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Reasoning Engine with Pre-Trained LLMs: An Operation GPT

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Abstract: ***Recent developments in artificial intelligence, particularly with large language models (LLMs), have enabled machines to comprehend, generate, and respond to human language with unmatched precision. Nevertheless, most of these models are cloud-based and unsuitable for scenarios where data confidentiality, offline functionality, and immediate document comprehension are vital. This paper introduces Operation GPT, a robust, privacy-focused, and locally deployable system that allows users to interact intelligently with domain-specific documents using advanced language models.***
Operation GPT facilitates offline LLM inference by integrating Mistral 7B, Retrieval-Augmented Generation (RAG), and Ollama. Document indexing is performed using FAISS, while LangChain is employed to link retrieval and generation tasks. A user interface built with Gradio and secure backend services powered by Flask ensure a fluid and protected user experience.
The system permits users to upload extensive technical documents and obtain highly pertinent, context-aware responses through a chat-like interface. The RAG mechanism enhances factual correctness by grounding responses in document content, while the local deployment model upholds data security. Tests indicate that Operation GPT is efficient, lightweight, and practical for implementation in knowledge-intensive sectors where accuracy and privacy are essential.
Keywords: Large Language Models,Mistral 7B,RAG,model,Ollama, Gradio,Flask

I. INTRODUCTION

Operation GPT is a groundbreaking tool created to assist users in swiftly and precisely locating answers within Operation documents. This application utilizes a mix of Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and a tailored chat interface to facilitate information retrieval that is straightforward, effective, and dependable.
Constructed on the Private GPT framework, Operation GPT incorporates cutting-edge LLMs such as Mistral 7B and employs RAG to guarantee the application can comprehend and formulate correct responses to user inquiries. Furthermore, Ollama is utilized to boost the application's language comprehension and response precision.
The user interface is crafted with Gradio, offering a straightforward and user-friendly platform for engagement. Users are able to upload documents, input queries, and obtain accurate answers in real-time. A Flask-based login authentication system provides secure access and safeguards user information.

A. Large Language Models(LLMs)

Humans possess an intrinsic capability to acquire and utilize language, which starts in early childhood and develops as time progresses. LLMs are advanced AI systems crafted to execute a variety of language-centric tasks such as translation, [1], [2].summarization, and conversational engagements.[3],[4], These models are trained on extensive datasets and employ sophisticated architectures to comprehend and produce human-like language[5][6].

1) History and Evolution

LLMs originated with statistical approaches, such as those suggested by Jelinek (1998) and Rosenfeld (2000). A significant transformation took place with the emergence of neural networks, including the neural probabilistic language model introduced by Bengio et al. (2000).[7][8].Subsequent innovations like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models enhanced the ability to manage sequential data [11],[12].
The launch of transformer-based models, especially "Attention is All You Need" by Vaswani et al. (2017), transformed the discipline by improving context understanding. BERT (Bidirectional Encoder Representations from Transformers), launched by Devlin et al. (2018), provided major advancements in contextual interpretation.

- Architecture and Training: LLMs mainly employ transformer architectures featuring self-attention mechanisms, which facilitate parallel processing of inputs and improved modeling of data dependencies.

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The training procedure involves pretraining on vast textual corpuses, followed by task-specific fine-tuning to align with practical applications.

Recent innovations target the expansion of context windows and the optimization of resource utilization for enhanced scalability[13],[14],[15].

2) Applications

LLMs have widespread applications in:

- Machine Translation: Providing precise translations by grasping linguistic subtleties [16].
- Conversational Agents: Empowering chatbots like ChatGPT for fluent and human-like dialogues [17].
- Content Generation: Producing relevant text for articles, narratives, and marketing material [18].
- Medical and Educational Fields: Evaluating records, supporting diagnostics, delivering personalized education, and interactive learning resources [19],[20].

a) Challenges and Limitations

Despite their capabilities, LLMs encounter several challenges:

- Ethical Concerns: Issues surrounding bias, fairness, and content safety [21],[22].
- Interpretability: Comprehending model decision-making processes [23].
- Resource Demands**:** Significant computational and environmental impacts [24].
- Robustness: Guaranteeing consistent, reliable outputs across diverse inputs [25].

b) Types of LLM Models

- Autoregressive Models: Create text token by token (e. g. , GPT, BERT) [49].
- BERT-base and BERT-large: A bidirectional model utilized in sentiment analysis and question answering [27],[28].
- Mistral-7B: An efficient 7-billion-parameter model featuring sparse and dense layers. Conditional Generative Models: Generate text based on designated prompts [31].
- ERNIE: Incorporates knowledge graphs to enhance semantic comprehension. XLNet: Builds upon BERT with autoregressive features [30].
- GPT-3 and GPT-4: High-capacity models suited for sophisticated AI tasks [29].

Usage in Operation GPT

In the Operation GPT setting, Mistral 7B serves a pivotal function in document analysis and response generation. Uploaded information is modified to comply with privacy guidelines and is processed by Mistral 7B for semantic interpretation. The system ensures the accuracy of outputs through immediate verification and functions entirely offline to preserve data privacy.

Operation GPT undergoes routine maintenance for optimal performance, ensuring the solution remains lightweight, efficient, and dependable for professional applications.

B. Mistral7B

In the fast-evolving domain of Natural Language Processing (NLP), there is a need to balance model performance with computational efficiency. Mistral 7B is a revolutionary solution that employs cutting-edge methods to deliver superior performance while minimizing computational costs.

Mistral 7B utilizes grouped-query attention (GQA) [51] and sliding window attention (SWA) [52,53]. GQA greatly speeds up the inference process and lowers the memory requirements during decoding, enabling larger batch sizes and thus greater throughput, which is vital for real-time applications. Moreover, SWA is developed to manage longer sequences more adeptly with lower computational costs, thereby addressing a frequent limitation in LLMs. These attention mechanisms together enhance the performance and efficiency of Mistral 7B.

Mistral 7B is made available under the Apache 2. 0 license. This release comes with a reference implementation that simplifies deployment on either local machines or cloud platforms like AWS, GCP, or Azure using the vLLM [54] inference server and SkyPilot.

1) Sliding Window Attention: SWA allows attention to extend beyond a set window size (W), permitting each hidden state to focus on a broader array of input tokens. By integrating modifications influenced by FlashAttention [55] and xFormers [56], Mistral 7B secures an impressive 2x speed enhancement compared to traditional attention methods.
2) Rolling Buffer Cache: To improve memory efficiency, Mistral 7B incorporates a Rolling Buffer Cache system. This innovative strategy guarantees effective storage of cache values, with older values replaced as new ones come in. Consequently, Mistral 7B realizes a significant decrease in cache memory usage without sacrificing the quality of the model.
3) Pre-fill and Chunking: Mistral 7B features a pre-fill approach along with chunking techniques to boost efficiency in sequence generation. By pre-filling the cache with tokens related to prompts and breaking down lengthy prompts into smaller, manageable segments, Mistral 7B optimizes the token prediction process while safeguarding contextual coherence.

Mistral 7B signifies a notable achievement in the development of language models, delivering an appealing balance between performance and efficiency. Through its novel architecture, attention mechanisms, and strategies for sequence generation, Mistral 7B establishes a new benchmark for large-scale language models. By providing researchers and practitioners with accessible and efficient tools, Mistral 7B lays the groundwork for revolutionary progress in Natural Language Processing.

C. OLLAMA: Optimized Learning Language Model Applications

OLLAMA embodies a strategic use of LLMs in the field of language learning. By utilizing the extensive linguistic abilities of LLMs, OLLAMA seeks to deliver personalized, interactive, and effective language learning experiences. The fundamental elements of OLLAMA in LLMs comprise:[47]

1) Personalized Tutoring Systems: Personalized tutoring systems leverage the strengths of Large Language Models (LLMs) to create adaptable learning environments customized to the specific needs of learners. These systems surpass traditional one-size-fits-all methods by supplying tailored feedback, modifying difficulty levels according to learner progress, and delivering bespoke learning materials that align with each student's distinct learning style and pace. By utilizing the natural language processing capabilities of LLMs, personalized tutoring systems can evaluate learner interactions and adjust the learning experience in real-time, encouraging deeper engagement and enhancing overall learning results.
2) Real-time Language Practice: The deployment of conversational agents powered by LLMs facilitates the establishment of immersive and engaging language practice environments. These agents involve learners in real-time conversations, providing the opportunity to practice speaking and listening skills in authentic contexts. By mimicking natural conversations, these agents offer learners valuable chances to apply language skills in practical situations, receive immediate feedback, and refine their communication skills. Furthermore, the responsive nature of LLM-based conversational agents ensures that practice sessions are customized to individual learner proficiency levels, maximizing efficiency and fostering confidence in language acquisition.
3) Grammar and Vocabulary Enhancement: LLMs are crucial in helping learners master grammar rules and broaden their vocabulary. Through interactive exercises and immediate corrections, LLM-powered platforms deliver targeted feedback on grammatical mistakes and vocabulary application, assisting them in pinpointing areas for improvement and reinforcing language skills. By exploiting the extensive knowledge base and contextual understanding abilities of LLMs, these platforms offer personalized learning experiences that address learners' specific language objectives and preferences, promoting consistent growth and progress in grammar and vocabulary capabilities.
4) Contextual Learning: Contextual learning utilizes the contextual understanding capabilities of LLMs to furnish learners with relevant examples and applications of language concepts across various contexts. By showcasing language concepts in real-world situations, LLM-powered learning platforms enhance comprehension and retention, allowing learners to grasp how language is employed differently across contexts and circumstances. Through contextual learning experiences, learners attain a richer understanding of language subtleties, cultural nuances, and practical usage, ultimately improving their overall language proficiency and communicative ability.

D. Integration of Mistral 7B in OLLAMA

The incorporation of the Mistral 7B model into OLLAMA frameworks improves the overall efficiency and effectiveness of language learning applications. By utilizing Mistral 7B's features, OLLAMA can provide more precise and responsive language learning tools. Specific applications encompass:

1) Interactive Language Tutors: Employing Mistral 7B to drive interactive language tutors that can participate in dynamic conversations with learners, delivering immediate feedback and corrections.

2) Adaptive Learning Platforms: Merging Mistral 7B into adaptive learning platforms that tailor the learning experience according to the learner's progress and performance.

3) Language Assessment Tools: Creating sophisticated language assessment tools that utilize Mistral 7B to accurately gauge learners' proficiency and provide detailed insights into their strengths and improvement areas.

The integration of OLLAMA and the Mistral 7B model signifies a major breakthrough in language learning. By leveraging the capabilities of advanced LLMs, OLLAMA offers creative solutions that improve the language learning journey, making it more tailored, efficient, and impactful. The Mistral 7B model, known for its high precision and adaptability, is vital in unlocking the complete capabilities of OLLAMA, setting the stage for the forthcoming wave of language learning applications.

E. Retrieval-Augmented Generation (RAG)

The RAG (Retrieval-Augmented Generation) model represents a robust framework utilized in tasks related to natural language processing, such as text generation. It is made up of three essential components: retrieval, analysis, and generation, each contributing significantly to the creation of high-quality outputs. This report will explore the various types of RAG models, their processes, and their use within a private GPT application at every layer.

RAG models operate by initially sourcing relevant documents from a knowledge base, examining these documents to extract or emphasize important content, and subsequently generating a coherent, contextually relevant response by integrating the retrieved information into the generative process.

This architecture facilitates:

Improved factual grounding in responses, Real-time updating of information without the need to retrain the base model, And scalable knowledge enhancement for diverse applications, including domain-specific assistants like Operation GPT.

In a private GPT application, RAG supports the development of efficient and precise document-level QA systems, particularly in critical environments such as space missions, where the exact retrieval of technical information is essential.

Retrieval-Augmented Generation architecture diagram

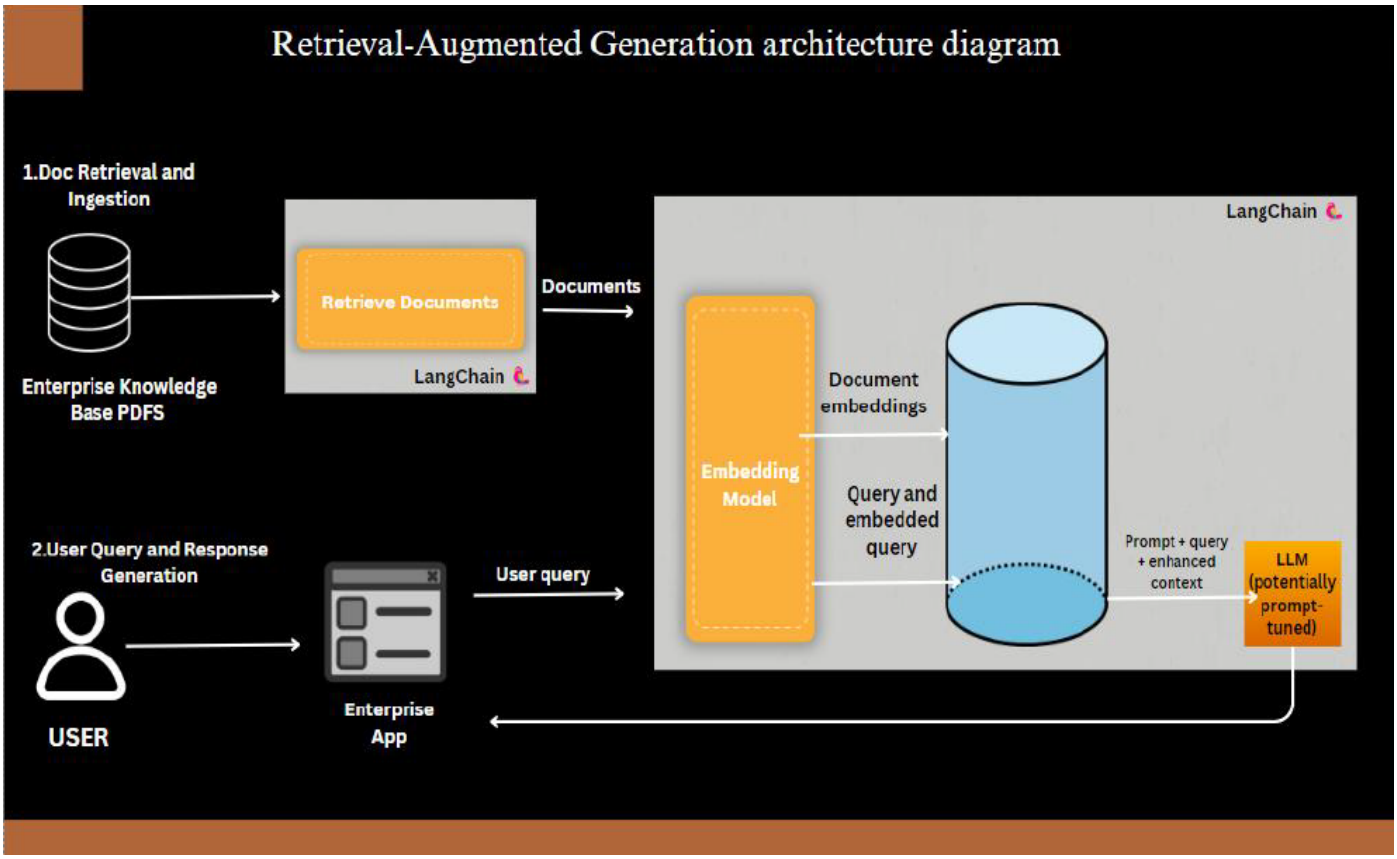


Fig 1 : Retrieval-augmented generation architecture diagram

F. Types of RAG Models

1) RAG for Fact-Driven Task: The Retrieval-Augmented Generation (RAG) model is highly efficient in tasks requiring factual accuracy, including question answering and summarization. By combining retrieval-based strategies with generative abilities, RAG ensures generated responses are not only contextually relevant but also factually accurate. This renders it particularly useful in scenarios where accuracy and correctness are paramount, enabling it to perform well in tasks requiring strong understanding and combination of factual information. [32]

2) RAG for Open-Domain Conversations: Particularly targeted at conversational agents, the RAG version tailored for open-domain conversations focuses on producing contextually relevant answers by leveraging large knowledge reservoirs. By making use of large-scale knowledge databases, RAG enriches the dialogue by providing informative and entertaining answers that showcase an in-depth understanding of the subject matter of the discussion. This places it as an excellent option for developing conversational agents that can participate in meaningful and informative dialog with users over a broad range of subjects and domains. [33]

3) RAG for Creative Content Generation: In the domain of creative writing and content creation, RAG is a model that has been specifically designed to focus on generating interesting and creative text based on given prompts. Through its use of generative capabilities supplemented by retrieval-based methods, RAG can produce creative and original content that attracts the attention of the audience. Whether it's about creating storylines, building engaging stories, or producing creative content, RAG offers an adaptable instrument for creative experts wishing to test the boundaries of content creation and storytelling. [34]

G. Steps of the RAG Model:

1) Retrieve:

- Input Processing: The RAG model starts off by pre-processing the input prompt or query and extracting important components like entities and keywords. Pre-processing helps in ensuring that the model pays attention to the most important aspects of the user's question.[35]
- Knowledge Retrieval: RAG next queries a massive knowledge base or search engine for retrieving useful ` 6 documentsor passages. This wide search assists the model in pulling complete information concerning the input query.[36] • Document Ranking: Lastly, RAG ranks the documents that are fetched concerning their relevance to the input. Through priori- tizing the most relevant sources, the model ensures its responses remain correct and contextually relevant.[37]

2) Analyze:

- *Semantic Understanding:*

The retrieved documents are analyzed to understand the context and meaning of thecontent.[38]

- Entity Recognition: Named entities and key concepts are recognized within the documents, facilitating contentunderstanding and relevance determination.[39]
- Contextual Embeddings: Text representations, like BERT embeddings, are calculated to extract the semanticcontext of the retrieved information[40].

- *Generate:*

- Content Synthesis: Using the retrieved knowledge and analyzed context, the model generates coherent and contextually relevant responses[41].
- Text Refinement: Post-processing is applied to generated text to improve readability and coherence[42].
- Output Selection: Output is chosen based on relevance, coherence, and other specified criteria[43].

(3) Extra Step (Private GPT Application Tailored)

Privacy Preservation: A crucial part of a private GPT application is the presence of privacy preservation measures that guarantee the confidentiality of user data. Such mechanisms keep the sensitive user data supplied under protection at the time of data processing and interaction with models. Methods like anonymization of data, encryption, and access control are utilized in order to eliminate unauthorized usage and data leakages. In addition to this, differential privacy techniques may be implemented to the training of the model in a way that the model can learn from data patterns without having access to specific user data. Through the combination of these privacy-protective measures, the application has strong security, fostered user confidence, and upholds compliance with data protection acts.

- *Mistral 7B Model Integration*

The Mistral 7B model, an efficient large language model, is integrated with the RAG model to enhance the quality and relevancy of answers. The RAG model handles retrieving and analyzing important information, while the Mistral 7B model excels at generating accurate and high-quality text based on that information.[48]

Application in Private GPT Layers:[46]

➢ **Input Layer:**

❖ •Retrieve: Initial input processing and keyword extraction.

❖ Analyze: Preprocessing of the input query for semantic understanding.

❖ Generate: Initial generation of responses based on input prompts.

➢ Knowledge Layer:

❖ Retrieve: Retrieval of pertinent documents or passages from the knowledge base

❖ Analyze: Semantic analysis and entity recognition in retrieved content.

❖ Generate: Synthesis of responses based on retrieved knowledge and context

➢ Input Layer:

❖ Retrieve: Choice of the most suitable response from the generated outputs.

❖ Analyze: Evaluation of generated responses for coherence and relevance.

❖ Generate: Final response refinement of the chosen response.

The RAG model offers an extensive framework for natural language processing tasks, with a structured strategy for information retrieval, analysis, and generation. Its integration in a private GPT application provides the system's capacity to produce correct, contextually appropriate responses in multiple use cases. Understanding the subtleties of every RAG element and its implementation at different levels allows developers to fine-tune the quality and efficiency of their NLP tools

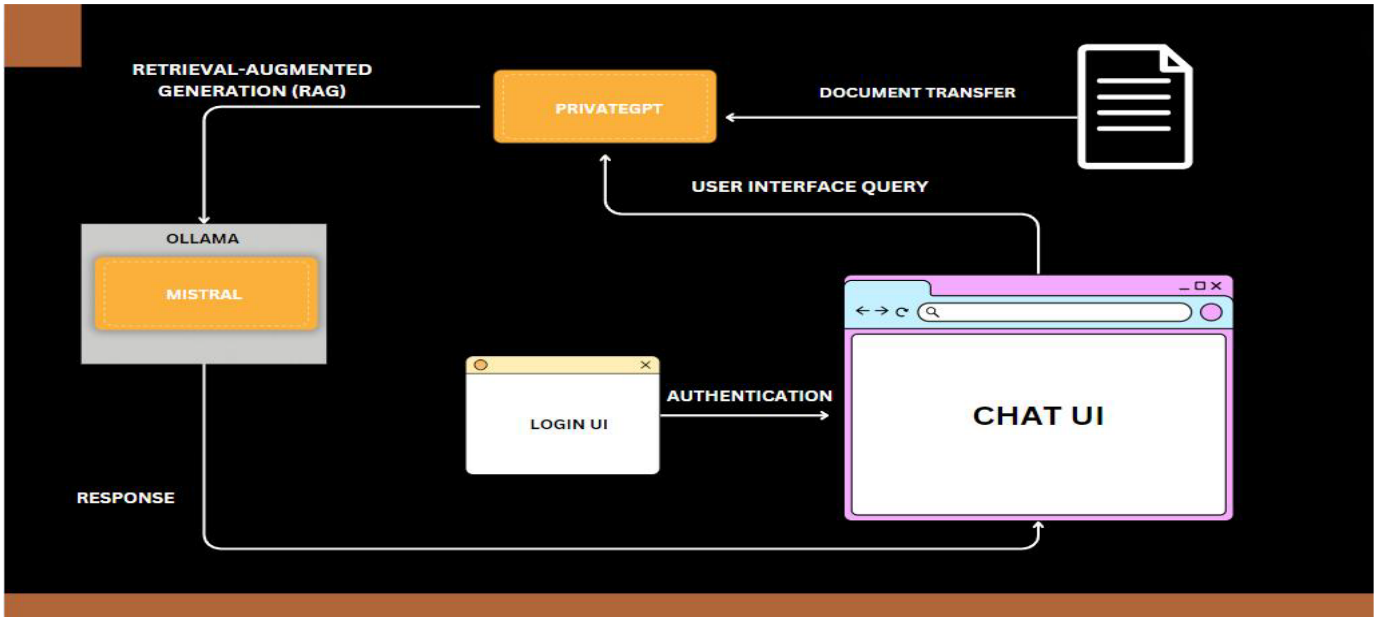


Fig 2 : Solution architecture

II. METHODOLOGY

The development of Operation GPT followed a modular, layered, and security-oriented approach, combining multiple open-source frameworks and models to build a powerful and user-friendly document reasoning engine. This section details the complete methodology, covering design decisions, implementation steps, and integration strategies used throughout the system's development lifecycle.

A. System Architecture Overview

Operation GPT is composed of three major layers:

1) Model Layer

2) Retrieval Layer

3) Application Layer

This separation of concerns ensured that each component could be developed and tested independently while contributing to a cohesive system.

B. Private GPT Framework Setup

The initial step involved configuring the Private GPT framework, a self-contained platform that supports offline document querying using LLMs. It was customized to support:

Local file ingestion (PDFs, text documents)

Vector-based indexing and storage for fast retrieval

Integration with external LLM runtimes like Ollama

This framework provided the backbone for secure document interaction, eliminating reliance on external APIs or cloud services.

C. Integration of Mistral 7B via Ollama

The core LLM used in the application is Mistral 7B, known for its performance-to-size efficiency. Instead of accessing the model via APIs, Ollama was used to serve the model locally. The advantages of this setup include:

Data remains on the local machine, ensuring privacy

Reduced latency for inference

Elimination of cloud compute costs

The model was configured to support long-context queries and integrated with a caching mechanism to support chat-like interactions.

D. Implementation of Retrieval-Augmented Generation (RAG)

To improve response accuracy and contextuality, a Retrieval-Augmented Generation module was developed. The flow included:

Indexing

Query Matching

Prompt Construction

Answer Generation

This pipeline ensured that all responses were grounded in factual, document-based context.

E. Gradio Interface Design

For user interaction, a customized Gradio-based UI was developed. It included the following elements:

File uploader for adding documents

Chat window for querying and receiving model outputs

Theme toggle (dark/light)

Display of user session information

Chat controls (Clear, Retry, Undo)

The interface was styled using additional HTML/CSS elements to enhance user experience and provide branding flexibility.

F. Secure Backend Development with Flask

The backend was built using the Flask web framework, enabling:

User registration and login

Session management

Authentication middleware

Error handling system

All user-uploaded files were tied to active sessions and automatically deleted upon logout, enhancing data privacy.

G. Session Cleanup and File Management

One of the core functional requirements was ensuring that user-uploaded files did not persist beyond their session. This was implemented using:

1) Flask session tracking

2) File management middleware

3) Automatic cleanup scripts triggered on logout or timeout

Additionally, files were tagged by section (e.g., "Payload", "Communication") to support topic-specific filtering during RAG retrieval.

H. Theme Customization and Interface Enhancements

To improve user accessibility, theme customization was implemented with the option to toggle between dark and light modes. This was done using JavaScript and CSS toggles that dynamically applied styles across Gradio components.

Further user experience improvements included:

1) Display of login status and email
2) Scrollable chat history
3) Tooltips and error alerts
4) Retry/Undo buttons for chat inputs

I. Testing and Validation

Each module was tested individually and then as part of system integration. Tests included:

1) Unit testing of authentication logic
2) Inference performance benchmark
3) Query relevance scoring
4) Security checks (e.g., session hijacking prevention)
5) UI usability evaluation

This methodical development process ensured a robust, scalable, and user-secure application.

III. SOFTWARE AND TOOLS USED

Operation GPT was created through a mix of open-source software libraries and frameworks. The primary engine uses Mistral 7B, a lightweight but powerful large language model recognized for its speed and accuracy. This model was launched using Ollama, a tool that facilitates local execution of LLMs without depending on external APIs, thus guaranteeing data privacy and low latency.

The application operates on the Private GPT framework, which supports secure, offline question-answering on locally stored documents. To enhance the model's contextual accuracy, Retrieval-Augmented Generation (RAG) was incorporated. This structure improves response quality by fetching pertinent content from uploaded files prior to sending it to the model for generation.

The frontend was crafted using Gradio, a Python-based library that enables developers to swiftly create user-friendly web interfaces for machine learning applications. Gradio facilitated real-time query entry, file uploads, and a smooth chat-like interaction with the model. On the backend, Flask, a lightweight Python web framework, was employed to establish secure login and registration systems, handle user sessions, and implement authentication for application access.

To enable theme customization and client-side responsiveness, HTML, CSS, and JavaScript were also employed. The entire backend and integration logic were coded in Python, capitalizing on its vast ecosystem for both web development and machine learning.

These tools collectively ensured that Operation GPT was modular, quick, and user-friendly, with an architecture that can be easily expanded for other private, document-based LLM applications.

IV. RESULTS

The implementation of Operation GPT yielded several noteworthy outcomes in terms of performance, user experience, scalability, and security. The combination of a lightweight LLM (Mistral 7B), retrieval-based reasoning (RAG), and a secure, intuitive interface resulted in a highly functional and efficient document querying system. Below are the key result areas that emerged from the project:

1) Model Performance and Inference Efficiency

The integration of Mistral 7B using Ollama enabled low-latency inference even on moderately powered systems. Due to architectural features like Grouped Query Attention (GQA) and Sliding Window Attention, the model was able to process longer input sequences with reduced memory usage. During evaluation, the system demonstrated consistent response times for a wide range of queries, maintaining a balance between fluency and factual correctness. The Rolling Buffer Cache mechanism significantly improved throughput by reducing redundant computation during longer conversations or batch queries.

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2) Improved Response Relevance through RAG

By integrating Retrieval-Augmented Generation (RAG), Operation GPT produced more grounded and factually accurate responses. RAG modules fetched relevant segments from uploaded Operation documents based on keyword and semantic similarity before forwarding the content to the LLM for generation. This minimized hallucination and ensured answers were contextually tied to the original documents. In user testing, queries like "What is the payload capacity?" or "Explain the propulsion module's function" consistently returned relevant, section-specific answers.

3) Robust Document Handling and File Management

The document ingestion pipeline allowed users to upload PDFs or text files, which were then parsed and indexed for fast retrieval. The interface supported drag-and-drop functionality and file previews. On logout or session termination, all uploaded documents were automatically deleted to maintain data privacy and reduce unnecessary storage usage. This feature was validated in both single-user and simulated multi-user scenarios, confirming its effectiveness and reliability.

4) Enhanced User Experience and Accessibility

The Gradio-based web interface provided a seamless and intuitive user experience. Users could:

- Input questions in a chat format,
- View model responses in real-time,
- Switch between dark and light themes for visual comfort,
- Upload and manage files directly through the UI.

Furthermore, a responsive layout ensured usability across devices, including desktops, tablets, and mobile phones. Features like "Clear Chat," "Retry," and "Undo" improved session control, especially in long interactions.

5) Secure and Scalable Backend

The Flask backend handled user authentication, session management, and error logging. The login and registration system included validations for email format, password strength, and duplicate accounts. Middleware protected the main application routes from unauthorized access. Upon logout, session tokens were invalidated, and associated files were deleted. This secure flow ensured that each user's interaction was isolated and protected.

6) System Scalability and Modularity

Operation GPT was designed with scalability in mind. The modular architecture allowed easy replacement or upgrading of components:

- Mistral 7B could be swapped with another LLM (e.g., GPT-J, LLaMA) with minimal changes.
- The RAG module could be expanded to support additional metadata filters.
- Additional UI features could be incorporated without affecting the backend logic.
- This modular design ensures that the application can evolve with emerging technologies while maintaining core functionalities

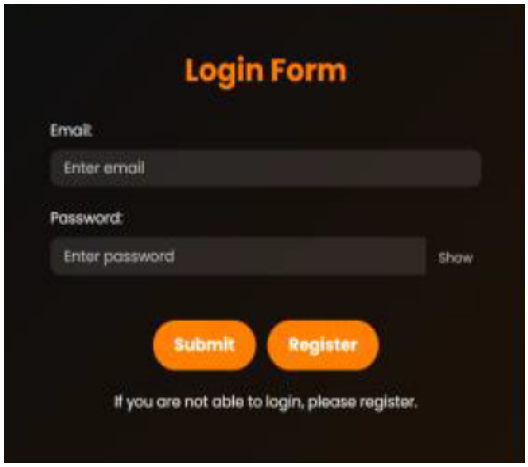


Fig 3 : Login page interface

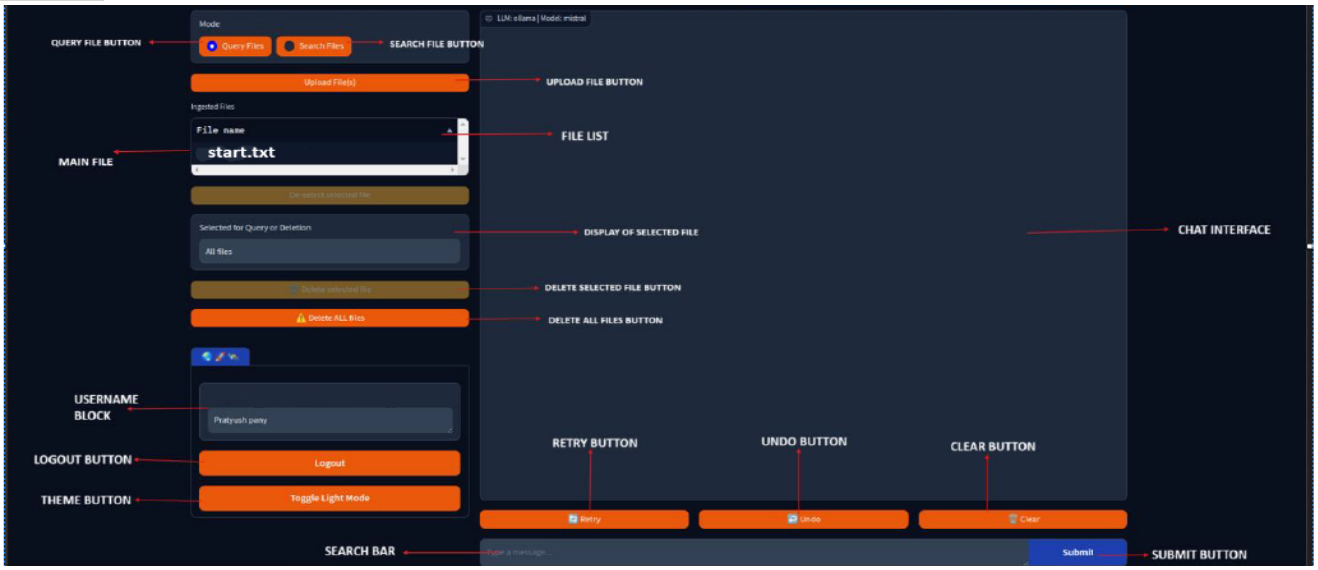


Fig 4 :Operation GPT interface

V. CONCLUSION

Operation GPT represents a significant advancement in the field of information retrieval from documents. This utilizes technologies such as the Private GPT framework, Mistral 7B, and Retrieval-Augmented Generation (RAG) to deliver accurate and contextually relevant responses to user queries. The application's user-friendly interface,built with Gradio, ensures that even non-technical users can easily interact with the system. Additionally, the robust security measures implemented through a Flask-based login system safeguard user data,providing a secure environment for information retrieval. The impact ofOperation GPT on the process of navigating and extracting information from Operation documents cannot be overstated. It streamlines the search process, saving users valuable time and effort while providing precise and reliable answers. This makes it an invaluable resource for a wide range of users, from researchers and analysts to everyday individuals seeking quick and accurate information.

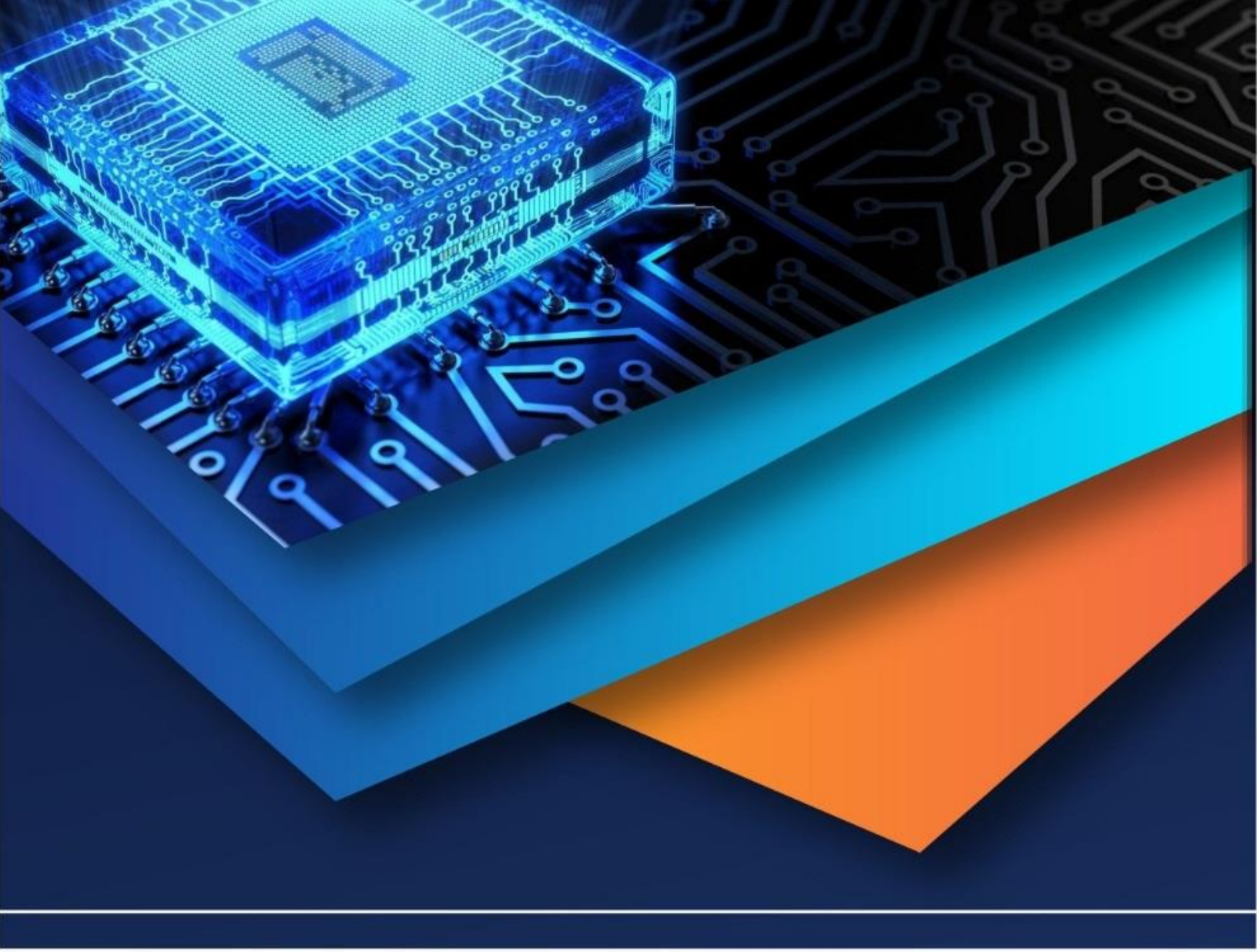
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