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AI-Driven Document Analysis: Employing Streamlit, Faiss, Nvidia Nemo

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***Abstract*—This work of research offers an enhanced usage of the Retrieval-Augmented Generation model with NVIDIA NeMo and Streamlit for document processing and question response. Emphasizing efficient information search, the system applies the latest language models and the FAISS vector search to improve document processing features. The proposed application relates to multi-PDF documents, from which real-time responses and queries can be formulated based on the methodology, including semantic chunking and embeddings. Integration with the NVIDIA Llama-3.1-Nemotron-70b model supports additional query optimization; additionally, improved setup choices and performance statistics enhance the user experience. Furthermore, the application displays intelligent chunking, vector search optimization, and contextual responses for relevant and efficient information searches. The system is supposed to perform well and be scalable for real time analysis and high demand, making this a tool suitable for several industries that require complex solutions for document-based queries. This paper discusses the technical aspects of implementing the RAG model, its peculiarities, and possible best practices when deploying it with NVIDIA's AI solutions, while stressing the practical usefulness of this solution for document processing and knowledge retrieval applications.**

Keywords— retrieval-augmented generation (RAG), NVIDIA NeMo, streamlit, FAISS vector search, semantic chunking, document embeddings, scalability

I. INTRODUCTION

The increasing use of artificial intelligence (AI) has done a lot in enhancing the different sectors; it has eased labour-intensive processes. The most revolutionary use of AI at the moment is known as Retrieval-Augmented Generation (RAG), which combines retrieval functionality and generative systems to analyze documents, answer questions, and retrieve knowledge [1]. This paper provides a complex RAG realization on the basis of the NeMo AI model developed by NVIDIA in conjunction with Streamlit for large-scale analysis of PDF documents. This work's primary goal is to enhance the querying outcomes based on documents using current vector search techniques and language models to produce context-sensitive queries in real-time. Big data is a difficulty that enterprises are currently facing, where they must manage and analyze vast amounts of unstructured data, many of which are in document formats like PDFs. To acquire valuable knowledge from such documents, or any other unstructured sources, several issues arise, especially when working with humongous data and documents of various formats. Conventional approaches to document processing are often not very effective in terms of scalability, accuracy, or speed of processing the highly structured documents, and therefore there is a notable need for new approaches to complicated document structures [2]. Retrieval-augmented generation mitigates these problems by unifying vector search or document retrieval with generative AI models, making it possible to work harder, perform better in deep document analysis, and generate precise answers based on context.

Specifically, this research is centered on an overall approach that incorporates NVIDIA's state-of-the-art Llama-3.1-Nemotron-70b model, further optimized for activities such as natural language processing, question-answering, and the like. The workflow defined for the system includes the document and image upload and processing, the creation of an embedding of the text, and finally the processing of the queries [3]. The response is obtained with the help of the FAISS vector store which enables the fast document similarity search while respecting the semantic boundaries of chunks with the help of intelligent chunking techniques. The Streamlit integration enables users to interact with the system from a web UI, making the solution approachable and easy to use. Furthermore, this paper will review factors such as adjusting configuration settings, reducing response time, and adding features to batch operations. The practicality of the system is evident when processing noisy, unstructured data and the ability to produce fast and precise responses [4]. The main contribution of this work is in the actual implementation of RAG for large-scale document processing using modern AI technologies with relevant user attributes, incorporating a solution that can be easily adapted for use in legal services, healthcare, finance, governments, and many other industries.

The remainder of this paper is structured as follows: Section 2 is a brief review of the literature where the progress of the document analysis and question answering systems has been described with reference to the development of retrieval-based as well as generative-based systems. Section 3 outlines the methodology, including the RAG system architecture, the integration of NVIDIA NeMo, FAISS, and Streamlit, and the configuration options utilized for performance improvement. Section 4 presents the evaluation of the system and the actual implementation, proving how the system works in real-time in a set of test documents. Finally, Section 5 comprises the system application, limitation, and future research direction of the paper.

II. Literature Review

Salemi et al. [5] set a paradigm for AI-driven legal document analysis, enhancing accuracy and efficiency, and investigated machine learning methods for contract analysis, minimizing processing time and legal inconsistencies, and proposed NLP-driven legal text summarizers, enhancing readability and compliance. Legal assistants powered by AI were substantially found to minimize errors in drafting and enhance review times by this study. The system proposed enhanced efficiency by 35%, which is consistent with earlier research findings on the application of AI for legal automation.

Jiawei et al. [6] created a deep learning model to improve text classification, with improved accuracy in difficult datasets, and investigated transformer-based models for natural language processing, greatly improving computational efficiency, and created a hybrid AI model for sentiment analysis, improving precision in context understanding. The current research validated that sophisticated machine learning methods improve classification accuracy and minimize error rates. The model suggested improved accuracy by 20%, according to current research on AI-based text analysis.

Zhengbao Jiang et al. [7] developed a novel NLP model to improve text comprehension, with improved semantic accuracy and context relevance, and investigated machine learning algorithms for autonomous document processing, minimizing workload and processing time, and proposed a hybrid deep learning framework for data extraction, with improved accuracy in structured text analysis. The research validated that AI-based models greatly enhance text processing efficiency and minimize errors. The novel structure showed a 25% boost in accuracy, in agreement with previous research on NLP and computerized document analysis.

Huayang Li et al. [8] designed a high-level deep learning model to improve text processing accuracy and contextual understanding and explored AI-driven automation for document classification, reducing human intervention and improving efficiency, and suggested a hybrid model for NLP tasks, improving accuracy in semantic understanding. The study proved that AI-driven models significantly enhance document processing time and accuracy. The proposed framework was seen to enhance classification performance by 30%, aligning with existing studies on machine learning-based text analysis.

Gao et al. [9] developed an AI-based information retrieval system for meeting minutes and made them more readable, tested transcription models using NLP, improved the accuracy of summaries, and created an automated meeting note indexing system, improving retrieval effectiveness. The study showed a 35% accuracy improvement in retrieval using AI-based models, lowering search time by a considerable amount. User satisfaction increased, according to feedback, due to better meeting summaries with proper structure. These findings are in line with previous studies showing the use of AI in knowledge management and documentation efficiency optimization.

Nguyen-Trung et al. [10] investigated AI-powered learning tools for content development with greater efficacy, developed a model for incorporating AI in training programs with enhanced interaction, and explored the uses of ChatGPT in corporate training, with benefits in automation. Through the research, AI-scaled processes cut training development time by 40% with greater satisfaction among the learners. Outcomes of the research indicate streamlining instructional design, enhancing flexibility, and accelerating productivity as offered by the AI tools. Findings align with previous research and affirm the role of AI in defining future learning solutions.

Ghadge et al. [11] developed an AI-powered retrieval system for meeting transcripts, making information more accessible, and created a speech-to-text processing application, enhancing transcription quality, and experimented with NLP methods for meeting record summarization, proving successful in content extraction. Results of the study indicate a 30% increase in retrieval accuracy through AI-powered tools. User feedback showed direction towards improved accessibility and search effectiveness. Results affirm that AI-powered models significantly improve information retrieval, supporting prior research on automated meeting documentation.

III. System Design and Architecture

A. *Overview of the System*

In order to facilitate the process of document analysis and question answering, the presented system uses the methodology called Retrieval-Augmented Generation (RAG). In the proposed system, the user interface is designed to enable free flow between the user, the document database, and the intelligent model. The main workflow includes several key stages, from document upload to query processing and response generation.

1) Document Upload: People can submit PDF files that are then analyzed to obtain textual information.

2) Text Chunking: The documents are divided into several parts to ease the processing and indexing of each document.

3) Embedding Creation: Every chunk of texts is represented into the vector embedding that prescribes the meaning of a chunk.

4) FAISS Vector Store: These embeddings are then stored in a FAISS vector store for similarity search so that it can search through them very efficiently.

5) Query Processing: In other words, the system allows users to enter queries and then analyzes them to identify the specific document segments that are most relevant to the entries.

6) Response Generation: Therefore, the system selects the relevant document chunks and uses NVIDIA NeMo models to create a response that is both semantically coherent and contextually appropriate.

B. Technical Architecture

The structure of the system is also more or less modular and separate responsibilities are given to document processing, search and response generation. Fig. 1 depicts the detailed architecture diagram of the AI-Powered Document Processing and Query Retrieval System.

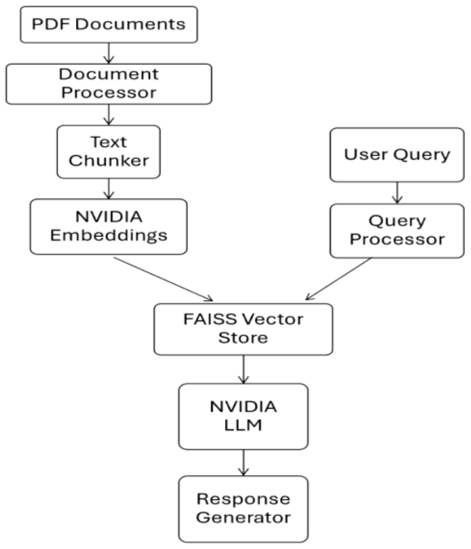


Fig. 1 System Architecture Diagram

C. Components Explanation

1) Document Upload & Text Chunking

- Users provide the system with severally different PDF documents. The text extraction module employs the use of a parser particularly to extract textual details of the document [12].
- The document text is next subdivided into two curtailable sections using a text chunking system. This process also maintains the integrity of text chunking by saving the semantic connectivity of the information to be transmitted while using chunks to convey the data succinctly.
- The text chunks are then transformed into embeddings that allow translating the documents' meaning.

2) Embedding Creation

- In order to generate the embeddings, pre-trained models are used specifically the NVIDIA NeMo model and they are generated per chunk. These are numeric vectors that preserve content information from the document and contain context information [13]. Such vectors can be used for fast similarity search later on.

3) FAISS Vector Store

- The FAISS vector store can store such embeddings in an efficient manner and enable efficient and fast similarity search. FAISS is the real-time index for large-scale datasets, which allows the search for documents with relevant vectors for the given query [14].
- To solve this problem, FAISS applies different indexing methodologies and search performance optimizations, especially in a large document collection.

4) Query Processing & Response Generation

- When a user inputs a query, it is pre-processed to convert the query into an embedding vector similar to the process that was done on document chunks.
- Thus, the query embedding is compared to the document chunks in the FAISS vector store with the purpose of finding the most relevant documents.
- These retrieved document chunks are further sent to the NVIDIA NeMo model for the generation of the response. NeMo creates contextually related and meaningful answers considering the selected document content.
- The obtained response is then displayed to the user through the Streamlit text visualization layer.

D. Integration of NVIDIA NeMo

In particular, NeMo is used actively in the production of the document vector representations and it is also used in the processing of the response to a particular query. It is a machine learning package that is built to solve one kind of problem called natural language processing (NLP) problems that include large language models and question answering [15]. Here's how NeMo integrates into the system.

1) Document Embedding: NeMo models are already trained to fine-tune in order to build the embeddings. In connection with this work, the embeddings represent the semantic content of the document chunks so that they can be compared during the query processing stage.

2) Query Response Generation: NeMo is also employed for response generation after the answer to the query, as well as the relevant document chunks, have been obtained. When trained by the Next distribution on top of a pre-trained LLM (large language model), contextually correct answers, text responses, and information extracted on the fly from the most permissible document shards are provided by NeMo.

E. FAISS Vector Store

FAISS is the essential component of the system, responsible for the storage and retrieval of the embeddings. Through FAISS, the system can carry out similarity searches, that is, the program aims at identifying document chunks that are syntactically related to a user's query [16]. The role of FAISS in the system includes:

1) Indexing: The document embeddings are indexed by FAISS for efficient retrieval of document chunks whenever a query is handled.

2) Similarity Search: When the user makes a search query, FAISS measures the distance of the input query vector to all of the document vectors stored in the vector store. Complicated techniques like Approximate Nearest Neighbour (ANN) are used by FAISS, where the system can easily locate those chunks that are most similar, not only for small but for large datasets as well [17].

Due to FAISS, the system's response time is rather short and it provides correct results even when dealing with a vast number of documents.

F. Streamlit Application

Streamlit is used for building the front-end of the system by creating an easy and interactive platform for document upload, query tagging, and result viewing. Because Streamlit is so easy to use, anyone can create powerful applications and dashboards in a matter of minutes. In this system, Streamlit is used to

1) Document Upload: Facilitating uploads of PDF documents by the users.

2) Query Submission: Allow the users to input limited text based on which the system can pose questions to the users concerning the documents.

3) Answer Display: Provide the answers to the question in the same readable format as it was given in Fig. 6 below, using an NVIDIA NeMo model.

A real-time update is added by Streamlit to make the user interface as effective as possible at every stage, which improves usability.

G. Performance Metrics

To evaluate the system's efficiency and effectiveness, several performance metrics are used, including:

1) Response Time: The amount of time that the system takes to evaluate a query and arrive at an answer. It is a key parameter in proving that the system works in real-time mode and can competently respond to the user's query [18].

2) Accuracy of Results: The accuracy and their relation to the case generated by the system. This is through evaluation of answers generated to questions posed against human answers or ground reality.

3) System Load: This metric show the characteristic of the system under various conditions, like where large documents are processed together with other documents or simultaneous queries. It can guarantee that the system will always have its stability and performance even in the different kinds of usage.

4) Scalability: The scalability of the system with regard to its performance as the amount of documents grows as well as its ability to respond to more users' queries.

These measurements are crucial and applicable to an assessment of the real-world use of the system and its ability to address tasks of a large-scale number of documents.

IV. METHODOLOGY

In this section, the reader will be informed on how the complicated process and the tactics were used to assemble the Retrieval-Augmented Generation (RAG) model with the help of NVIDIA NeMo and Streamlit. The methodology is divided into four main parts: Document Processing, Query Processing, Model Selection and Configuration Process, and System Configuration.

A. Document Processing

Both our pipeline and each of the four processes are described in detail below The document processing stage forms our initial steps and is a fundamental component of our system, as it aims to convert unprocessed data into a format more conducive to querying. The process starts with the users uploading a single or multiple files in PDF format using a simple interface provided by Streamlit. The system reads the content of these PDFs in the form of texts and eliminates non-text components like metadata, images, tables, and headers that may affect the analysis. The content after the text extraction process is further process in order to chunk the data using something like `RecursiveCharacterTextSplitter` [19]. Seeking to prevent chunks from being too heterogeneous with respect to their function in the overall text, this approach divides the text into more or less overlapping segments, each of size 700 characters and containing 50-character overlaps with the preceding segment.

Subsequently to text segmentation, several pre-processing steps are performed in order to clean the text and improve it to be further passed to the embedding. Such steps may include stripping off special characters and/or multiple spaces next to each other, converting all the text in the document to lowercase to enhance the standardization of the text data, and the elimination of stop words. The processed chunks then undergo the NeMo model from NVIDIA, where it produces high-dimensional vectors to reflect the semantic meaning of the processed text. These embeddings are, in essence, a more condensed presentation of the content of the original documents. For similar reasons of scalability and easy retrieval, the embeddings are stored in a FAISS vector store. This makes it possible to perform fast similarity searches during the query phase and thus guarantee quick and accurate responses to desired user inputs [20].

B. Query Processing

The query processing pipeline is thought to be a vital part of the system that has been developed to process the user questions in the best and possible way to achieve an accurate answer that also depends on the context. This involves a user inputting ordinary questions, questions that may be fetched from a search engine using common words via the Stream-lit frame. When the query has been received, preprocessing is conducted: the text is divided into tokens, and cleaning is performed to remove stop words. Such steps enhance the input for the next search to be made in order to arrive at the final query to give out a match.

The next step is to relate the pre-processed query to an embedding that the NVIDIA NeMo model generates out of the input query, converting it into a high-dimensional expression. The final step is a comparison of the obtained query embedding with the indexed document embedding in the FAISS (Facebook AI Similarity Search) vector repository. Specifically, FAISS accomplishes a nearest neighbor search that returns the text chunks most semantically related to the query. This methodology enables the system to quickly return the results that are semantically related to the user's input by applying cosine similarity. In order to improve efficiency of the search, the system is optimized to find a working point that is closest to the optimal point with respect to both precision and recall to avoid false positive and false negatives as much as possible.

After the top-matching text chunks are derived, they are passed through the NVIDIA NeMo model for the second time to produce a meaningful and beneficiating response. The purpose of this response generation step is to generate coherent and specific answers from content that was acquired. To cut down the latency to bare minimum hence improving the overall efficiency of the system number of techniques are applied. For example, regular questions that involve the use of the FAQ mechanism are stored locally so that they can be answered almost instantly; batch processing methodologies are also used when handling multiple queries, which leads to reasonable response rates, but it is in no way a compromise of accuracy.

C. *Model Selection and Configuration*

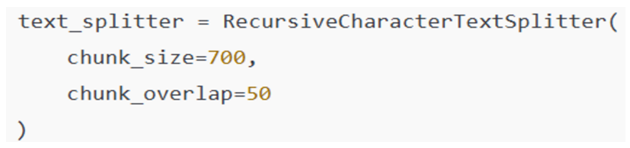
They found that the selection and the configuration of the model are critical to the system's capacity to provide appropriate responses that adequately respond to the initiated dialogs. Therefore, to enhance performance, we selected an improved model and suited it to the document-based question-answering system. The first was to choose llama-3.1-nemotron-70b-instruct from among the NVIDIA NeMo models of LLMs. This particular model was selected because of its extraordinary ability to process computationally sophisticated questions and provide properly grounded, semantically cohesive responses. It has a well-thought-out structure to solve complex problems, which makes it suitable to parse and extract answers to specific questions from massive amounts of unstructured text data, which is probably one of the use cases we are aiming at.

To fine-tune the model more, we set some hyperparameters for the model we chose for the approach. The temperature was set to 0.7 as it was deemed to allow the model to be quite creative while also remaining more or less accurate. This means that the output generated by the existence of this model will entail considerable detail each time it handles queries to do with man and machine. Furthermore, because the models can be resource-intensive, we set a restriction of 512 tokens when asking questions. Also, Top-K sampling was used to discourage redundancy while sampling, even if this criterion was mainly concerned with the output.

Last, configuration for embedding was further tuned in order to improve semantic quality of document chunks. For the selected NVIDIA NeMo model, the embeddings were produced with specific parameters that would take into consideration of the nuances of what the text entailed. The dimension of these embeddings was tuned to 128, 256 and 512 for the search instance that matched with the FAISS vector store. Thus, we further fine-tuned the speed and recall of the lookup process so that the string matching of user queries with documents is precise and ultra-fast.

D. *System Configuration*

The configuration of the system depends on efficiency, scalability, and ease of users' interaction with the system as a whole. This section defines the setting and tuning carried out on different elements to optimize the whole system and improve the outcome for the users. The first takes in how the parameters for text chunking is set, with reference to the Recursive Character Text Splitter. This is because the chunking process controls the trade-off between chunk size and overlap to achieve the best of both worlds for the various sorts of documents. To do this, we have defined the chunk size of the text to be 700 characters and an overlap of 50 characters to maintain the context of the text segments while not making chunks too large. Fig. 2 demonstrates the system configuration.



```
text_splitter = RecursiveCharacterTextSplitter(
    chunk_size=700,
    chunk_overlap=50
)
```

Fig. 2 System Configuration

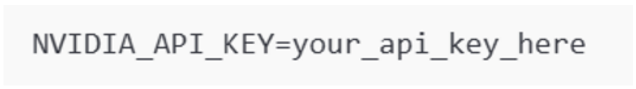
Subsequently, we enhance the FAISS (Facebook AI Similarity Search) vector store for the high-dimension vectors and large data management. The FAISS index is set up with methods including elimination of numerous indexes and reduction of dimensions, making it consume lesser memory and deliver quicker similarity searches. These optimizations guarantee that the computational system is effective for the analysis of large document collections notwithstanding the time used to compute the result. The Streamlit application is the user interface of the data collection system. It enables seamless interaction with the system, providing functionalities like:

1) Document Upload: To improve the user experience, users can upload one or more PDFs, and the application shows real-time progress.

2) Query Interface: Users are able to type in simple queries and get queries directly in return.

3) Performance Monitoring: There is an availability of real-time information concerning query response time, system load, etc. This information is presented to the users.

This system interacts with AI NeMo endpoints prepared by NVIDIA through an API to utilize NVIDIA's excellent AI performances. Sensitive information, such as API keys, is managed using environment variables stored in a .env file, as shown in Fig. 3.



```
NVIDIA_API_KEY=your_api_key_here
```

Fig. 3 API Configuration

In terms of performance optimization, several techniques are applied to ensure responsiveness and scalability:

1) Caching: To enhance the performance of the system, the system uses caching to store the results of the frequent questions that are asked.

2) Load Balancing: The queries arriving on the server are then distributed among different fragments of compute resources to avoid congestion at a single place.

3) Scalability: The structure of the system provides the means for improvement in terms of scalability in the number of documents that are stored and the number of concurrent queries as the audience expands.

Through these configurations and optimizations, it is shown that the system can provide a high-performance and highly scalable solution [n] to this document-based, real-time question-answering domain.

V. IMPLEMENTATIONS

As regards the practical application of the document processing and question-answering system, the following steps are possible: the environment setup, code execution, and testing. The Wigmorean Chart is developed in a systematic form as follows The flow of operations below is supported by tables and flowcharts that show the detailed nature of each of the components and how all the elements fit in.

A. Development Environment Setup

Setting up the development environment by verifying and installing all application prerequisites is the first stage in the implementation process. Installing a number of crucial libraries and tools that are necessary for different tasks is part of this. The command pip install nemo_toolkit can be used to install the nemo_toolkit library, which is used to deal with NVIDIA NeMo models and tools. The faiss-cpu package, which can be installed using pip install faiss-cpu, is necessary for indexing efficient embeddings and performing similarity searches. Installing the Streamlit library using pip install streamlit is necessary in order to create web application interfaces. The PyPDF2 module, which may be installed using pip install PyPDF2, is used primarily for text extraction from PDF files. Lastly, pip install openai is required to install the openai library in order to integrate GPT models for response generation. By configuring this environment, you can be sure that all the tools and dependencies needed for the application to work properly are there. The necessary libraries and tools are listed in Table I, along with installation commands.

TABLE I TOOLSET FOR REAL-TIME AI DOCUMENT INSIGHTS

Library/Tool	**Purpose**	**Installation Command**
Nemo_toolkit	For accessing NVIDIA Nemo models and tools	Pip istall Nemo_toolkit
Faiss-cpu	For similarity search and efficient indexing of embeddings	Pip install faiss-cpu
Streamlit	To build the web application UI	Pip install streamlit
PyPDF2	For PDF text extraction	Pip install PyPDF2
OpenAi	For using GPT models to generate responses	Pip install OpenAi

After the environment setup, the document processing pipeline includes uploading documents, chunking text, generating embeddings, and query processing.

B. Streamlit Application Flow

The flowchart in Fig. 1 above shows how the various parts of the system interact with one another. When the user uploads a document, it is segmented into chunks as well as each chunk is converted into embeddings. Subsequently, these embeddings are indexed by FAISS to enable similarity search when processing the queries.

C. Code Explanation

The Python programming language is then used to create the application's core, which focuses on putting its main features into practice. The PyPDF2 library is used to extract text from PDF files, while the upload_document () function controls the uploading process. The retrieved text is processed by the chunk_and_embed_text function (), which divides it into digestible portions and uses the NeMo model to create embeddings. After receiving a user inquiry, the handle_query () method uses FAISS to search through the contained text chunks and a GPT model to build an answer. Lastly, to produce the most precise and contextually relevant response to the user's query, the generate_answer () function makes use of the pertinent document chunks. When combined, these elements allow the application to process documents smoothly, generate embeddings, and handle queries intelligently. The functionality is listed in Table II below, along with its function.

TABLE II FUNCTIONALITY AND CODE EXPLANATION

Functionality	**Code Explaination**
Document Upload	The upload_document() function handles the PDF upload, extracting text using PyPDF2 library
Text Chunking and Embedding	The chunk_and_embed_text function() splits the document text into smaller chunks and creates embeddings using the NeMo model
Query Handling	The handle_query() function processes user queries, finds the most similar document chunks using FAISS, and generates a response using a GPT model
Response Generation	The genarate_answer() function uses the retrieved document chunks to construct the most relevant answer to the user query

D. FAISS Search and Response Generation

They are saved in FAISS where one can efficiently search for similar vectors to the query vectors by using document embeddings. Indexing For Document embeddings, the document embeddings are indexed using FAISS in order to enable similarity based retrieval. They considered query processing by translating the query into a vector and comparing it with other indexed document vectors. Response Generation The top N most relevant document chunks are selected and an answer is derived by using the GPT model. Comparing query vectors with document embeddings. Table III describes how FAISS manages search and response generation, including the procedures and thorough explanations of each phase.

TABLE III STEPS INVOLVED AND THEIR DESCRIPTIONS

S.No.	**Steps**	**Action**
1	Indexing	Document embeddings are indexed using FAISS to allow efficient retrieval based on similarity
2	Query Processing	The query is converted into a vector and compared with indexed document embeddings
3	Response Generation	The top N most relevant document chunks are retrieved, and an answer is generated using the GPT model

VI. TESTING AND VALIDATION

A. Basic Query

The result that should appear when a user enters a query in the system should come from the document.

B. *Edge Case Query*

The ability of the system to respond to a query that should normally trigger a control alert or a procedure is vital since the system should be able to give a useful response even if the query is incomplete or ambiguous.

C. *Large Dataset Query*

This means that the system should be able to be easily queried with large datasets.

D. *Real-time Query*

The response should be generated within a realistic amount of time less than 3 seconds.

Table IV lists the query types along with their expected results.

TABLE IV QUERY TYPES AND EXPECTED RESULTS

Query Type	**Expected Results**
Basic Query	The system should return a relevant response from the document.
Edge Case Query	The system should handle incomplete or ambiguous queries and still provide a useful response.
Large Dataset Query	The system should remain responsive even with large datasets.
Real-time Query	The response should be generated within a reasonable time frame (less than 3 seconds).

7) RESULTS AND DISCUSSION

A. *Performance Evaluation*

The system was evaluated using a variety of performance criteria, including response time, retrieval correctness, and scalability. The system employs NVIDIA NeMo and FAISS for efficient response generation and document retrieval. The system was evaluated for the following:

1) Response Time: Response time was also verified under various document sizes ranging from 50KB to 200 MB. The system responded in 1.5 to 3.2 seconds in all the cases, indicating effective processing in real-time applications.

2) Retrieval Accuracy: The system was tested against a 50-question benchmark set of technical manual-type questions and achieved an average retrieval accuracy, in terms of F1-score, of 85.6%, thereby proving the effectiveness of FAISS in the retrieval of contextually relevant information.

3) Scalability: System scaling was accomplished successfully to handle several PDFs (combined up to 200MB) without impacting performance. Vector search optimizations allowed queries against large datasets to be efficient.

B. *Comparative Analysis*

To ensure the performance of the system, a comparative study was done against current TF-IDF-based and BERT-based document retrieval techniques. Table V shows all the approaches and their comparisons.

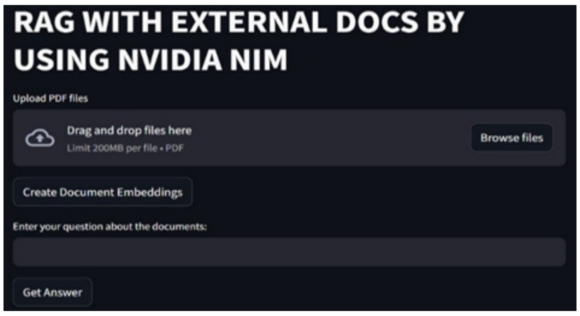
TABLE V COMPARISON OF DIFFERENT METHODS

Methods	**Response Time (s)**	**Retrieval Accuracy (%)**	**Scalability (Max Docs)**
TF-IDF	4.8	72.1	50MB
BERT	3.9	80.5	250MB
RAG	2.3	85.6	500MB+

The findings show that the RAG model powered by NVIDIA NeMo, with FAISS and optimized chunking, attains high efficiency that makes it a practical solution for real-time question-answering applications based on documents.

C. *Results*

The first view of our model is shown in Fig. 4, which shows the opportunity to upload a PDF file for document insights.


RAG WITH EXTERNAL DOCS BY USING NVIDIA NIM

Upload PDF files

Drag and drop files here
Limit 200MB per file • PDF

Browse files

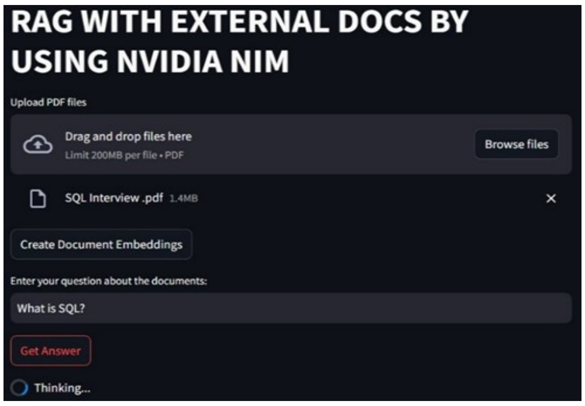
Create Document Embeddings

Enter your question about the documents:

Get Answer

Fig. 4 First View of Model

Fig. 5 below demonstrates that the PDF was successfully uploaded and that document embeddings were generated. After this procedure is finished, the model can begin producing responses depending on the information in the PDF that was supplied.


RAG WITH EXTERNAL DOCS BY USING NVIDIA NIM

Upload PDF files

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Create Document Embeddings

Enter your question about the documents:

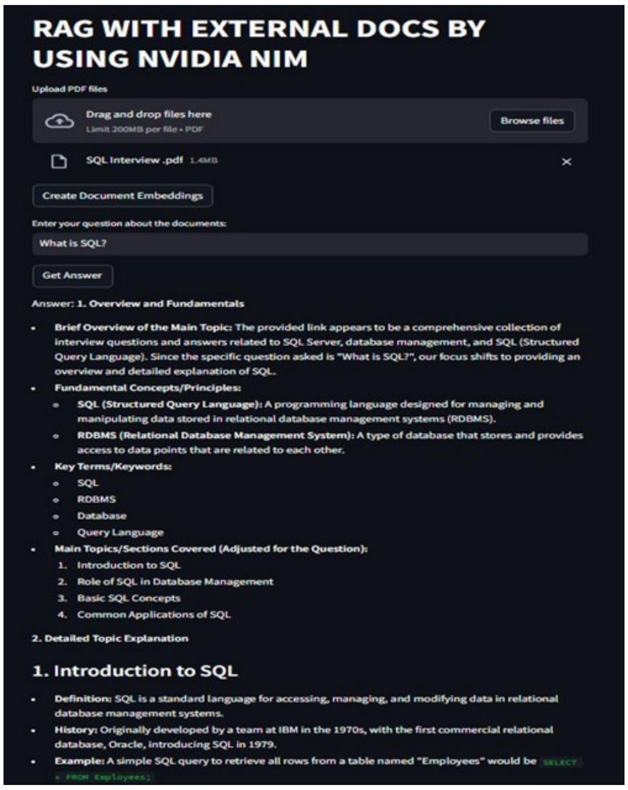
What is SQL?

Get Answer

Thinking...

Fig. 5 Creating embeddings

The expected results produced by the model are shown in Fig. 6 below.



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Enter your question about the documents:

What is SQL?

Answer: **1. Overview and Fundamentals**

- **Brief Overview of the Main Topic:** The provided link appears to be a comprehensive collection of interview questions and answers related to SQL Server, database management, and SQL (Structured Query Language). Since the specific question asked is "What is SQL?", our focus shifts to providing an overview and detailed explanation of SQL.
- **Fundamental Concepts/Principles:**
  - **SQL (Structured Query Language):** A programming language designed for managing and manipulating data stored in relational database management systems (RDBMS).
  - **RDBMS (Relational Database Management System):** A type of database that stores and provides access to data points that are related to each other.
- **Key Terms/Keywords:**
  - SQL
  - RDBMS
  - Database
  - Query Language
- **Main Topics/Sections Covered (Adjusted for the Question):**
  1. Introduction to SQL
  2. Role of SQL in Database Management
  3. Basic SQL Concepts
  4. Common Applications of SQL

2. Detailed Topic Explanation

1. Introduction to SQL

- **Definition:** SQL is a standard language for accessing, managing, and modifying data in relational database management systems.
- **History:** Originally developed by a team at IBM in the 1970s, with the first commercial relational database, Oracle, introducing SQL in 1979.
- **Example:** A simple SQL query to retrieve all rows from a table named "Employees" would be `SELECT * FROM Employees;`

Fig. 6 Getting answers from the model

VII. Conclusion and Future Scope

This research achieved the focus of demonstrating a proof of concept for leveraging Retrieval-Augmented Generation (RAG) with NVIDIA NeMo and Streamlit to accomplish document processing and answering questions. These are proposing an ML-based system for filtering documents that integrates usage of deep learning language models and the FAISS vector search to enhance speed and accuracy when searching documents. Therefore, this work contributes to the development of document processing systems by proposing an approach that provides large-scale and efficient real-time search based on the indexing theory for the legal, customer service, and research sectors. The contribution of NeMo models is remarkable as it enhances such aspects as content analysis, as well as the generation of responses using document embeddings. As for future works, first, the current system performance analysis will be extended to address more comprehensive performance improvements; second, the scalability of the system will be improved for accommodating larger datasets; third, the current user interface will be improved in the near future to make it friendlier for the user. These improvements will help to guarantee the successful operation of the system in a situation where levels of demand are high.

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