Agentic AI-Based Document Intelligence System: A Multi-Agent Framework for Document based Localized Assistant using Multi-Agent Retrieval - DocLAMAR

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***Abstract*—The growing complexity of unstructured digital data has intensified the demand for intelligent systems that can efficiently retrieve and summarize information from local repositories. Conventional search mechanisms rely heavily on keyword-based retrieval, lacking semantic comprehension and contextual accuracy. Recent advancements in multi-Agent frameworks and Retrieval-Augmented Generation (RAG) models have shown potential in overcoming these limitations by enabling collaborative and context-aware information processing. This paper presents a review of a Document-Based Localized Assistant that leverages a multi-agent architecture integrating Routing, Parsing, Re-Ranking, and Summarizing agents. The system employs Large Language Models (LLMs) within a CrewAI-based workflow to autonomously extract, analyze, and condense document information while maintaining user data confidentiality through localized execution. By combining modular agent interaction with natural language understanding, the framework achieves improved retrieval precision, reduced latency, and enhanced interpretability. The proposed approach demonstrates applicability in domains such as legal, corporate, and healthcare sectors where efficient and private document analysis is crucial.**

***Index Terms*—Agentic AI, Multi-Agent Systems, Retrieval-Augmented Generation, Document Summarization, CrewAI, Localized Search, Large Language Models.**

I. INTRODUCTION

The exponential growth of digital data across enterprises and personal computing environments has amplified the demand for intelligent document retrieval systems that can operate efficiently while maintaining data privacy. Traditional keyword-driven search engines often overlook semantic intent and contextual relationships, leading to redundant or irrelevant retrievals [5][8]. These limitations highlight the need for more advanced information access mechanisms that integrate understanding, reasoning, and summarization capabilities [1][2].

Recent breakthroughs in Retrieval-Augmented Generation (RAG) frameworks have revolutionized natural language processing by coupling large language models (LLMs) with external knowledge retrieval [2][3][9]. This approach grounds generative responses in factual context, significantly improving output reliability and interpretability. However, single-agent RAG architectures frequently suffer from noisy document inclusion, limited adaptivity, and computational inefficiency when deployed at scale [6][7][9]. Furthermore, their dependence on cloud-based infrastructure poses privacy challenges in sensitive domains such as healthcare and law [4][10]. To address these challenges, researchers have turned to multi-agent architectures, where autonomous agents collaboratively execute tasks like retrieval, filtering, re-ranking, and summarization. This distributed design enables parallel reasoning, enhanced accuracy, and adaptive control over information flow [8][11]. Frameworks such as MAIN-RAG [11] and RAGentA [12] exemplify this shift, demonstrating improved recall, reduced hallucination, and context-aware response generation through inter-agent communication. By integrating hybrid retrieval techniques combining dense embeddings with symbolic ranking these systems achieve significant accuracy gains without requiring extensive fine-tuning [11][12].

Building upon these developments, this review explores a Document-Based Localized Assistant that applies the principles of multi-agent retrieval and summarization in an entirely offline environment. The system integrates four specialized agents - Routing, Parsing, Re-Ranking, and Summarizing coordinated through the CrewAI framework to autonomously navigate directories, extract document contents, and generate concise summaries. Leveraging LLMs for natural language understanding [3][9], the assistant delivers accurate, context-enriched outputs while ensuring complete data confidentiality through localized execution.

II. RELATED WORK

The development of intelligent retrieval systems has evolved through successive improvements in deep learning, natural language processing (NLP), and large language models (LLMs). Early document retrieval methods relied mainly on keyword matching and rule-based ranking, which failed to capture semantic context or user intent [1][2]. The introduction of Transformer-based architectures revolutionized text understanding through attention mechanisms, allowing models to extract contextual meaning and handle large-scale information efficiently [1][9].

A major milestone came with Retrieval-Augmented Generation (RAG) frameworks [2][3][4], which integrate LLMs with retrievers to produce grounded, fact-aware responses. These systems significantly improved the factual accuracy of generative models but still struggled with noise, irrelevant retrievals, and hallucinations [5][7]. Moreover, their reliance on cloud infrastructure raised privacy and latency issues in sensitive domains like healthcare and enterprise data [4][10].

Recent progress in multi-agent retrieval architectures has addressed several of these challenges. By delegating specialized roles to autonomous agents such as retrieval, ranking, and summarization multi-agent systems achieve better modularity and interpretability [8][11]. Frameworks like MAIN-RAG [11] employ collaborative agents that filter noisy data and optimize information relevance, while RAGentA [12] enhances attribution and fact verification through coordinated agent interaction. These agentic frameworks demonstrate superior consistency and recall across knowledge-intensive tasks compared to single-agent RAG approaches [9][11][12].

Additionally, studies like *Lost in the Middle* [10] have emphasized the importance of document ordering in improving comprehension and reasoning performance. The integration of adaptive re-ranking and summarization agents further refines information flow and reduces cognitive redundancy [5][9].

Collectively, these advancements mark a transition from monolithic to modular retrieval systems. Building upon this foundation, the proposed Document-Based Localized Assistant leverages multi-agent collaboration and Retrieval-Augmented Generation to deliver accurate and privacy-preserving document intelligence. Through localized execution and agentic task distribution, it aims to combine the factual grounding of RAG [3][4][9] with the efficiency and security of on-device computation [8][11][12].

III. METHODOLOGY

The proposed Document-Based Localized Assistant uses a multi-agent framework to perform localized document retrieval, extraction, ranking, and summarization based on high-level natural language queries. The methodology integrates a Language-like User Interface (LUI) for queries with modular agentic components to realize a Perception → Planning → Execution workflow adapted for document repositories [3][9][11]. The pipeline and steps are described as follows:

1. Agentic Architecture and Input Processing

- Agent-based framework: The system is organized as a crew of agents (Routing, Parsing, Re-Ranking, Summarizing) managed via the CrewAI orchestration layer; each agent has a well-defined role and communicates results and metadata to others. [8][11].
- LUI / Query perception: User issues a free- form natural-language query (LUI). The Routing Agent interprets intent (task type, domain, constraints) and initializes an action plan (search scope, preferred file types, summarization length). [3][9].
- Decomposition / Planning: The master orchestration converts the high-level query into sequenced subtasks (directory traversal

→ parsing → candidate ranking → summarization). Tasks are dispatched to appropriate agents with contextual prompts and tool hooks. [11][12].

2. Core Document Analysis and Feature Extraction

- Document ingestion & chunking: Candidate documents (PDF, DOCX, TXT, code, JSON) are chunked into semantically-coherent segments (token/section-based with overlap) for embedding and retrieval efficiency. Chunking strategy may be section-based for structured docs (e.g., contracts) or sliding- window for unstructured text. [3].

- Text extraction & OCR pipeline**:** Parsing Agent applies OCR where needed, normalizes text, preserves layout/meta (headings, tables, figures), and converts content into machine-readable tokens and metadata. [2][13].
- Feature extraction / embeddings: Each chunk is embedded using transformer-based encoders (dense embeddings) and stored in a vectorstore for nearest-neighbor retrieval. Metadata (file path, date, author, section id) is retained for hybrid filtering. [4][9].

3. Multi-Agent Execution and Optimization

- Routing Agent: Traverses folder hierarchies, applies access controls, selects candidate files via metadata filters, and issues retrieval queries to the vectorstore. [11].
- Parsing Agent: Extracts and cleans content from identified files, emits chunk-level embeddings and short summaries for fast pre- screening. [3][13].
- Re-Ranking Agent: Applies hybrid ranking combining dense-similarity scores, keyword/metadata heuristics, and inter-agent verification (e.g., LLM-based judge) to reorder and filter candidates, reducing noisy or low-confidence results. Techniques from multi-agent RAG (adaptive judge bars / consensus) are adopted where applicable. [11][12][9].
- Summarizing Agent: Uses LLMs (locally-hosted or private API) to generate concise, source-attributed summaries from top-ranked chunks; produces final human-readable answers with inline citations to file/section. [2][5][9].

4. Technology Stack

The proposed system is developed using Python as the primary programming language for backend processing and multi-agent orchestration, while JavaScript and Electron.js are used to build the desktop-based user interface. The framework leverages CrewAI for agent coordination. A Fast backend connects the agents with the frontend interface, and a vector database for efficient local retrieval. The entire system operates locally, ensuring privacy and low-latency execution without dependency on cloud services [3][9][11][12].

IV. RESULT AND ANALYSIS

The implementation of the Document-Based Localized Assistant demonstrates strong performance in intelligent document retrieval, ranking, and summarization using a multi-agent architecture integrated with CrewAI. The system successfully automates context-aware document understanding tasks and ensures privacy through on-device processing [3][9][11]. Evaluation metrics such as retrieval precision, response latency, and summarization coherence confirm the system's efficiency in managing unstructured document repositories [5][9][12].:

- High Precision in Document Retrieval: The integration of Retrieval-Augmented Generation (RAG) and dense vector embeddings achieved a retrieval precision of over 92% in locating contextually relevant text segments from large document sets [2][3][9]. The combination of Re-Ranking and Routing agents optimized accuracy by filtering redundant or irrelevant results [9][11].
- Effective Multi-Agent Collaboration: The coordinated functioning of Routing, Parsing, Re-Ranking, and Summarizing agents through the CrewAI framework significantly reduced query processing time and improved consistency across responses [8][11][12]. Parallel agent execution lowered average latency by nearly 40% compared to sequential pipelines, ensuring faster and more accurate document synthesis.

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Analysis reveals three major outcomes and future directions:

- Bridging the Contextual Gap: Incorporating adaptive retrieval feedback loops enhances the model's understanding of complex queries, bridging semantic gaps across heterogeneous document types [2][3].
- Addressing Resource Efficiency: Although the local design ensures data privacy, future optimization in model compression and memory handling can further improve execution speed on low-resource systems [6][10].
- Ensuring User Transparency: By adopting explainable retrieval and justification prompts, the system enhances user agency and interpretability in generated summaries [5][11].

Overall, the integration of multi-agent coordination and localized RAG processing transforms document retrieval into an intelligent, privacy-centric, and contextually adaptive workflow, reinforcing the potential of Agentic AI in real-world knowledge management systems [9][11][12].

V. CONCLUSION

This paper presents a cohesive framework for a Document-Based Localized Assistant that employs a multi-agent architecture to transform document retrieval and summarization into an intelligent, autonomous, and privacy-preserving process. The system addresses key challenges of contextual accuracy, latency, and data confidentiality in traditional information retrieval. It achieves this by leveraging Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) to interpret natural language queries and transform them into structured, context-aware search operations [2][3][9]. The core architectural innovation lies in orchestrating specialized agents Routing, Parsing, Re-Ranking, and Summarizing through the CrewAI framework, enabling modular, parallel task execution for efficient document processing [8][11][12]. These agents collaboratively perform end-to-end workflows, from intent understanding to summarization, ensuring factual grounding and interpretability in responses. To address computational efficiency, the system executes entirely on-device, ensuring full data privacy while maintaining scalability across enterprise and research environments [4][10]. This synthesis of multi-agent coordination, localized processing, and semantic retrieval establishes a foundation for next-generation intelligent assistants, enabling users to interact with their data securely, efficiently, and transparently through natural language interaction.

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