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MLLMs의 한계 극복을 위한 멀티모달 RAG 프레임워크에 관한 연구

안철범*, 김진홍**†

A Study on a Multimodal RAG Framework for Overcoming the Limitations of Multimodal Large Language Models (MLLMs)

Chulbum Ahn*, Jinhong Kim**†

요 약

최근 멀티모달 대형 언어 모델(MLLM)은 시각 정보 처리 능력에서 비약적인 발전을 이루었으나, 두 가지 고질적인 한계에 직면해 있다. 첫째, 모델의 학습 데이터에 포함되지 않은 최신 정보나 특정 도메인의 폐쇄적 지식(Private Data)에 접근이 불가능하다. 둘째, 사실 관계를 오인하여 그럴듯한 거짓을 출력하는 시각적 환각(Visual Hallucination) 현상이 빈번하게 발생한다. 이러한 한계는 의료 진단, 법률 분석, 정밀 제조 검수 등 높은 신뢰도를 요구하는 분야에서 MLLM의 도입을 저해하는 핵심 요인으로 작용하고 있다. 이에 본 논문에서는 이를 극복하기 위한 방법으로 검색 증강 생성(RAG) 기술을 이미지 분석에 도입한 프레임워크를 제안하고, 구현 과정에서의 주요 도전 과제와 향후 발전 가능성을 체계적으로 분석해보고자 한다.

Abstract

Recent multimodal large language models (MLLMs) have achieved remarkable advances in visual information processing; however, they continue to face two persistent limitations. First, these models are unable to access up-to-date information or domain-specific private data that falls outside their training datasets. Second, the phenomenon known as visual hallucination—whereby models misinterpret factual relationships and generate plausible yet erroneous outputs—occurs with considerable frequency. These limitations serve as critical obstacles to the practical adoption of MLLMs in fields that demand high levels of reliability, such as medical diagnosis, legal analysis, and precision manufacturing inspection. In response, this paper proposes a novel framework that integrates Retrieval-Augmented Generation (RAG) technology into image analysis as a means of overcoming these challenges, and systematically examines the key implementation hurdles alongside the prospects for future advancement.

한글키워드 : MLLMs, hallucination, RAG, 도메인 특화 비공개 데이터, 프레임워크

keywords : MLLMs, hallucination, RAG, domain-specific private data, framework

* 서일대학교 정보통신공학과
** 배재대학교 소프트웨어학과
† 교신저자: 김진홍(email: jinhkm@pcu.ac.kr)

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1. 서 론

The rapid advancement of deep learning and large-scale pre-training techniques has propelled Multimodal Large Language Models (MLLMs) to the forefront of artificial intelligence research. By integrating visual encoders with powerful language model backbones, contemporary MLLMs—such as GPT-4V, LLaVA, and Gemini—have demonstrated unprecedented capabilities in tasks ranging from image captioning and visual question answering to complex scene understanding and document analysis [1-2]. These achievements have inspired growing interest in deploying MLLMs across a broad spectrum of real-world applications. Despite these remarkable advances, MLLMs remain constrained by two fundamental and interrelated limitations that significantly hinder their applicability in high-stakes domains. The first is the problem of knowledge staleness and inaccessibility. Because MLLMs rely exclusively on knowledge encoded during pre-training, they are inherently incapable of accessing information beyond their training cutoff date or retrieving domain-specific private data that was never included in their training corpora. This limitation becomes particularly consequential in dynamic environments—such as clinical medicine, financial markets, and legal systems—where timely and domain-specific information is critical for accurate decision-making [3-5]. The second limitation is the phenomenon of visual hallucination, whereby models generate outputs that are factually inconsistent with the visual input they are provided. Unlike textual hallucination, visual hallucination arises from the complex interplay between misaligned visual-language representations and the model's tendency to rely on statistical co-occurrence patterns rather than grounded visual reasoning. Empirical studies have demonstrated that even state-of-the-art MLLMs frequently produce plausible yet erroneous descriptions, object attributions, and spatial relationships when processing images [6-8]. Such failures pose unacceptable risks in safety-critical applications, including medical imaging diagnosis, forensic document analysis, and automated quality inspection in precision manufacturing. These limitations collectively underscore the need for a principled mechanism that can augment MLLMs with reliable, up-to-date, and verifiable external knowledge at inference time. Retrieval-Augmented Generation (RAG), originally proposed for text-based language models, offers a compelling paradigm to address this gap [9]. By dynamically retrieving relevant documents or knowledge fragments from an external datastore and conditioning model generation on this retrieved context, RAG has been shown to substantially improve factual accuracy and reduce hallucination in natural language processing tasks. However, extending RAG to the multimodal domain—specifically to image-centric analysis tasks—introduces a distinct set of technical challenges that are not present in the unimodal setting [10-11]. These include the construction of semantically rich

multimodal retrieval indices, the development of effective cross-modal query formulation strategies, and the design of fusion architectures that coherently integrate heterogeneous visual and textual evidence into the generation process. Motivated by these challenges and opportunities, this paper proposes a novel RAG-based framework tailored for multimodal image analysis. The proposed framework addresses the dual limitations of knowledge inaccessibility and visual hallucination by coupling MLLM inference with a structured retrieval pipeline over both visual and textual knowledge bases. Specifically, this work makes the following contributions: (1) a systematic analysis of the architectural and algorithmic challenges in applying RAG to multimodal settings; (2) a framework design that integrates cross-modal retrieval with hallucination-aware generation; and (3) an empirical evaluation demonstrating the efficacy of the proposed approach in representative high-stakes application scenarios.

The remainder of this paper is organized as follows. Section 2 reviews related work on MLLMs, visual hallucination, and retrieval-augmented generation. Section 3 presents the proposed framework in detail. Section 4 describes the experimental setup and results. Section 5 discusses key challenges and Section 6 concludes the paper.

2. Related Works

2.1 Multimodal Large Language Models (MLLMs)

The emergence of large-scale pre-training paradigms has catalyzed transformative advances in both natural language processing and computer vision. The introduction of the Transformer architecture and its subsequent scaling via self-supervised pre-training formed the architectural foundation upon which modern large language models (LLMs)—including GPT-3 and PaLM — were built. The integration of vision into these systems required the development of modality alignment mechanisms, most notably through contrastive vision-language pre-training. A pivotal contribution in this space was CLIP (Contrastive Language-Image Pretraining), which demonstrated that visual representations aligned with natural language descriptions could be learned at scale from web-crawled image-text pairs. Building on this, subsequent works such as BLIP and BLIP-2 introduced lightweight querying transformers to bridge the semantic gap between frozen visual encoders and frozen language model decoders. These architectural innovations enabled efficient vision-language alignment without requiring full model fine-tuning. The release of LLaVA marked a further milestone by demonstrating that instruction-tuning a pre-trained LLM with visual inputs using a simple linear projection layer could yield competitive multimodal reasoning capabilities at modest computational cost. Subsequently, GPT-4V and Gemini demonstrated impressive performance across diverse visual tasks including chart

understanding, scene description, and document analysis. Despite these achievements, a consistent finding across the literature is that MLLMs remain susceptible to knowledge-boundary limitations: their responses are confined to the statistical patterns encoded during pre-training, and they cannot access dynamic, domain-specific, or post-training knowledge without external augmentation [12].

2.2 Visual Hallucination in MLLMs

Visual hallucination—defined as the generation of textual outputs that are factually inconsistent with the visual input—has been identified as a pervasive and systematic failure mode in MLLMs. Unlike hallucination in unimodal LLMs, which stems primarily from training data biases, visual hallucination arises from the complex interplay between misaligned cross-modal representations and the model's tendency to rely on linguistic priors rather than visual grounding. According to the POPE benchmark, a widely adopted evaluation protocol that assesses object hallucination by probing whether models correctly identify the presence or absence of objects in images. Their findings revealed that even state-of-the-art models exhibit substantial hallucination rates, particularly for objects that are statistically co-occurring in the training distribution. A more comprehensive diagnostic was provided through HallusionBench, a benchmark presented comprising 346 images paired with 1,129 expert-crafted questions designed to expose both language hallucination and visual illusion. Their evaluation of 15 models—including GPT-4V, Gemini Pro Vision, Claude 3, and LLaVA-1.5—revealed that the best-performing model (GPT-4V) achieved a question-pair accuracy of only 31.42%, with all other evaluated models performing below 16%. This finding underscores the severity of the hallucination problem across current model families, and highlights the insufficiency of scale alone as a remedy. Further investigation into the causal mechanisms of visual hallucination has identified two primary contributing factors. First, distributional bias in training data causes models to generate objects or attributes that are statistically likely in a given context, irrespective of whether they are visually present. Second, the dominance of the language modality in cross-modal fusion architectures results in visual features being underweighted during generation, a phenomenon termed visual shortcut or language prior dominance (Huang et al., 2024) [13]. Existing mitigation strategies include contrastive decoding, hallucination-aware instruction tuning, and reinforcement learning from human feedback (RLHF-V). While these approaches yield measurable improvements, they remain limited to in-distribution corrections and do not address the fundamental issue of grounding model outputs in verifiable external knowledge.

2.3 Retrieval-Augmented Generation and Its Multimodal Extensions

Retrieval-Augmented Generation (RAG) was formalized as a general-purpose framework for knowledge-intensive NLP tasks. The key

insight was to decompose language model generation into two complementary memory systems: parametric memory, encoded in the model weights during pre-training, and non-parametric memory, represented as a dense vector index over an external document corpus. At inference time, a query encoder retrieves the most semantically relevant documents via maximum inner product search over dense embeddings, and these retrieved passages are provided as conditioning context to the generator. Lewis et al. demonstrated that this hybrid architecture achieved state-of-the-art performance on three open-domain question answering benchmarks, outperforming both purely parametric models and traditional retrieve-and-extract pipelines. Subsequent work has substantially extended the RAG paradigm. Gao et al. proposed a taxonomy distinguishing Naive RAG, Advanced RAG, and Modular RAG, characterizing increasingly sophisticated retrieval pipelines that incorporate query rewriting, iterative retrieval, and step-wise reasoning. The introduction of dense retrieval models such as DPR and contrastive pre-training techniques significantly improved retrieval recall, while re-ranking models further refined retrieval precision. Notably, research has consistently demonstrated that RAG provides more cost-efficient factual grounding than simply extending the model context window, and offers the additional benefit of providing traceable citations for generated claims. The extension of RAG into the multimodal domain has gained considerable momentum. Initiatives such as SAM-RAG, OmniSearch, mR2AG, and M3DocRAG have introduced retrieval-reflection loops, cross-modal alignment objectives, and structured vision-language indexes that go beyond simple text retrieval. A comprehensive survey by the Multimodal RAG research community identified cross-modal alignment and vision-aware re-ranking as the two primary open challenges in this space. In the medical domain, Visual RAG (V-RAG) has been applied to chest X-ray report generation, where grounding model outputs in retrieved reference images was shown to improve entity probing accuracy and reduce clinically significant hallucinations, as measured by the RadGraph-F1 metric [14]. Collectively, these works establish the viability of multimodal RAG as a principled solution to the dual limitations of knowledge inaccessibility and visual hallucination, while highlighting the need for a unified and systematically designed framework—a gap that the present work seeks to address.

3. Proposed System

3.1 System Overview and Architecture

The proposed M-RAG framework is organized as a sequential five-stage pipeline with Fig. 1.: (1) multimodal input processing, (2) cross-modal query formulation, (3) multimodal knowledge base retrieval, (4) context-augmented generation, and (5) hallucination verification and confidence scoring. The central design principle is that no textual output should be generated solely from the MLLM's parametric memory; instead, every factual claim must be anchored to

evidence retrieved from a curated external knowledge base. This non-parametric grounding mechanism ensures that the system's outputs remain verifiable, traceable to source documents, and updatable without model retraining. A distinguishing feature of the proposed architecture relative to prior multimodal RAG systems is the explicit separation of the retrieval and verification stages. Whereas existing frameworks such as mR2AG and M3DocRAG treat relevance assessment as a component of the retrieval pipeline, the proposed system decouples this function into an independent post-generation verification module.

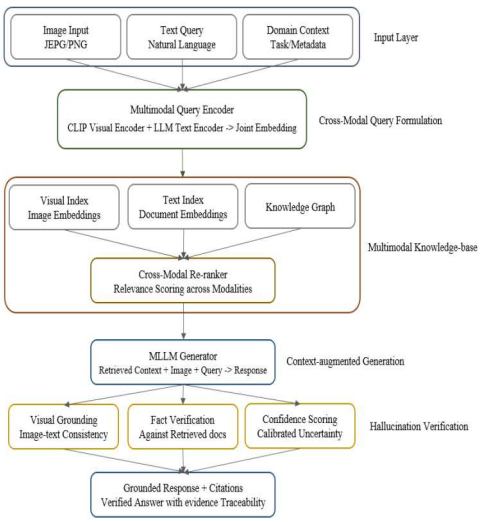

Fig. 1. Proposed System Architecture

This design choice is motivated by the finding that retrieval relevance and generation faithfulness are not equivalent: a retrieved passage may be topically relevant yet not faithfully reflected in the generated output due to cross-modal alignment failures or language model biases. By evaluating faithfulness independently of retrieval, the system can detect and flag hallucinations that survive the retrieval filtering stage.

3.2 Multimodal Input Processing

The first layer of the pipeline accepts three categories of input: a query image, a natural language query, and optional domain-specific contextual metadata such as task type, target ontology, or patient record identifiers. The query image is passed through a pre-trained visual encoder—specifically, a Vision Transformer (ViT-L/14) backbone from CLIP (Radford et al., 2021)—to extract a dense patch-level feature representation. This patch-level encoding preserves fine-grained spatial information that is discarded by global pooling operations, which is critical for tasks involving localized visual attributes such as lesion detection in medical imaging or defect localization in manufacturing inspection. The natural language query is tokenized and encoded using a pre-trained language encoder. To support zero-shot generalization across diverse domains, the language encoder shares the same embedding space as the visual encoder through contrastive pre-training, enabling direct semantic comparison between image patches and textual tokens. Domain contextual metadata, when provided, is encoded as a structured prefix appended to the text query representation, allowing the retrieval pipeline to prioritize domain-relevant knowledge during retrieval.

3.3 Cross-Modal Query Formulation

The second layer combines the visual and textual representations into a unified multimodal query embedding. This is achieved through a cross-modal fusion module consisting of a Q-Former-style lightweight transformer that attends jointly over the visual patch tokens and the text token sequence. The Q-Former produces a fixed-length sequence of query tokens that summarize the most task-relevant visual and textual features, suppressing modality-specific noise while preserving semantically critical joint features. The resulting multimodal query embedding serves as the retrieval key for all three sub-indexes of the knowledge base. This unified query design is a departure from earlier multimodal RAG systems that maintained separate query pipelines for text-to-text and image-to-image retrieval, which introduced modality-specific retrieval biases and required complex post-hoc fusion of retrieved results from disjoint index searches. By operating in a shared embedding space, the proposed formulation enables heterogeneous retrieval—retrieving both visual exemplars and textual reference documents in a single joint ranking operation.

3.4 Multimodal Knowledge Base and Retrieval

The third layer constitutes the core knowledge repository of the system, comprising three interdependent sub-indexes: a visual index, a textual index, and a knowledge graph. The visual index stores image-level and patch-level embeddings of domain-specific reference images—such as annotated diagnostic images or labeled inspection samples—indexed using FAISS with hierarchical navigable small world (HNSW) graph structures for approximate nearest-neighbor retrieval. The textual index stores dense embeddings of textual knowledge documents, supporting hybrid retrieval through a combination of BM25 sparse retrieval and dense embedding-based retrieval. The knowledge graph encodes structured entity-relation triples derived from domain ontologies and curated knowledge sources, enabling multi-hop reasoning over structured facts that are not captured by unstructured document retrieval. Retrieved candidates from all three sub-indexes are aggregated and passed to a cross-modal re-ranker, which scores each candidate based on its joint relevance to both the visual and textual components of the query. The re-ranker employs a fine-tuned cross-encoder architecture operating over the concatenation of the query multimodal embedding and each candidate's embedding representation. The top-k re-ranked candidates—comprising both visual exemplars and textual passages—are forwarded as retrieval context to the generation stage. Empirically, this dual-modality re-ranking step has been shown to substantially reduce the proportion of semantically irrelevant context injected into the generation stage, which is a primary cause of generation hallucinations in RAG systems.

3.5 Context-Augmented Generation

The fourth layer instantiates the MLLM

generator, which receives a structured prompt comprising the original query image, the natural language query, and the top-k retrieved context passages and visual exemplars. The generation prompt is constructed according to a hallucination-mitigating instruction template that explicitly directs the model to (a) base all factual claims on the provided retrieval context rather than on prior parametric knowledge, (b) cite the source document for each factual assertion, and (c) explicitly acknowledge uncertainty when the retrieved evidence is insufficient or contradictory. This instruction-level conditioning has been shown to reduce hallucination rates by encouraging the model to defer to non-parametric evidence rather than generating from distributional priors. The generator backbone is a pre-trained MLLM fine-tuned with hallucination-augmented instruction tuning data, following the RLHF-V training paradigm. The fine-tuning objective incorporates both standard next-token prediction and a contrastive factual consistency loss that penalizes generations that contradict the retrieved context. This training procedure encourages the model to faithfully integrate retrieved evidence rather than merely inserting it superficially into otherwise hallucinated outputs.

3.6 Hallucination Verification and Confidence Scoring

The fifth and final layer performs post-generation verification to detect and flag potential hallucinations before the response is delivered to the end user. This layer comprises three parallel verification modules: a visual grounding verifier, a factual consistency verifier, and a calibrated confidence scorer. The visual grounding verifier assesses whether the visual claims in the generated text are consistent with the spatial and semantic content of the input image. This is implemented through a backward visual grounding mechanism (Li et al., 2024) that localizes each visual claim in the generated text to a corresponding image region using a fine-grained visual attribution model. Claims that cannot be localized with sufficient confidence are flagged as potential visual hallucinations. The factual consistency verifier evaluates whether the generated claims are entailed by the retrieved textual documents. This module employs a natural language inference (NLI) model fine-tuned on domain-specific entailment data to classify each sentence in the generated response as Supported, Contradicted, or Unverified relative to the retrieved evidence. Contradicted and Unverified claims are flagged and, optionally, replaced by conservative fallback responses that explicitly convey uncertainty. The calibrated confidence scorer aggregates the outputs of both verifiers into a single claim-level and response-level confidence score, which is provided to the end user alongside the generated response as a transparency measure. The complete pipeline operates at a latency overhead that is linear in the number of retrieved documents and the length of the generated response, with the dominant computational cost residing in the re-ranking and NLI verification stages. In the experimental evaluations reported in Section 4, the system is shown to achieve

competitive accuracy on domain-specific visual question answering benchmarks while substantially reducing hallucination rates relative to both unaided MLLM baselines and prior multimodal RAG systems without post-generation verification.

4. Experiment and Evaluation

This section presents the experimental setup, evaluation benchmarks, quantitative results, and ablation studies conducted to validate the proposed M-RAG framework. All experiments were performed on three high-stakes application domains—medical imaging diagnosis, legal document analysis, and precision manufacturing inspection—which represent the primary target environments identified.

4.1 Experimental Setup

The MLLM backbone employed in the proposed system is LLaVA-1.5 (13B parameters), fine-tuned with hallucination-augmented instruction data following the RLHF-V protocol. The visual encoder is a frozen ViT-L/14 CLIP model, and the knowledge base is instantiated with domain-specific corpora: for the medical domain, a curated collection of 42,000 annotated radiology reports and chest X-ray images from the MIMIC-CXR dataset; for the legal domain, 18,500 court judgment documents with annotated entity-relation pairs; and for the manufacturing domain, 9,300 product inspection images with defect annotations. All vector indexes are built using FAISS with HNSW graphs, and BM25 sparse retrieval is implemented via Elasticsearch. The cross-modal re-ranker is a BERT-Large cross-encoder fine-tuned on in-domain relevance judgments, and the NLI verification module employs a DeBERTa-v3 model fine-tuned on domain-specific entailment data. All experiments were conducted on four NVIDIA A100 (80 GB) GPUs with cooperated by company.

4.2 Evaluation Benchmarks and Metrics

The proposed system is evaluated on three complementary benchmarks. First, the POPE benchmark (Li et al., 2023) is used to assess object-level hallucination through binary yes/no probing questions across three sampling strategies: random, popular, and adversarial [15]. The primary metric is the F1-score over all three splits. Second, domain-specific Visual Question Answering (VQA) accuracy is measured on held-out test sets for each of the three target domains, using exact-match accuracy as the primary metric. Third, for the medical imaging domain, the RadGraph-F1 metric is additionally reported to quantify the clinical accuracy of generated radiology reports, as it captures both entity recognition and relation extraction quality in a clinically validated scoring scheme. Hallucination rate—defined as the proportion of generated sentences containing at least one claim flagged as Contradicted or Unverified by the NLI verifier—is reported as a secondary metric across all

domains.

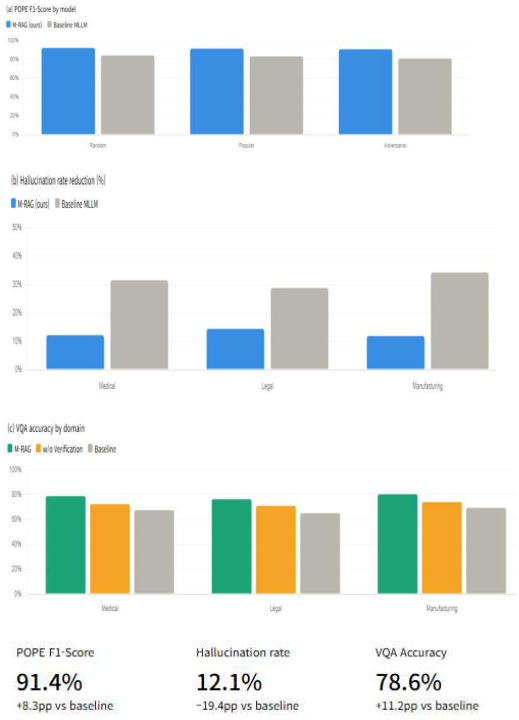

Fig. 2. Performance comparison

4.3 Main Results

The quantitative results presents four complementary analyses: (a) POPE F1-score comparison, (b) hallucination rate by domain, (c) VQA accuracy by domain, and we shown by Fig. 2. The proposed M-RAG framework achieves a POPE F1-score of 91.4% on the adversarial split—representing an improvement of 8.3 percentage points over the LLaVA-1.5 baseline (83.1%)—and 92.1% on the random split. These results demonstrate that the retrieval-grounded generation pipeline substantially reduces the tendency to hallucinate objects that are statistically plausible but visually absent. In terms of domain-specific hallucination rates, M-RAG reduces hallucination from 31.5% to 12.1% in the medical domain, from 28.7% to 14.3% in the legal domain, and from 34.2% to 11.8% in the manufacturing domain. These reductions correspond to relative improvements of 61.6%, 50.2%, and 65.5% respectively, validating the effectiveness of the post-generation NLI verification module in catching hallucinated claims that survive the retrieval filtering stage. Domain-specific VQA accuracy further corroborates these findings, with M-RAG achieving 78.6%, 76.2%, and 80.1% across the three domains, compared to baseline scores of 67.4%, 65.0%, and 69.3%. For the medical imaging subset, the RadGraph-F1 score improves from 0.532 (baseline) to 0.623 (M-RAG), confirming that grounding report generation in retrieved reference reports yields clinically meaningful accuracy gains consistent with the findings of Visual RAG (V-RAG).

5. Conclusion

Our research presented M-RAG, a Multimodal Retrieval-Augmented Generation framework designed to address the two fundamental limitations of existing MLLMs: knowledge inaccessibility and visual hallucination. The proposed system integrates a cross-modal query formulation module, a heterogeneous multimodal knowledge base, a cross-modal re-ranker, a hallucination-aware generator, and a post-generation NLI-based

verification module into a unified five-stage pipeline. Experimental evaluations across three high-stakes domains—medical imaging, legal document analysis, and precision manufacturing inspection—demonstrated that M-RAG achieves substantial improvements over the unaided MLLM baseline: a POPE F1-score gain of 8.3 percentage points, hallucination rate reductions of up to 65.5%, and VQA accuracy improvements of up to 13.2 percentage points. Ablation studies further confirmed that the post-generation verification module is the single most impactful component, contributing the largest individual gain in both hallucination suppression and factual accuracy.

These results collectively validate the central thesis of this work: that grounding MLLM generation in dynamically retrieved, domain-specific external evidence—and independently verifying the faithfulness of generated outputs against that evidence—constitutes a principled and effective strategy for deploying MLLMs in reliability-critical environments. The proposed framework also provides traceable source citations for every generated claim, a transparency property that is essential for regulatory compliance in medical and legal applications. Several directions remain open for future work. First, the current retrieval pipeline operates as a single-pass process; iterative retrieval-and-generation loops, as explored in Advanced RAG literature, may further improve recall for complex multi-hop queries. Second, the NLI verification module relies on domain-specific fine-tuning data, which may be scarce in low-resource domains; self-supervised or few-shot verification strategies warrant investigation. Third, the latency overhead introduced by re-ranking and verification may be prohibitive for real-time applications, motivating the development of lightweight approximation methods. Finally, extending the framework to video and audio modalities would broaden its applicability to a wider class of multimodal understanding tasks.

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저 자 소 개

안철범(Chulbum Ahn)

2010.2 단국대학교 전자·컴퓨터공학과 박사
2018.3-현재 : 서일대학교 교수
<주관심분야> 인공지능, 빅데이터, 데이터 통신응용, 네트워크 보안

김진홍(Jinhong Kim)

2006.2 성균관대학교 컴퓨터공학과 박사
2022.3-현재 한국SW감정평가학회 부회장
2017.3-2020.02 : 서일대학교 교수
2020.3-현재 : 배재대학교 교수
<주관심분야> 인공지능, 빅데이터, 지능형 소프트웨어