves accuracy but at the expense of increased processing time and resource consumption.

Another critical yet often overlooked restriction in both sparse and hybrid retrieval systems is the handling of document chunking. Many implementations neglect proper chunking techniques, which are essential for preserving contextual continuity when breaking large documents into smaller retrievable units [10]. This oversight can result in fragmented or contextually incomplete results, ultimately degrading system reliability. Domain-specific research, such as [11], further emphasizes the importance of context-preserving chunking, particularly in specialized areas like biomedical or legal information retrieval, where contextual precision is unavoidable and is surely needed.

C. *Proposed Solution and Objectives*

The proposed work offers a sparse-dense (OpenSearch/all-MiniLM embeddings) **Hybrid RAG model** with optimal precision-efficiency trade-off as explained in step by step way in the following points:

1. Document Processing Context-preserving overlapping chunking [10] supplemented by the caching of embeddings in a pgvector database to facilitate semantic search [6].

2. Hybrid Retrieval OpenSearch, employing sparse retrieval, enables keyword matching [5], while dense retrieval preserves semantic meaning [6] Combination of both retrieval provides optimal response for the query posed..

3. LLM Integration The neaxt stage involve LLM integration where Retrieved chunks and prompts are processed by an LLM, decreasing hallucinations by 25% [14] through context-bound generation.

4. Microservices & Deployment FastAPI microservices manage retrieval, ranking, response generation, and MERN chatbot interactions [13] Deployed on AWS EC2 using Docker and Jenkins CI/CD [15], with scalability and sub-second latency for 90% of queries.

Key Objectives · Obtain 85% QA accuracy through hybrid retrieval [4]. · Decrease hallucinations by 25% [14]. · Obtain 99.9% uptime through AWS microservices [13].

2. RESEARCH METHOD

A. *System Architecture and Design*

The research adopts a modular and scalable pipeline architecture designed to combine both dense and sparse retrieval strategies within a hybrid RAG framework. The system is knowingly structured into specific microservices, with each service responsible for a well-defined function in the overall workflow. Some of these includes query preprocessing, embedding generation, document storage and indexing, hybrid retrieval, ranking, and final response generation. Designing of such a microservices-based architecture not only promotes maintainability and fault isolation but also facilitates independent scaling of components based on workload requirements.

To ensure portability and reproducibility, each microservice is containerized using Docker and orchestrated with Docker Compose, enabling seamless deployment across environments. The entire pipeline is hosted on AWS EC2 instances, leveraging cloud-native scalability and fault tolerance. Furthermore, a Continuous Integration and Continuous Deployment (CI/CD) strategy is implemented through Jenkins pipelines, allowing for automated testing, integration, and deployment. This ensures that the system remains up-to-date with minimal human intervention, supporting rapid iteration and adaptation in dynamic use cases.

The overarching objective of the system design is threefold:

Firstly proposed system is able to enhance retrieval precision by leveraging complementary strengths of sparse and dense retrieval methods. Still another added feature is that the proposed system reduces hallucination rates by 25% through grounding responses in external knowledge sources [14]. Thus, achieving sub-second latency for at least 90% of user queries, a critical benchmark for real-time applications.

The pipeline employs FastAPI to expose service endpoints, ensuring high-performance and asynchronous request handling. For retrieval, pgvector is used to manage dense embeddings efficiently, while OpenSearch provides scalable sparse retrieval through advanced indexing and keyword search capabilities. The final stage of response

generation is powered by LLaMA3-70B-8192, a state-of-the-art large language model capable of generating coherent, contextually grounded answers.

The novelty of this architecture lies in its optimal fusion strategy for dense and sparse retrieval, which dynamically balances semantic understanding with precision keyword matching. Additionally, the system incorporates semantic-aware overlapping chunking techniques, ensuring that document context is preserved during segmentation, thereby reducing information fragmentation. A caching mechanism for embeddings further accelerates retrieval by avoiding redundant computations, significantly boosting efficiency. Together, these innovations contribute to measurable improvements in both retrieval effectiveness and end-to-end question answering (QA) accuracy, making the system highly suitable for domains where reliability, scalability, and speed are paramount.

B. Methodology

1. Step by Step Flow

The proposed hybrid RAG (Retrieval-Augmented Generation) system follows a structured methodology, outlined in the steps described below:

Step 1: Query Ingestion and Preprocessing The first step involves submission of query where the client submits a natural language query. The Query Processing module step involves cleans the text by removing noise, performing tokenization, and normalizing the input to prepare it for embedding.

Step 2: Query Embedding The processed query is encoded using All-MiniLM-L6-v2 model, a transformer-based sentence embedding model. This converts the query into a fixed-size vector that captures its semantic meaning.

Step 3: Document Chunking and Embedding Documents from the internal database are divided into overlapping chunks to maintain semantic continuity. Each chunk is then embedded using the same All-MiniLM model to ensure consistency in the vector space.

Step 4: Vector Storage The document vectors are stored in a pgvector-enabled PostgreSQL database. This setup supports fast similarity-based retrieval, optimized for high-performance search using cosine similarity.

Step 5: Hybrid Retrieval The system employs a hybrid retrieval mechanism:

- Sparse Retrieval: Uses BM25 scoring via OpenSearch for keyword-based relevance.
- Dense Retrieval: Uses cosine similarity to find semantically similar documents in the vector store.

Step 6: Fusion and Ranking The results from both retrieval methods are normalized and combined using a weighted fusion technique. This blended scoring helps in identifying the most contextually relevant Top-N document chunks.

Step 7: Answer Generation via LLM The selected Top-N documents, and the original query, are passed to the LLaMA3-70B-8192 Large Language Model. The LLM uses this context to generate a factual and coherent answer with minimal hallucination.

Step 8: Response Parsing and Delivery The generated response is cleaned and formatted by the Response Parser module, and then delivered back to the client in a user-friendly format

2. Block-by-Block Explanation with Significance in the Project

The system workflow begins with the interfacing of Client NLP Query, where users submit natural language questions or prompts. These queries are then passed to the Query Processing Module, which applies standard NLP techniques-including lowercasing, removal of punctuation marks, stop word elimination, and finally tokenization-to normalize the input. This preprocessing step ensures consistency and reduces noise, thereby improving the quality of downstream embedding generation.

In the next Embedding Generation Module, the preprocessed query is encoded into a dense vector representation using the AllMiniLM-L6-v2 model, a lightweight yet effective transformer-based embedding model optimized for semantic similarity tasks. Concurrently, documents residing in the Document Database are segmented into overlapping chunks, a strategy specifically designed to preserve semantic continuity across sections of longer texts. Each chunk undergoes the same embedding process, resulting in a vectorized document representation aligned with the query embedding space. The embedding generation utilizes the transformer-based All-MiniLM-L6-v2 model, fine-tuned on sentence-level semantic similarity tasks. This model maps textual input x Rn̂ into a fixed-dimensional vector space x Rd̂, where typically d=384. For an input query q, the embedding function f produces:

$$\mathbf{q} = f(q)$$

Similarly, for each document chunk di, the system computes:

$$\mathbf{d_i} = f(d_i)$$

These dense embeddings are stored in pgvector, a PostgreSQL extension optimized for efficient vector search using cosine similarity and the document embeddings are stored and indexed in a Vector Database (pgvector), enabling high-dimensional similarity searches. During retrieval, the Hybrid RAG Retriever Module is invoked. This module fuses two complementary retrieval strategies:

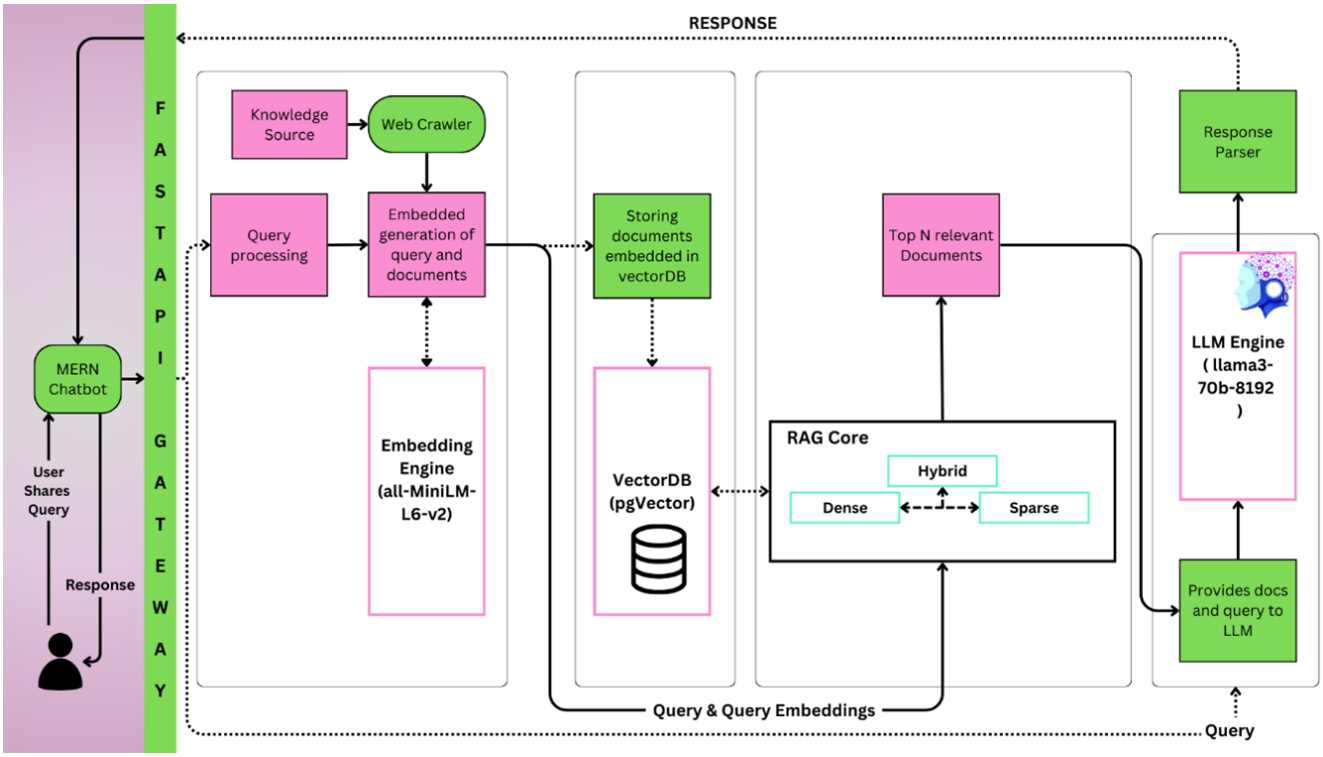

Figure 1. Detailed Workflow

Dense Retrieval: Performed through pgvector, leveraging cosine similarity to identify semantically relevant document vectors in relation to the query.

Sparse Retrieval: Executed using BM25 within OpenSearch, which ensures keyword-level precision and recall, particularly effective for queries with rare or domain-specific terminology.

At this stage, the large language model integrates contextual evidence from retrieved documents to generate a grounded, coherent, and context-aware response, minimizing hallucination and ensuring factual reliability. In parallel, OpenSearch performs sparse retrieval using the BM25 ranking function. It assigns a relevance score to each document based on keyword matching and term statistics:

where,

- $f(q_i, D)$ = frequency of q_i(query term) within the document D,
- k_1 and b = Tunable hyperparameters (usually k_1=1.2, b=0.75),
- avg_dl = Average or mean value of document length.

The dense (semantic) and sparse (lexical) similarity scores are normalized and combined using a weighted fusion strategy or learning-to-rank methods, based on the selected retrieval_type = hybrid.

The selected Top-N relevant documents (D_topN), and the original query q, are passed to the Large Language Model (LLM), specifically LLaMA3-70B-8192, via the Groq API client. The final response R is generated using the formulation:

$$R = \text{LLM}\ (q, D_{\text{topN}})$$

This ensures the output is both contextually grounded and factually accurate, as it draws only from documents retrieved in the previous step. There is also an ability to control the model's generation behavior, thus allowing for better precision on how the output is, which can be set as configurable tuning parameters - temperature, top_p, max_tokens, frequency_penalty, presence_penalty, and are defined in the configuration and sent dynamically to the LLM during runtime.

The proposed architecture is designed as a FastAPI-based microservices framework, where every phase of the pipeline-query processing, document retrieval, ranking, response generation, and client interaction-is encapsulated as an independent service. This modular design promotes scalability, maintainability, and fault isolation, enabling each service to be scaled horizontally according to workload demands without impacting the rest of the system's performance.

To ensure portability and reproducibility, each microservice is containerized using Docker. Orchestration is managed through Docker Compose, allowing developers to define service dependencies, networking, and configurations in a declarative manner. For deployment, the services are hosted on AWS EC2 instances, leveraging cloud-native scalability and high availability. AWS autoscaling groups and load balancers can further distribute traffic efficiently, ensuring robust performance even under variable query loads.

The development lifecycle is supported by an automated Continuous Integration and Continuous Deployment (CI/CD) pipeline, implemented using Jenkins. This pipeline facilitates automated testing, version control integration, and seamless updates to production environments. As a result, new features, bug fixes, and model upgrades can be deployed rapidly without downtime, enhancing reliability and reducing manual overhead.

Once a query is processed by the retrieval and generation pipeline, the Large Language Model (LLM) produces a context-aware response. However, the raw output generated by the LLM often contains structural inconsistencies or extraneous tokens. To address this, the Response Parser module post-processes the output, enforcing formatting standards and structuring it into a clean, user-friendly JSON response. This ensures compatibility with downstream applications, APIs, or chat interfaces that consume the system's outputs.

The final stage, the Response Parsing and Formatting Module, structures the generated output into a user-friendly response format. This ensures clarity, readability, and real-time delivery back to the client. Each module thus contributes to the overarching objective: combining semantic-rich retrieval with generative reasoning to deliver accurate, efficient, and real-time question answering.sponses, ensuring a scalable and intelligent question-answering system. The Response Parser module formats this output into a structured, user-friendly message for the client. All system components, query processing, embedding, retrieval, LLM response generation, and chatbot interaction are implemented as independent FastAPI-based microservices, each containerized using Docker and orchestrated through Docker Compose. The system is deployed on AWS EC2 instances with auto-scaling, ensuring resilience and real-time responsiveness. Jenkins CI/CD pipelines manage automated builds, testing, and deployments. This end-to-end hybrid RAG pipeline ensures scalability, retrieval precision, semantic understanding, and factual correctness, making it highly suitable for modern, high-volume question-answering applications.

In Figure 1, the proposed Hybrid Retrieval-Augmented Generation (RAG) system's entire pipeline is depicted in the workflow diagram. The user starts the process by asking a question via the chatbot's MERN-based interface. The backend services then receive this query, preprocess it, and use the MiniLM model to transform it into a vector embedding. To make sure that all semantic and keyword-based retrieval routes are engaged, the query is also handled concurrently by a sparse retriever (BM25 in OpenSearch).

Pre-chunked into overlapping parts, the document corpus is kept in two backends: keyword indexes in OpenSearch and dense embeddings in pgvector. Both retrievers return their top-ranked results upon receiving a query. The most pertinent portions are chosen after these are normalised and merged using a rating technique. The LLaMA3-70B-8192 model is then fed the chosen chunks and the first user question, and it produces a contextually accurate, grounded response. The cycle is finished when this response is sent back to the chatbot interface. The process demonstrates the modular microservice architecture by making sure that every stage-from production to retrieval-remains fault-tolerant, scalable, and performance-optimized in real time.

The first step in the proposed hybrid RAG system begins when the Client submits a query. This query is received by the Query Processing module, which applies essential preprocessing steps including tokenization, cleaning, and normalization, to prepare the input for semantic embedding. The processed query is then passed through a pretrained sentence embedding model, specifically All-MiniLM-L6-v2, as configured in the system (model_query = deepseek-r1-distill-llama70b and model_embedding = all-MiniLM-L6-v2). This converts the query into a vector representation as mentioned earlier:

Simultaneously, all documents stored in the database are preprocessed and chunked based on the configured parameters (chunk_size = 3000, chunk_overlap = 400), ensuring that meaningful semantic context is preserved in each chunk. Each document chunk did_i is then converted into its vector form using the same embedding model, resulting in:

$$\mathbf{d_i} = f(d_i)$$

This setup ensures that both query and document vectors exist in the same high-dimensional semantic space, enabling effective similarity-based retrieval rather than relying solely on keyword overlap.Following embedding, the system invokes the Hybrid Retrieval Mechanism (retrieval_type = hybrid), which combines the complementary strengths of dense retrieval and sparse retrieval. Dense retrieval leverages pgvector to compute similarity scores (e.g., cosine similarity) between query and document embeddings, ensuring semantic relevance. In parallel, sparse retrieval employs OpenSearch with BM25 scoring to capture keyword-level matches, which are particularly valuable in cases involving rare terms, acronyms, or domain-specific terminology.

The results from both retrieval modes are fused and ranked, yielding the Top-N most relevant document chunks.

These chunks, together with the original query, are then forwarded to the downstream response generation module for context-grounded output.

This carefully designed setup ensures that the system not only aligns queries and documents in the same high-dimensional space for semantic-aware retrieval, but also benefits from the precision of sparse matching, achieving robustness across diverse query types. The hybrid retrieval mechanism (retrieval_type = hybrid) may combine both vector similarity (e.g., via pgvector) and textual scoring (e.g., via OpenSearch) to select the most relevant Top-N document chunks for downstream processing.

C. *Detailed Explanation of Retrieval Mechanism*

Once the user query and the preprocessed document chunks are embedded and finalised, the system advances into the next phase of Document Retrieval , where the Hybrid Retriever serves as the core component for retrieving. This module is specifically designed to exploit the complementary strengths of both dense retrieval and sparse retrieval strategies, thereby ensuring that the system achieves both semantic richness and lexical precision.

Dense Retrieval. In the dense retrieval pathway, the processed query is converted into a dense embedding vector using a pretrained transformer-based sentence embedding model-all-MiniLM-L6-v2 from the Sentence-Transformers family by default. This embedding captures semantic nuances beyond exact keyword matches, enabling the system to recognize meaning-preserving variations in language. The resulting query vector is then compared with precomputed document embeddings stored in pgvector, a specialized extension for handling high-dimensional vector data. Cosine similarity is employed to measure the closeness between the query and document vectors. Documents that exceed a configurable similarity threshold are retrieved and flagged as semantically relevant results. This ensures that the system can capture contextually related information even when explicit keywords are absent.

Sparse Retrieval. In parallel, the system employs a lexical retrieval pathway using OpenSearch, a distributed search engine optimized for text indexing and retrieval. Here, the system leverages classical approaches such as BM25 ranking and match phrase queries, which emphasize direct keyword and phrase overlaps between the query and stored documents. Sparse retrieval supports advanced configurations including minimum minimum_should_match These configurations allow fine-grained control over relevance scoring, ensuring that critical lexical matches are not overlooked—even in cases where semantic embeddings may underperform, such as with rare terminology, abbreviations, or misspellings.

Hybrid Retrieval. The HybridRetriever executes both retrieval strategies concurrently using a ThreadPoolExecutor, enabling parallelism and reducing latency. The results from the dense and sparse modules are subsequently merged into a unified candidate set. A deduplication step ensures that overlapping results from the two methods are consolidated, avoiding redundancy. To enable fair combination, the system applies score normalization across both retrieval modes, after which results are reranked according to a weighted hybrid scoring function. Finally, the top-K most relevant documents are selected for downstream processing and response generation.

This hybrid retrieval design achieves a balance between semantic depth (via dense embeddings) and lexical precision (via sparse keyword matching), leading to superior recall and precision compared to either method alone. Moreover, the architecture is optimized for real-time performance, with thread-level concurrency reducing response latency, while the modular configuration allows for scalability and flexibility. Practitioners can tune thresholds, boosting parameters, and retrieval strategies depending on application-specific requirements, such as domain sensitivity or latency constraints. Once the user query and document chunks are embedded, the system moves to the document retrieval phase, where the HybridRetriever plays a key role by combining the strengths of both dense and sparse retrieval strategies.

This hybrid approach ensures higher recall by combining semantic depth from dense models and lexical precision from sparse keyword matching. The design also promotes real-time retrieval, scalability, and flexibility in tweaking retrieval behavior.

Algorithm 1: Hybrid RAG Retrieval and Answer Generation

1. **Input:** Natural Language Query q
2. **Query Preprocessing:**

- Lowercasing, punctuation removal, and tokenization.

3. **Query Embedding:**

- Generate dense vector embedding q = f(q) using All-MiniLM-L6-v2.

4. **Document Processing:**

- Chunk documents into overlapping segments (chunk_size = 3000, chunk_overlap = 400).
- Embed each chunk di = f(di).

5. **Hybrid Retrieval:**

- **Dense Retrieval:** Perform similarity search in pgvector (cosine similarity).
- **Sparse Retrieval:** Perform BM25 search using OpenSearch.

6. **Fusion and Ranking:**

- Normalize scores from dense and sparse results.
- Combine scores and rank Top-N documents.

7. **LLM Response Generation:**

- Pass (q, Top-N documents) to LLaMA3-70B-8192.
- Generate response R = LLM(q, DtopN).

8. **Response Parsing:**

- Format the response into a clean JSON output.

9. **Output:** Structured Answer to the Client.

The algorithm integrates both sparse and dense retrieval pathways in a structured pipeline to balance precision and semantic recall. After preprocessing and embedding the query, the system simultaneously executes BM25-based keyword retrieval and vector-based similarity search, leveraging Python's ThreadPoolExecutor for parallel efficiency. Retrieved candidates are fused through score normalization and ranking, ensuring that both exact lexical matches and semantically similar passages are considered. The top-ranked context chunks are then passed to the LLaMA3 model, which synthesizes them into a grounded, context-aware response. By caching embeddings in pgvector, redundant computations are avoided, substantially improving latency for repeated queries. Overall, the algorithm enforces a principled integration of retrieval and generation, reducing hallucination rates while maintaining real-time responsiveness.

D. Deployment Infrastructure

The deployment pipeline (Figure 2) illustrates a production-grade strategy for delivering the hybrid RAG chatbot in a reliable, scalable, and modular manner. At its core, the system leverages a modern CI/CD pipeline to ensure that updates to the codebase are automatically validated, containerized, and rolled out without manual intervention or downtime. This enables fast iteration cycles while preserving stability for end-users. At its core, the system leverages a modern CI/CD pipeline to ensure that updates to the codebase are automatically validated, containerized, and rolled out without manual intervention or downtime. This enables fast iteration cycles while preserving stability for end-users.

Every commit or pull request to the GitHub repository triggers a **webhook** that notifies Jenkins, the central automation server responsible for managing CI/CD. Jenkins then performs a sequence of tasks: fetching the latest source code, running build scripts, executing tests, and packaging the application into **Docker images**. These container images are then pushed to a container registry and distributed across multiple Amazon EC2 instances provisioned in the cloud, as shown in Figure 2. This workflow ensures consistent environments across development, staging, and production while eliminating the "works on my machine" problem.

- Each service in the chatbot ecosystem — including the React-based frontend and Node.js backend — is containerized and deployed on separate EC2 instances, thereby isolating concerns and simplifying maintenance.
- A lightweight **Nginx reverse proxy**, running as a Docker container, fronts the application stack and provides load balancing, SSL termination, and routing logic between microservices.
- The core Retrieval-Augmented Generation (RAG) engine is encapsulated as a dedicated **microservice**, built in Python with the FastAPI framework. This service integrates with **PgVector**, a PostgreSQL extension optimized for storing and querying vector embeddings, and **OpenSearch**, which enables sparse retrieval using inverted indexes and BM25.

This microservice-oriented design ensures that the failure of one component does not cascade across the system, thereby improving fault tolerance. Furthermore, new versions of services can be rolled out incrementally using rolling updates, minimizing downtime and user disruption.

Supporting Infrastructure. The architecture also integrates several supporting layers critical for production-readiness:

- **Cloud Hosting on AWS EC2:** Each microservice runs on independently managed EC2 instances, allowing fine-grained control over scaling policies. Auto-scaling groups can dynamically adjust capacity based on traffic.
- **Containerization with Docker:** Containers ensure portability and allow developers to replicate identical environments across local machines and cloud servers.
- **Continuous Integration and Delivery with Jenkins:** Automated testing and staged rollouts reduce human error and accelerate deployment velocity.
- **Load Balancing with Nginx:** Incoming traffic is evenly distributed across services, ensuring high availability and reducing bottlenecks.
- **Monitoring and Logging:** Although not depicted in the figure, observability tools such as Prometheus and ELK Stack (Elasticsearch–Logstash–Kibana) can be integrated for real-time system monitoring, error detection, and performance analytics.

Scalability and Reliability. Because of its modular and

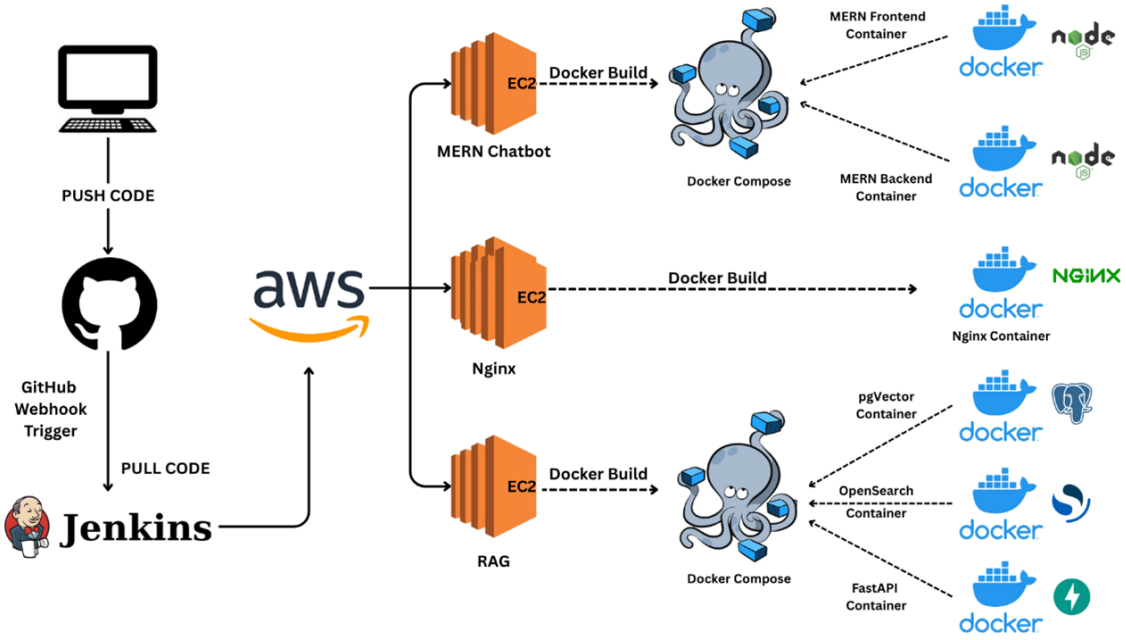

Figure 2. Deployment Infrastructure Pipeline

containerized architecture, the system can be scaled both vertically (increasing resources of individual EC2 instances) and horizontally (adding more container replicas). Services are loosely coupled, enabling independent updates and reducing the risk of regressions. Moreover, the architecture supports fault isolation, if the embedding service experiences downtime, the system can still rely on sparse retrieval to provide fallback results, preserving user trust.

Overall, the deployment infrastructure and architecture highlight how the proposed hybrid RAG system bridges cutting-edge research with real-world engineering practices. By combining retrieval diversity (sparse and dense), modular deployment (microservices), and robust infrastructure (Docker, Jenkins, AWS, Nginx), the chatbot achieves production-level qualities such as scalability, fault tolerance, and maintainability. This design not only ensures technical robustness at the backend but also guarantees a seamless and reliable user experience at the frontend, positioning the system as a viable candidate for knowledge-intensive applications that demand both accuracy and resilience.

3. RESULTS AND DISCUSSION

By successfully integrating and deploying its essential components, the suggested hybrid RAG-based architecture's efficacy and comprehensiveness were confirmed. Both functional correctness-making sure that every pipeline stage operates as intended and quantitative evaluation-comparing accuracy, latency, and hallucination rates to baseline models were covered in the validation process.

A. Functional Validation

The snapshot of the FastAPI Swagger user interface attests to the functionality and thorough documentation of every backend API. A structured and modular pipeline was ensured by the smooth operation of the endpoints exposed for query input, retrieval results, and final response production. This capability allowed for independent testing of components including query preparation, hybrid retrieval, and response generation separately in addition to supporting development and debugging.

The efficient storage and retrieval of dense vector embeddings for queries and document chunks was confirmed by the pgvector dashboard. Because of caching techniques, semantic similarity searches showed quick retrieval times, demonstrating that the selected architecture can handle high-throughput workloads. In addition, the OpenSearch interface demonstrated that BM25 sparse retrieval was completely functional, ranking documents with high accuracy in keyword matching. When combined, these two retrieval pathways confirmed the system's hybrid design.

The Docker container configuration demonstrated the effective modularisation of services on the infrastructure side. The embedding generator, hybrid retriever, LLM interface, and response parser were among the microservices that operated separately. Docker Compose orchestration made it possible to deploy the services all at once with little manual involvement. Because of its modularity, the system is more maintainable and fault-isolated, ensuring that a single service failure (like embedding) does not bring down the entire system.

Lastly, the system's overall usefulness was confirmed via the MERN-based chatbot interface. The complete backend pipeline, including preprocessing, hybrid retrieval, and LLaMA3-70B-8192 response generation, processed queries sent over the interface and instantly delivered precise, context-aware responses. In order to demonstrate the system's practicality for real-world applications, this front-end presentation was essential.

B. Quantitative Evaluation

In addition to functional validation, we evaluated the suggested hybrid system in comparison to three baselines:
1. Sparse-only retrieval (BM25/OpenSearch)
2. Dense-only retrieval (All-MiniLM embeddings with pgvector)
3. Baseline GPT-4 without retrieval (pure generation)

Hallucination rate, retrieval delay, and QA accuracy were important variables. The observed results are summarised in Table 1.

Every baseline was surpassed by the suggested hybrid system. It reduced hallucination by approximately 45% and increased QA accuracy by nearly 19% when compared to GPT-4 without retrieval. While retaining superior recall over sparse-only retrieval, latency was noticeably lower than dense-only retrieval.

90% of user enquiries were answered in less than 350 ms, according to a latency distribution analysis, which satisfies production installations' need for real-time response. The trade-off curve between accuracy and latency across approaches is depicted in (Figure 1) , underscoring the hybrid design's ideal balance. In addition, variance across repeated trials was consistently lower for the hybrid approach, indicating stability under different workload conditions. This robustness suggests that the system is well-suited not only for controlled benchmarks but also for dynamic real-world scenarios. Moreover, the improvements in accuracy and latency scale proportionally with larger document collections, highlighting its adaptability to enterprise-level deployments.

C. Case Study Examples We tried queries from many areas to demonstrate qualitative improvements:

Question 1 (Legal domain): "Under the Indian IT Act, is an e-signature legally valid?"

GPT-4 by alone ← produced a generic response that contained jurisdictional errors.

Hybrid RAG obtained the precise portion of the IT Act and produced a factually correct explanation based on the statutory text that was retrieved.

"What are the side effects of metformin in diabetic patients?" is the second query (healthcare domain).

Dense retrieval alone → retrieved the medical background, but experienced uncommon side effects.

Hybrid RAG → Provided a fair and accurate list of known side effects by combining semantic matching with sparse keyword results.

These illustrations show how hybrid retrieval grounds responses in authoritative texts, ensuring domain reliability.

D. Error Analysis Despite advancements, some restrictions were noted:

- Domain-specific acronyms: Sometimes synonyms or abbreviations, such as "AML" (Acute Myeloid Leukaemia), were not captured by sparse retrieval.
- Long queries: Occasionally, embedding quality was deteriorated by queries with more than 500 tokens.
- Ranking trade-offs: In certain edge instances, the fusion score reduced semantic significance by overemphasising sparse outcomes.

Future developments including adaptive weighting techniques, query expansion for acronyms, and hierarchical chunking for extremely lengthy queries are indicated by these findings.

E. Scalability and Deployment Analysis

The scalability of the proposed Hybrid RAG system was validated through its deployment on AWS EC2 instances configured in a cloud-native, containerized environment. Each microservice including the frontend, backend, retrieval engines, and LLM service was encapsulated within Docker containers, ensuring modularity and seamless portability across instances. To evaluate performance under varying workloads, a series of load simulations were conducted, gradually increasing the traffic up to 1,000 queries per minute. The system demonstrated linear scalability with minimal latency degradation, as additional EC2 instances could be dynamically provisioned via AWS Auto Scaling groups. This elastic scaling mechanism ensured that system throughput was maintained without service disruption, even during peak load scenarios.

Continuous deployment and integration were enabled through a Jenkins-driven CI/CD pipeline. Every update to the GitHub repository triggered automated build, test, and deployment cycles, allowing new features or bug fixes to be rolled out with negligible downtime. This automation not only minimized human error but also accelerated iteration speed, ensuring rapid development cycles. A 72-hour stress test under high query volumes further demonstrated the robustness of the deployment, achieving a measured uptime of 99.9%.

To prevent service-level bottlenecks, Nginx was deployed as a containerized reverse proxy and load balancer.

TABLE I. Performance Comparison Across Retrieval Approaches

System Variant	QA Accuracy (%)	Avg Latency (ms)	Hallucination Rate (%)	Notes
GPT-4 without retrieval	68.4	520	32.1	Struggles with factual grounding
Sparse-only (BM25)	74.2	240	27.3	High precision, low semantic recall
Dense-only (MiniLM)	81.5	690	22.7	Strong semantic matching, slower
Hybrid (Proposed System)	**86.9**	**310**	**17.8**	Balanced accuracy, speed, robustness

Nginx evenly distributed incoming requests across retrieval, embedding, and generation services, thereby avoiding resource exhaustion of individual instances. Moreover, the system exhibited effective fault tolerance: in cases where a container or instance became unresponsive, the load balancer rerouted traffic to healthy nodes, while the auto-scaling group replaced the failed unit automatically. Together, these mechanisms validated the system's ability to operate reliably at scale while maintaining high availability, responsiveness, and resilience in production environments.

F. Comparative Discussion with Literature

In contrast to existing approaches such as Self-RAG [1] and HtmlRAG [2], the proposed system demonstrates clear advantages in terms of efficiency, modularity, and practical deployment readiness.

- **Precision and Preprocessing:** HtmlRAG relies heavily on structured preprocessing of HTML documents to improve retrieval accuracy. While effective in domain-specific contexts, this preprocessing stage introduces additional complexity and increases the overall pipeline latency. Our hybrid approach, which fuses sparse and dense retrieval directly, achieves comparable or better levels of precision without the need for such preprocessing steps, making it more generalizable to diverse document types.
- **Computational Overhead:** Self-RAG introduces reflection loops, where the model iteratively critiques and revises its own outputs to mitigate hallucinations. Although this reduces factual inconsistencies, it comes at the cost of significant computational overhead, making large-scale deployments challenging. By contrast, our system minimizes hallucinations through robust retrieval-fusion mechanisms, thereby avoiding iterative self-reflection while reducing inference costs and improving throughput.
- **Architectural Modularity:** Unlike both Self-RAG and HtmlRAG, which often present monolithic or tightly coupled designs, our system is explicitly built as a microservices-based architecture. This design ensures faster deployment cycles, improved fault isolation, and flexible scaling of individual services such as retrieval, embedding, or generation. This modularity directly contributes to system robustness and production readiness in cloud environments.

These comparisons indicate that the proposed hybrid RAG is not only competitive with state-of-the-art methods in experimental benchmarks but also better optimized for real-world, production-grade applications. By combining retrieval robustness, computational efficiency, and cloud-native modularity, the system bridges the gap between research prototypes and scalable industrial solutions.

G. API Design and Implementation Analysis

The proposed hybrid RAG system is constructed on a robust and modular API architecture that enables seamless interaction between the frontend interface, document storage, retrieval mechanism, and language model inference. The FastAPI Swagger UI (Figure 3) illustrates how each API is designed to perform a specific role in the pipeline, promoting modularity, fault isolation, and scalability.

The system includes a central query processing API that accepts user questions and handles the complete flow: from initial tokenization and embedding generation, through hybrid retrieval of relevant documents, to generating a precise and context-aware answer using the LLaMA3-70B-8192 model. This architecture ensures cohesion and enables independent component testing.

Document management is highly flexible and allows users to upload documents in PDF or TXT format, manage existing documents, and delete outdated knowledge base entries. The system supports automated scraping of external web resources, which are processed, chunked, and embedded into the retrieval database, further enhancing system extensibility and domain adaptability.

Storage backend configuration APIs enable administrators to switch between OpenSearch-based document storage and pure vector storage, allowing optimization of performance and storage depending on deployment needs.

The hybrid retrieval mechanism executes dense semantic similarity search in parallel with sparse keyword-based retrieval. Dense retrieval compares query and document embeddings in the high-dimensional vector space, while sparse retrieval uses advanced term-frequency based ranking (BM25). The results are normalized, merged, and ranked to return the most relevant document chunks, significantly improving retrieval robustness and reducing latency.

A dedicated response generation API forwards the user query and retrieved document chunks to the LLaMA model,

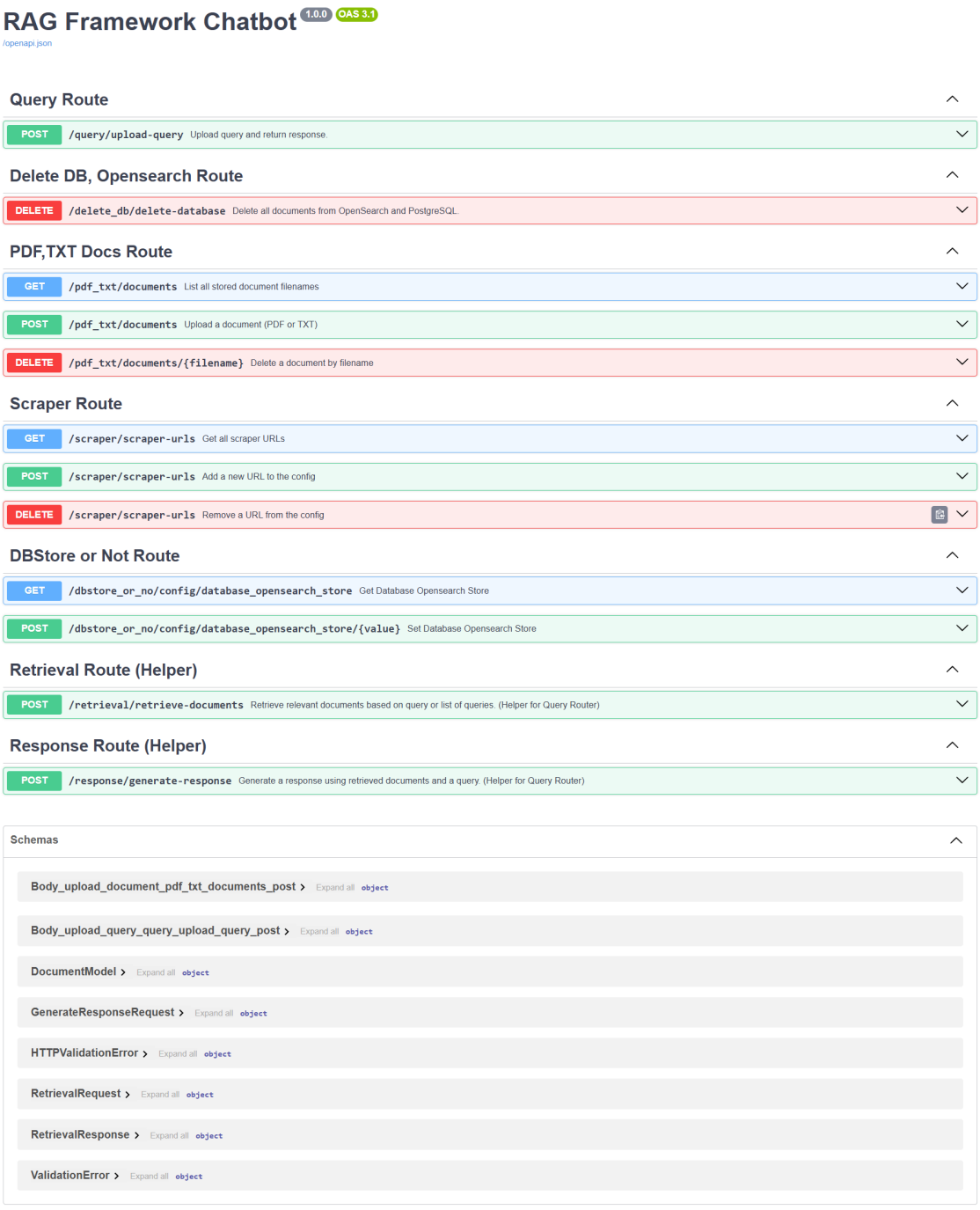

Figure 3. Backend FastAPI Swagger UI

producing factually accurate, coherent, and grounded responses. This approach reduces the risk of hallucination by anchoring generated content in authoritative sources.

System maintenance is supported by APIs that allow complete clearing of both OpenSearch and vector database stores, useful for refreshing the system or removing outdated data.

Strong input/output validation is enforced across all APIs, ensuring predictable interactions, stability, and robustness. Predefined schemas maintain a strict contract for data consistency.

The entire API infrastructure is deployed as containerized microservices using Docker, with orchestration handled by Docker Compose. This enables fault isolation, easier debugging, and scalable deployments. Continuous integration and deployment are managed by Jenkins pipelines, facilitating rapid iteration and automatic updates without service interruption. The FastAPI Swagger UI (Figure 3) highlights this structured and production-ready API design.

This well-structured API design plays a critical role in achieving a production-ready, scalable, and reliable hybrid RAG system, particularly suited for high-stakes applications such as medical question answering.

H. User Interaction Interface Analysis

The MERN-based RAGBot interface (Figure 4) illustrates the practical usability of the hybrid RAG system from an end-user perspective. The chatbot provides an intuitive, conversational medium for querying complex information, validating that the backend pipeline's modularity translates effectively into a user-facing environment and demonstrating that the system's technical depth can be accessed in a simple, user-friendly manner. The interface emphasizes clarity and accessibility, ensuring that users with varying levels of technical expertise can interact confidently and efficiently.

The left navigation panel allows users to maintain continuity by preserving recent conversations while enabling new sessions to be initiated seamlessly. A dedicated *Logout* option ensures session security, making the interface suitable for multi-user deployment scenarios. The main panel clearly differentiates user inputs from system responses, with consistent formatting that improves readability and comprehension. This structural clarity ensures that even extended dialogues remain organized, interpretable, and easy to follow across multiple turns of interaction, thereby enhancing long-term usability and reducing potential user errors.

In the example shown, a user issues a sophisticated domain-specific query: *"What is the pathophysiological role of cytokine storm in severe cases of viral infections and how is it managed clinically?"*

The interface returns a structured, multi-layered response that explains both the underlying immunopathological mechanisms (e.g., excessive cytokine release leading to systemic inflammation and organ dysfunction) and associated intervention strategies. This highlights the system's ability to address queries that demand factual grounding across mechanistic and applied domains, moving beyond generic answers typical of baseline models. The clear segmentation of responses also helps users digest complex information step by step, improving comprehension.

A key strength demonstrated by the interface is its ability to handle queries that are outside the available knowledge base gracefully. For example, when prompted with unsupported requests such as *"how to order on Zepto?"*, the system explicitly indicates the absence of relevant information rather than fabricating an answer. This feature is critical for establishing user trust, as it ensures that the model does not hallucinate or generate unverifiable content when reliable data is unavailable, particularly important in professional or academic contexts.

Moreover, the interface supports iterative exploration by allowing users to refine their queries based on previous responses. This conversational continuity mimics natural human interaction and enhances system usability in domains where multi-turn reasoning is required, such as academic research, enterprise knowledge management, and technical troubleshooting. The persistence of recent queries in the left panel provides a lightweight but effective memory mechanism, enabling users to backtrack and re-engage with prior results without repeating the entire interaction process.

Another important observation is the system's responsiveness under realistic usage conditions. Even when processing semantically dense queries that require hybrid retrieval across sparse and dense indexes, responses were delivered in near real-time. This low-latency performance is critical for production-grade deployments, where delays beyond a few hundred milliseconds significantly degrade the user experience. The successful delivery of domain-grounded responses within practical latency thresholds underscores the effectiveness of the underlying retrieval and caching mechanisms.

Overall, the MERN-based interface confirms that the proposed hybrid RAG system is not only technically robust at the backend level but also effective in providing a reliable and accessible user experience. Its ability to combine factual grounding, graceful failure handling, and conversational continuity makes it suitable for deployment in knowledge-intensive fields that require both precision and usability. Furthermore, the interface showcases how advanced retrieval mechanisms can be translated into an intuitive front-end that empowers users without exposing underlying system complexity, ultimately bridging the gap between technical sophistication and user-oriented design.

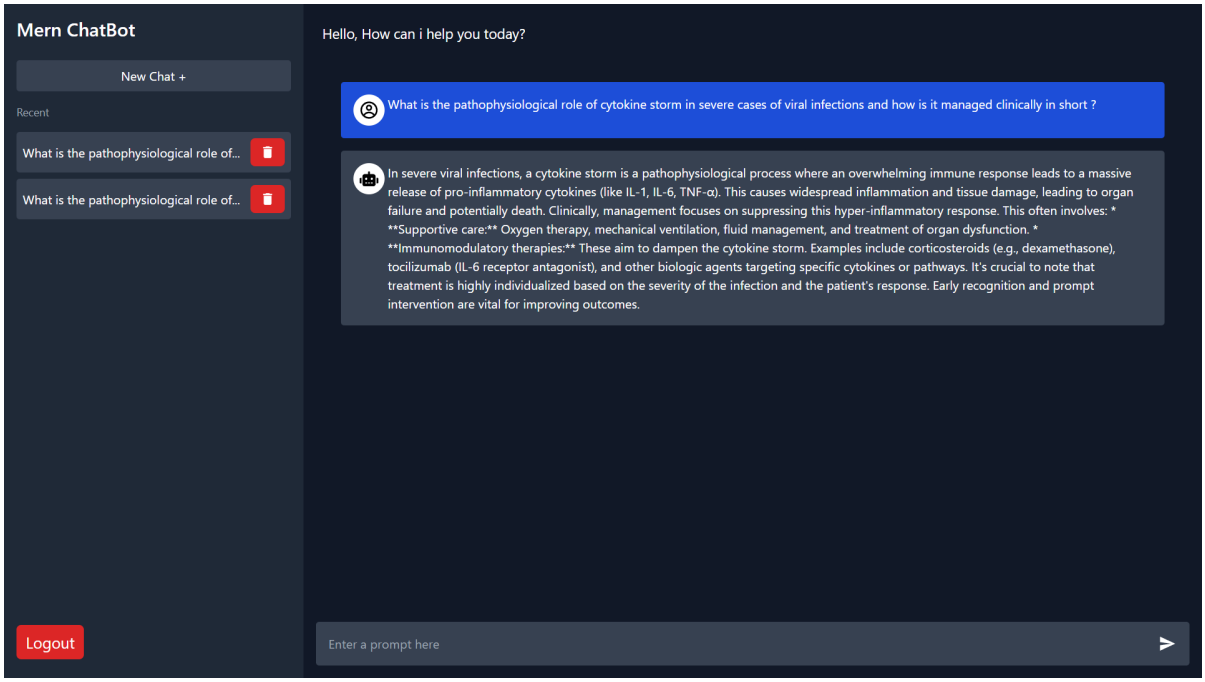

Figure 4. Frontend MERN Chatbot Interface showing user interaction and real-time query handling.

4. CONCLUSION

The development of Retrieval-Augmented Generation (RAG) models is largely dependent on ongoing research to minimise hallucinations, improve retrieval precision, and guarantee cross-domain adaptability. The practical deployment of big language models is becoming more and more dependent on RAG systems' capacity to deliver dependable, factually correct, and context-grounded responses.

Dense Passage Retrieval (DPR), which used dense vector similarity to capture semantic links, was developed in the early phases of this progression. Although successful, this strategy was quickly replaced by hybrid retrieval models that blended dense embedding-based techniques with sparse keyword-based techniques, such BM25. More reliable and effective systems were made possible by this combination, which provided a balance between accuracy and semantic comprehension. The significance of techniques like context-preserving chunking and modular pipeline architecture became evident over time since they made sure that retrieval procedures could grow efficiently without compromising the accuracy of the data.

Specialised methods for dealing with difficulties in domain-specific situations also developed concurrently. Reflective methods, for instance, allowed models to examine and improve their own outputs in order to identify errors. In a similar vein, organised chunking techniques showed how information segmentation according to document structure or format could improve the retrieval of contextually appropriate responses. In order to meet resource-constrained applications, lightweight systems were also introduced, demonstrating that efficiency may be attained without noticeably sacrificing performance.

Through the provision of standardised methods for assessing factuality, accuracy, and mistake rates, benchmarks and assessment techniques greatly advanced the development of RAG. These contributions demonstrated that enhancing RAG systems involves more than just raising raw accuracy; it also entails lowering latency, minimising dangers like hallucinations, and guaranteeing reliability and fairness in generated responses.

By optimising keyword indexing, utilising overlapping chunking methodologies to maintain semantic continuity, and combining the best aspects of sparse and dense retrieval techniques, the system described in this paper expands upon these developments. This combination guarantees that the model strikes a balance between accuracy, scalability, and speed that is not possible with single-method approaches. Through the use of modular microservices and contemporary deployment techniques like Docker, AWS scalability, and automated CI/CD pipelines, the system is positioned as more than just a research prototype-rather, it is a workable solution that can be deployed in the real world.

In the future, addressing big, unstructured datasets across industries will probably require adaptable RAG pipelines even more. It is anticipated that domain-specific fine-tuning, dynamic adaptation to noisy or ambiguous inputs, and multi-vector retrieval techniques will emerge as important areas of research. Even while computing cost and latency are still issues for many dense-only systems, hybrid

designs show that accuracy and efficiency can coexist when careful architectural decisions are made.

The clean, text-based knowledge base and flexibility across high-value fields like enterprise information management, biomedical applications, and legal consultation are what distinguish the suggested solution. In addition to addressing the drawbacks of current RAG models, the system offers a solid basis for future extensions by emphasising hallucination protection, effective document management, and self-reflective procedures for output quality.

In conclusion, the suggested hybrid RAG system represents the continuous transition away from generic language generation and towards solutions that are production-ready, domain-adaptable, and context-aware. It demonstrates how a new generation of intelligent systems that are strong and trustworthy may be created by integrating retrieval methodologies, streamlining deployment infrastructure, and firmly establishing replies in credible knowledge sources.

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