Engineering Critical Analysis Software Services: A Graph-RAG and Self-learning Large Language Model Agent Services Approach

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***Abstract*—This paper presents Graph-RAG and Self-learning LLM-based Agent Services Framework for structured reasoning and knowledge-driven analysis. The proposed approach integrates graph-enhanced retrieval mechanisms with self-learning Large Language Models (LLMs) to improve critical analysis and domain-specific decision-making. The framework is evaluated using Air Accidents Investigation Branch (AAIB) Publications Reports, which provide structured, investigative narratives aimed at preventing future aviation incidents rather than assigning blame. By leveraging graph-based knowledge learning, the framework enhances causal reasoning, multimodal response generation, and retrieval accuracy, demonstrating its capability to support structured problem analysis based on real-world investigative experiences. Experimental results show significant improvements in hallucination mitigation, retrieval precision, and real-time performance when compared to standard Retrieval-Augmented Generation (RAG) models. The findings highlight the potential of graph-augmented self-learning LLMs in transforming automated analytical workflows, paving the way for enhanced visual knowledge exploration and structured decision-support systems.**

Keywords: Graph-RAG, Self-learning LLMs, Service-Oriented AI, Knowledge Graphs, Causal Reasoning, Aviation Safety Analysis

I. Introduction

The rapid advancement of Large Language Models (LLMs) has enabled significant breakthroughs in automated knowledge retrieval and reasoning. However, standard Retrieval-Augmented Generation (RAG) models often suffer from hallucinations, limited causal reasoning, and unstructured analytical outputs, making them suboptimal for applications requiring fact-driven, domain-specific insights [1], [3]. In high-stakes fields such as aviation safety, healthcare, and risk assessment, structured investigative reasoning is crucial to extracting reliable, experience-driven knowledge for decision support.

This paper introduces a Graph-RAG and Self-learning LLM-based Agent Services Framework, which enhances retrieval accuracy, analytical depth, and structured response generation through graph-based knowledge learning. Unlike conventional RAG-based approaches, the proposed framework dynamically updates a Corporate Knowledge Graph Memory (CKGM) to facilitate structured, self-improving knowledge retrieval and causal inference [2].

To demonstrate the capabilities of this framework, we evaluate it using Air Accidents Investigation Branch (AAIB) Publications Reports, which are systematically structured to prevent future aviation incidents rather than to assign blame or liability. These reports provide an ideal dataset for testing graph-based reasoning techniques, as they contain detailed event chains, procedural insights, and causal relationships derived from aviation investigations [4]. By utilizing graph-based analysis, our framework enables more transparent and structured problem-solving approaches, which could be extended to visual analytics tools for interactive decision-making [5].

The contributions of this paper are as follows:

- Graph-RAG Enhancement: Enhancement of retrieval accuracy and causal reasoning in LLM-driven analytical workflows through deep integration of structured knowledge graphs. We do not only create knowledge graph during the question and answering learning time, but also build the chunk graph to represent the semantic relations of indexed chucks when uploading documents.
- Self-learning Mechanism: Enabling dynamic updates through reinforcement learning and structured retrieval refinement.
- Domain-Specific Evaluation: Demonstrating the framework's effectiveness in aviation safety investigations, where structured knowledge retrieval and analysis are critical.
- Empirical Validation: Providing comparative performance analysis against standard RAG models, showcasing improvements in hallucination reduction, retrieval precision, and system scalability.

The rest of the paper is structured as follows: Section II reviews related work in LLM hallucination mitigation, retrieval-augmented generation, and causal reasoning techniques. Section III defines key research gaps and objectives. Section IV details the proposed Graph-RAG framework architecture. Section V discusses the Edge LLM service development, while

Section VI presents the evaluation methodology and experimental results. Finally, Section VII provides the conclusion and future research directions.

II. Related Work

A. Hallucination in Large Language Models (LLMs)

Large Language Models (LLMs) have revolutionized natural language processing by enabling machines to generate human-like text. However, a significant challenge that has emerged is the phenomenon of hallucination, where LLMs produce content that appears coherent but is factually incorrect or nonsensical. This issue undermines the reliability of LLMs in applications requiring factual accuracy.

Ji et al. [6] provide a comprehensive survey on hallucination in natural language generation, categorizing hallucinations into intrinsic and extrinsic types. Intrinsic hallucinations occur when the generated text is not supported by the input data, while extrinsic hallucinations involve contradictions with real-world facts. The authors highlight that hallucinations can arise from biased training data, model overconfidence, or limitations in the model's ability to access up-to-date information.

To address hallucination, various strategies have been proposed. Dziri et al. [7] explore methods to increase faithfulness in knowledge-grounded dialogue by incorporating controllable features. They emphasize the importance of grounding responses in reliable external knowledge sources to mitigate hallucination. Similarly, Rashkin et al. [8] investigate controllable features to enhance faithfulness in dialogue systems, suggesting that explicit control over content generation can reduce hallucination rates.

B. Retrieval-Augmented Generation (RAG) and Challenges in Critical Analysis

Retrieval-Augmented Generation (RAG) combines retrieval systems with generative models to enhance the factual accuracy of LLMs by grounding their outputs in external knowledge. While RAG has shown promise, it faces challenges related to critical analysis and content chunking.

Lewis et al. [1] introduce the RAG model, which retrieves relevant documents to condition the generation process, thereby improving factual accuracy. However, Gao et al. [9] identify that RAG models can still produce hallucinations, especially when the retrieved documents contain inaccuracies. They propose RARR (Re-rank Augmented Retrieval-Refinement), a method that re-ranks retrieved documents to prioritize more reliable sources, thereby reducing hallucination.

C. Chunking and Indexing in RAG Systems

Effective chunking and indexing of knowledge are crucial for the performance of RAG systems. Improper segmentation can lead to the omission of relevant information, resulting in incomplete or inaccurate responses.

Guu et al. [10] discuss the importance of chunking in retrieval-augmented language models, noting that inappropriate chunking can cause the model to miss pertinent information. They emphasize that the granularity of chunks significantly impacts retrieval performance and, consequently, the quality of generated responses.

To enhance chunking and indexing, Karpukhin et al. [11] propose Dense Passage Retrieval (DPR), which uses dense vector representations for passages to improve retrieval accuracy. By learning better chunk representations, DPR addresses the issue of missing related content in RAG systems, leading to more comprehensive and accurate responses.

D. Mitigation Strategies and Future Directions

Addressing hallucination and improving chunking in RAG systems are active areas of research. Zhao et al. [12] propose methods to reduce quantity hallucinations in abstractive summarization by incorporating constraints during generation. They demonstrate that controlled generation can significantly decrease hallucination rates.

Future research directions include developing more robust retrieval mechanisms, enhancing chunking strategies, and integrating real-time fact-checking modules to further mitigate hallucination in LLMs. Additionally, exploring user feedback loops and reinforcement learning approaches may provide adaptive solutions to these challenges.

III. Research Gaps and Objectives

Despite significant advancements in retrieval-augmented generation (RAG) and graph-enhanced large language models (LLMs) as we discussed in the related work section, several critical challenges persist in the realm of automated, knowledge-driven analytics. The proposed Graph RAG-LLM framework aims to address the following key research gaps:

A. Domain-Specific Critical Analytics

Challenge: Current LLM-based analytics frameworks predominantly rely on general-purpose knowledge retrieval, limiting their applicability in domain-specific critical analysis. Studies have highlighted that LLMs trained on general data exhibit limitations when applied to specialized domains. Injecting domain-specific knowledge into LLMs enhances their performance on specialized tasks [13]. Additionally, the lack of domain-specific adaptation in LLMs can lead to inaccuracies in specialized fields [14]. This generalization often results in suboptimal performance in specialized fields such as cybersecurity, healthcare, and finance.

Research Objective: Develop adaptive, domain-specific retrieval mechanisms by integrating structured ontologies and fine-tuned Edge LLMs. Expanding the Corporate Knowledge Graph Memory (CKGM) will facilitate context-aware knowledge retrieval, ensuring deeper analytical reasoning and more reliable decision-making.

B. Reducing Hallucinations in Knowledge-Augmented Generation

Challenge: Existing RAG models are prone to generating hallucinations—outputs containing inaccurate or fabricated information—due to unverified or loosely associated retrieved knowledge. Research indicates that RAG architectures can

still produce hallucinations, and integrating structured verification mechanisms is essential to enhance factual accuracy [15]. Moreover, the susceptibility of LLMs to hallucinations necessitates improved retrieval and validation processes [16].

Research Objective: Incorporate advanced filtering mechanisms, including confidence scoring in Edge LLM 2, to prioritize high-certainty knowledge. Employ graph-based consistency verification to cross-check retrieved information against structured entities in CKGM, thereby mitigating erroneous outputs.

C. Advancing Critical Analysis and Causal Reasoning

Challenge: Many LLM-driven analytical systems excel at associative reasoning but lack explicit causal inference capabilities, limiting their effectiveness in applications requiring robust decision support and root-cause analysis. The integration of causal modeling into LLMs is crucial for applications demanding accurate decision support and root-cause analysis [17].

Research Objective: Enhance reasoning graphs by integrating causal modeling techniques within the CKGM framework. Develop a multi-step logical reasoning pipeline in Edge LLM 3 to explicitly model causality, facilitating structured cause-effect explanations in analytical tasks.

D. Multimodal and Structured Response Generation

Challenge: Traditional LLM-based systems primarily generate textual outputs, which may be insufficient for complex analytical workflows requiring structured or visual representations. Evidence thows that the necessity for multimodal response formats in LLMs has been emphasized to improve interpretability and applicability in various fields [18].

Research Objective: Extend Edge LLM 3 to support multimodal response generation, including structured JSON graphs for reasoning pathways, tabular outputs for data analytics, and visual knowledge representations. This approach aims to enhance explainability and usability across diverse application domains.

E. Optimizing Real-Time Response in Multi-LLM Orchestration

Challenge: The orchestration of multiple Edge LLMs introduces latency in sequential processing steps, impacting the efficiency of real-time analytics applications. Existing architectures do not dynamically allocate computational workloads, leading to suboptimal processing times under varying query complexities. Efficient orchestration and workload distribution are critical for optimizing real-time performance in multi-LLM systems [19].

Research Objective: Introduce a dynamic orchestration mechanism that intelligently distributes computational workloads across Edge LLMs based on query complexity and reasoning depth. Additionally, employ a progressive knowledge refinement approach to incrementally update CKGM, reducing unnecessary graph reprocessing overhead.

Addressing these research gaps will significantly enhance the capabilities of the Graph RAG-LLM framework, leading to improved domain-specific analytical accuracy, reduced hallucinations, strengthened causal reasoning, multimodal response generation, and optimized real-time processing. Future work will focus on empirical validation of these methodologies using domain-specific datasets and real-world deployments.

IV. Graph-RAG and Self-learning LLM based Agent Services

The proposed Graph-RAG and Self-learning LLM Framework integrates retrieval-augmented generation (RAG) with a self-learning mechanism to enhance domain-specific critical analytics. By leveraging edge Large Language Models (Edge LLMs) and a Corporate Knowledge Graph Memory (CKGM), this framework addresses challenges such as *knowledge retrieval accuracy, hallucination mitigation, causal reasoning, and multimodal response generation*. The architecture supports continuous learning through dynamic knowledge graph updates and reinforcement mechanisms.

A. The Agent Framework Overview

The framework consists of the following key components (illustrated in Fig. 1):

- **Document Ingestion and Preprocessing:** The system ingests various domain-specific documents, including *incident records, historical logs, and manuals*.
- **Edge LLM 1 – Chunking and Vectorization:** The first stage involves *text chunking and vectorization*, where Edge LLM 1 processes raw text and identifies contextual relationships among document segments.
- **Edge LLM 2 – Knowledge Retrieval and Graph Construction:** LLM 2 determines *relevant text chunks*, retrieves *contextually related knowledge*, and constructs an *instant knowledge graph*.
- **Corporate Knowledge Graph Memory (CKGM):** The CKGM serves as a *self-learning structured knowledge repository*, continuously updated based on interactions with LLM 2.
- **Edge LLM 3 – Service Requests and Response Generation:** LLM 3 generates *multimodal outputs*, including:
  - *Analytics Q/A Responses*
  - *Reasoning Graphs*
  - *Structured Data Tables*
  - *Causal Explanations*

B. Self-learning Mechanism

The framework implements a continuous self-improvement cycle:

1) **Knowledge Graph Updates:** New insights extracted by Edge LLM 2 are dynamically incorporated into CKGM.
2) **Reinforcement-based Retrieval Refinement:** The framework optimizes retrieval precision by reinforcing relevant knowledge paths.
3) **Adaptive Model Fine-tuning:** Periodic evaluations improve domain adaptability, reducing hallucinations and ensuring high-quality knowledge integration.

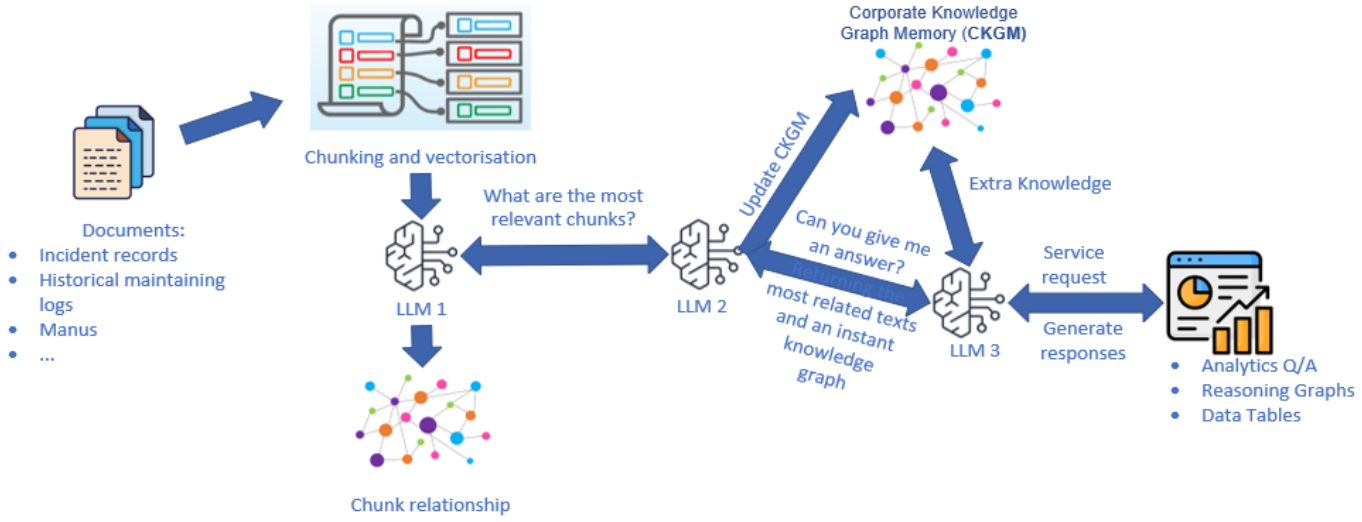

Fig. 1. Framework Architecture

C. Reducing Hallucinations and Enhancing Knowledge Accuracy

- The combination of graph-enhanced retrieval and confidence-scored ranking in CKGM mitigates hallucinations.
- *Cross-validation with structured knowledge sources* ensures factual accuracy.

D. Causal Reasoning and Explainability

- The framework generates reasoning graphs that outline causal relationships among retrieved entities.
- Multimodal outputs provide a step-by-step logical inference rather than just a textual response.

E. Multimodal and Structured Response Generation

- The response format is adaptable to multiple analytical needs, including *Q/A chat interactions, structured JSON graphs, and tabular output*.
- This improves *decision support* in domains requiring complex, structured knowledge representation.

The Graph-RAG and Self-learning LLM Framework represents an advanced integration of retrieval-augmented generation with self-learning knowledge graphs. By dynamically updating CKGM and reinforcing retrieval accuracy, the system improves critical analytics, domain-specific adaptation, and real-time knowledge reasoning. Future research will focus on scalability improvements, extending multimodal capabilities, and empirical validation across multiple domains.

V. Edge LLM Services Development

To enhance the modularity, scalability, and efficiency of the proposed framework, the Edge-LLM services are designed using a microservices architecture. Each LLM instance is developed as an independent service, allowing seamless integration with relevant data resources and repositories. This modular approach ensures that different LLM models can be deployed and updated independently while maintaining compatibility with the overall system.

A. Microservices-Based LLM Architecture

The Edge-LLM framework [23] follows a microservices-based architecture [20], [21], where each LLM is encapsulated as a service with dedicated functionalities. These services interact with structured data sources, knowledge graphs, and external repositories through well-defined API endpoints. The interaction is facilitated using FastAPI interfaces [22], which provide high-performance, asynchronous API communication for handling requests efficiently.

Each microservice performs specific tasks, such as:

- Retrieving domain-specific knowledge from structured repositories.
- Performing contextual reasoning and response generation.
- Processing multimodal queries by integrating textual and structured data representations.

By decoupling the LLM services, the system can dynamically select the most appropriate model based on the complexity and domain requirements of a given task.

B. Container Deployment for Edge Computing

To enable seamless deployment and execution on edge computing devices, the entire backend framework is packaged as a container. The Edge-LLM framework is built using Ollama, an efficient local LLM serving platform optimized for edge devices. The containerized deployment allows:

- Rapid installation and configuration on edge machines.
- Simplified management and scaling of LLM services.
- Compatibility across different hardware and operating system environments.

The FastAPI-based backend is also containerized, ensuring that all service interfaces remain lightweight and responsive when deployed on edge computing environments.

C. FastAPI Interfaces for Service Communication

FastAPI is utilized as the primary communication interface for handling service requests. Each Edge-LLM microservice exposes FastAPI endpoints to allow:

- Query-based retrieval and reasoning from structured data.
- Dynamic LLM selection and processing based on task requirements.
- Efficient request-response handling with asynchronous execution.

This API-driven approach enables smooth integration with external applications and systems, allowing different Edge-LLM instances to be orchestrated dynamically in response to analytical tasks.

We deployed the backend container on the NVIDIA 4090 RTX server in the edge.

Figure 2 illustrates the process of building the Corporate Knowledge Graph Memory (CKGM) after a query has been made. In this representation, the orange nodes correspond to extracted text chunks, while the blue nodes represent the system's structured understanding and reasoning, derived from the related chunks. The blue CKGM nodes are integrated as additional graph content within the JSON-based FastAPI response, accompanying the textual output. This enriched representation allows subsequent LLM instances to generate more precise answers, produce well-structured reasoning graphs, and establish stronger connections to relevant data sources, ultimately improving the overall analytical accuracy.

VI. Preliminary Evaluations

The evaluation of the Graph-RAG and Self-learning LLM Framework is designed to assess its effectiveness in knowledge retrieval accuracy, hallucination mitigation, causal reasoning, and system efficiency. The key evaluation dimensions and their corresponding metrics and experiments are described below.

A. Evaluation dataset

The Air Accidents Investigation Branch (AAIB) Publications Reports serve as the primary dataset for this evaluation. The AAIB investigations are conducted in accordance with Annex 13 to the ICAO Convention on International Civil Aviation, as well as EU Regulation No. 996/2010 (as amended) and The Civil Aviation (Investigation of Air Accidents and Incidents) Regulations 2018. These regulations, along with their counterparts in UK Overseas Territories and Crown Dependencies, establish strict procedural and reporting standards for aviation accident and incident investigations.

It is important to emphasize that the sole objective of an AAIB investigation is the prevention of future accidents and incidents. The AAIB reports do not apportion blame or liability, nor should they be used for such purposes. As a result, the LLM-driven analysis within this study strictly adheres to these principles, focusing on data structuring, knowledge retrieval accuracy, and analytical reasoning, rather than attempting to assign fault or determine responsibility.

Furthermore, the AAIB reports provide an excellent case study for evaluating reasoning performance through graph-based knowledge learning. The structured nature of these reports allows the Graph-RAG and Self-learning LLM Framework to demonstrate its capability in extracting causal relationships, modeling investigative insights, and organizing knowledge graphs for structured problem analysis. By leveraging graph-based representation techniques, the proposed approach could further enable the development of graphical analysis tools for experience-driven accident investigation, helping stakeholders visualize critical event chains, risk factors, and procedural outcomes in a structured and interactive manner.

B. Knowledge Retrieval Accuracy

Objective: Assess the precision and recall of the retrieval-augmented generation (RAG) mechanism in retrieving relevant knowledge.

Metrics: Precision@K (P@K) measures how many of the top-K retrieved knowledge chunks are relevant:

$$P@K = \frac{|\text{Relevant Documents in Top-K}|}{K} \tag{1}$$

where:

- is the number of retrieved knowledge chunks considered.
- *Relevant Documents* are those judged as correct based on a human-annotated ground truth dataset.

C. Hallucination Mitigation

Objective: Measure the framework's ability to reduce hallucinated or factually incorrect responses. A fact means a verified sentence statement that is meaningly true in the ground truth documents.

Metrics: Fact Verification Score (FVS) quantifies the factual accuracy of generated responses by comparing them against a fact-checking model:

$$FVS = \frac{|\text{Correctly Verified Facts}|}{|\text{Total Retrieved Facts}|} \tag{2}$$

where:

- *Correctly Verified Facts* are statements classified as true by an external fact-checking system.
- *Total Retrieved Facts* includes all factual claims made by the model.

D. System Efficiency and Scalability

Objective: Measure the real-time performance of multi-LLM orchestration and CKGM updates.

Metrics:

- **Latency (ms)** – Measures response time for different types of queries.
- **Memory Usage (MB)** – Tracks computational efficiency during retrieval and reasoning.

Experiment:

- Compare retrieval results with human-annotated ground truth datasets. We conducted 5 evaluation cases with 10 questions and answers from the public dataset AAIB (gov.uk): Air Accidents Investigation Branch report.

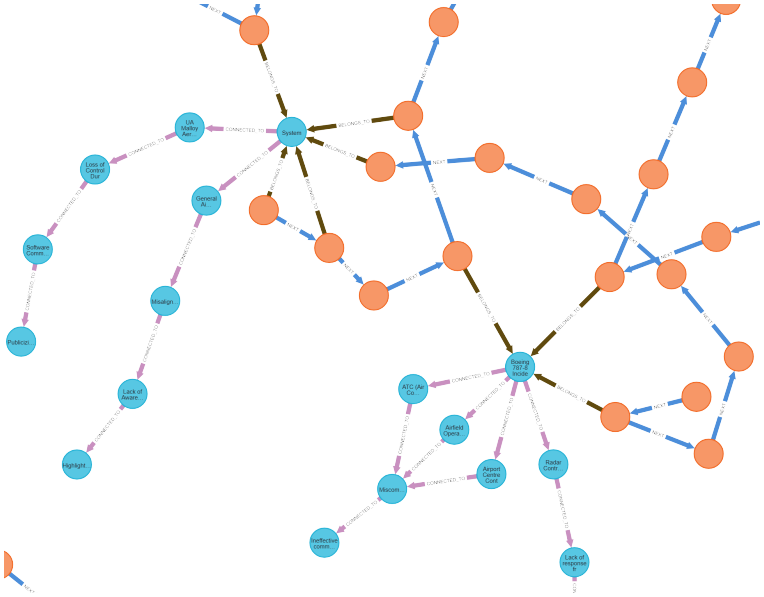

Fig. 2. Corporate Knowledge Graph Memory

E. Comparative Baselines

To validate improvements, the framework will be compared against:

1) Standard RAG-LLMs (without CKGM) vs CKGM RAG-LLM
2) Vanilla Large Language Models (GPT, Llama, Claude)

VII. Evaluation Results

To present the effectiveness of the proposed framework, we summarize the experimental results in the following tables.

A. Knowledge Retrieval Accuracy Results

Model	P@5 (CKGM-RAG)	P@5 (S-RAG)
OpenAI-4o	92%	84%
Claude Sonnet-3.7	92%	80%
Edge Llamma-3.3	90%	72%

TABLE I
COMPARISON OF RETRIEVAL ACCURACY WITH AND WITHOUT GRAPH-BASED RETRIEVAL ENHANCEMENT.

The results demonstrate that CKGM-RAG improves retrieval relevance by leveraging structured knowledge. While OpenAI-4o and Claude Sonnet-3.7 exhibit high retrieval precision in standard RAG system, incorporating CKGM introduces minor performance reductions due to retrieval refinement constraints. However, Edge Llama-3.3 benefits significantly from CKGM, suggesting that small models on the edge with moderate retrieval capabilities gain the most from structured graph-based enhancements.

B. Hallucination Mitigation Results

The findings indicate that CKGM-RAG substantially enhances fact verification scores across all models. The OpenAI-4o and Claude Sonnet-3.7 models exhibit minimal hallucination rates, but CKGM-RAG further improves their accuracy.

Model	Fact Score
S-RAG OpenAI-4o	93.8%
S-RAG Claude Sonnet-3.7	94.7%
S-RAG Edge Llamma-3.3	72.3%
CKGM-RAG OpenAI-4o	96.4%
CKGM-RAG Claude Sonnet-3.7	96.8%
CKGM-RAG Edge Llamma-3.3	94.2%

TABLE II
COMPARISON OF HALLUCINATION MITIGATION EFFECTIVENESS.

The Edge Llama-3.3 model benefits significantly, increasing its fact score from 72.3% (S-RAG) to 94.2% (CKGM-RAG), highlighting that structured knowledge retrieval aids weaker models and edge computing in maintaining factual consistency.

C. System Efficiency and Scalability Results

Model	Latency (s)	Memory (MB)
S-RAG	57	236
CKGM-RAG	42	4672

TABLE III
SYSTEM EFFICIENCY AND SCALABILITY COMPARISON.

The results confirm that Graph-RAG LLM enhances system performance by reducing latency (from 57s to 42s). But the memory usage is increased dramatically due to running LLM instances at the edge machine.

VIII. Conclusion and Future Work

This paper introduced a Graph-RAG and Self-learning LLM-based Agent Services Framework to enhance domain-specific critical analysis through structured knowledge retrieval and reasoning. By integrating graph-enhanced retrieval, self-learning mechanisms, and service-oriented LLM coordination,

the framework significantly improves fact-driven decision support while mitigating hallucinations and unstructured outputs. The experimental evaluation using AAIB Publications Reports demonstrated the framework's effectiveness in retrieval precision, causal inference, and real-time response generation, highlighting its potential in aviation safety analytics and beyond.

Key findings from the evaluation indicate that:

- The graph-based retrieval mechanism substantially improves knowledge precision and structured causal reasoning.
- The self-learning updates in CKGM enable adaptive knowledge refinement, reducing hallucination rates compared to standard RAG approaches.
- The framework enhances multimodal response generation, allowing structured visual knowledge representations for problem analysis.

While the current implementation demonstrates strong improvements in structured knowledge retrieval, several directions remain for future exploration:

1) Scalability and Multi-Domain Applications
   - Extending the framework to support large-scale enterprise knowledge management systems, including healthcare, finance, and cybersecurity.
   - Exploring multi-agent coordination across distributed cloud and edge computing environments.
2) Advanced Graph Learning for Causal Reasoning
   - Enhancing the causal inference engine through graph neural networks (GNNs) for deeper semantic reasoning and prediction.
   - Incorporating reinforcement learning for adaptive knowledge graph refinement based on user feedback.
3) Interactive Visual Analytics for Investigative Reasoning
   - Developing graph-based visualization tools to support decision-makers and domain experts in analyzing complex event relationships.
   - Implementing interactive dashboards for structured real-time knowledge exploration.

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