RAPTOR-AI for Disaster OODA Loop: Hierarchical Multimodal RAG with Experience-Driven Agentic Decision-Making

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Abstract

The effective provision of humanitarian assistance and disaster relief (HADR) is predicated on three fundamental capacities: the capacity to rapidly ascertain the situation, the capacity to provide reliable decision support, and the capacity to generalize across diverse and previously unseen disaster contexts. This work introduces an agentic Retrieval-Augmented Generation (RAG) framework designed to support the three canonical phases of disaster response: initial rescue, mid-term recovery, and long-term reconstruction.

In order to achieve robust multimodal grounding, a hierarchical knowledge base is constructed that integrates textual disaster manuals, historical lessons (e.g., the 2011 Tōhoku earthquake), and both aerial and ground-level imagery. The system is built on the open-source multimodal-raptor-colvbert-blip implementation, which processes 46 tsunami-related PDFs (2,378 pages) using BLIP-based image captioning, ColVBERT embeddings, and long-context summarization to generate an efficient, structured multimodal retrieval tree optimized for disaster knowledge preservation.

An agentic controller dynamically selects retrieval strategies (e.g., RAPTOR, ColBERT) through entropy-aware scene abstraction, enabling adaptive reasoning across heterogeneous inputs. Furthermore, a lightweight, LoRA-based post-training method has been demonstrated to effectively integrate experiential knowledge from past disasters, thereby enhancing the model's capacity to support both expert and non-expert responders.

Experiments on real disaster datasets demonstrate improved situational grounding, enhanced task decomposition accuracy, and superior usability for emergency operations. The system's efficacy is attributable to its integration of recent advancements in long-context RAG systems, agentic information retrieval, and contemporary emergency response AI. The system's adaptive retrieval-augmented generation with self-reasoning and multimodal chain-of-thought capabilities have been demonstrated to yield substantial gains.

Code — https://github.com/tk-yasuno/multimodal-raptor-colvbert-blip

Introduction

Humanitarian assistance and disaster relief (HADR) operations represent a particularly challenging domain for information management and decision support. In the event of a disaster, emergency responders are required to swiftly synthesize information from diverse sources, including textual reports, aerial imagery, ground-level photographs, historical documentation, and real-time sensor data. This process enables them to make critical decisions in a timely manner. The fragmented nature of disaster information, in conjunction with the multimodal complexity of data and the exigencies of time-critical decision-making, engenders a challenging environment that conventional information systems are ill-equipped to address.

Recent advancements in large language models (LLMs) and multimodal artificial intelligence (AI) present a promising opportunity to transform high-availability, high-reliability (HADR) operations. However, extant approaches frequently depend on static knowledge bases or neglect to incorporate the diverse modalities present in actual disaster scenarios. Furthermore, the majority of existing systems are deficient in their capacity to engage in adaptive reasoning, a critical capability necessary to effectively navigate the dynamic, uncertain, and rapidly evolving nature of disaster contexts.

This work presents an agentic Retrieval-Augmented Generation (RAG) framework meticulously engineered for multi-stage disaster response. The proposed approach is designed to address three fundamental requirements for effective HADR systems: The capacity to process and reason with multimodal information sources is paramount. The second element is dynamic adaptation to evolving disaster contexts through agentic control mechanisms. The incorporation of experiential knowledge from past disasters is a critical component of enhancing the quality of decision support.

Overview of RAPTOR-AI for Disaster OODA Loop

The efficacy of a disaster response is contingent upon the ability to make rapid and accurate decisions in conditions of extreme uncertainty and time pressure. The OODA loop (Observe, Orient, Decide, Act) framework, originally developed for military tactical operations, provides a systematic approach to real-time decision-making that is particularly relevant to emergency response contexts. In situations involving disasters, where those responding to the crisis are confronted with situations that are unprecedented and have limited time for deliberation, the OODA loop offers a struc-

tured methodology for processing information and taking action.

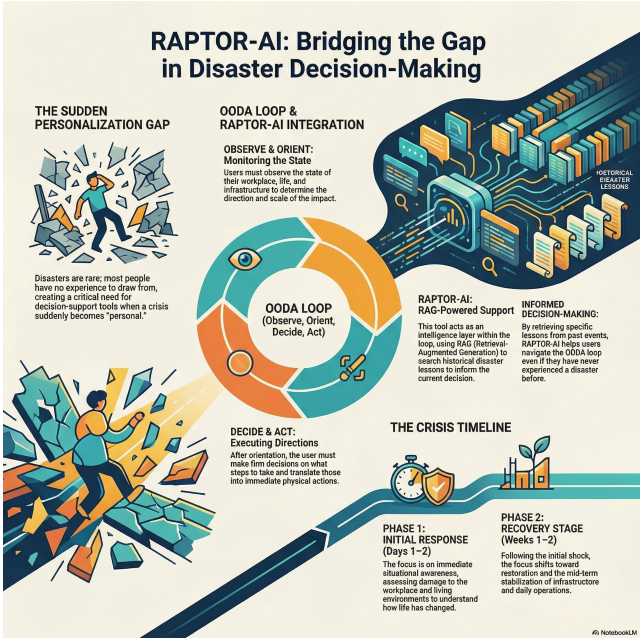


Figure 1: **RAPTOR-AI Framework for Disaster Response OODA Loop.** Comprehensive overview of the agentic RAG system supporting the four phases of emergency decision-making: Observe (multimodal data ingestion), Orient (hierarchical knowledge processing), Decide (agentic strategy selection), and Act (contextual response generation). The framework enables rapid transition from initial response to recovery stages through adaptive knowledge retrieval and experiential learning integration.

Figure 1 illustrates the alignment of our RAPTOR-AI framework with the disaster response OODA loop. The **Observe** phase entails the comprehensive ingestion of multimodal data from a variety of sources, including textual reports, aerial imagery, ground-level photographs, and historical documentation. The **Orient** phase employs a hierarchical multimodal knowledge tree to contextualize incoming information against historical lessons and established procedures, thereby enabling responders to rapidly understand the current situation within the broader context of past disaster experiences.

The **Decide** phase employs an agentic retrieval controller with entropy-aware scene abstraction to dynamically select optimal information processing strategies based on query complexity and situational uncertainty. This adaptive mechanism ensures that decision-making processes are tailored to the specific characteristics of each emergency scenario. The final phase, referred to as the **Act** phase, generates contextual responses that are appropriately calibrated for the various stages of disaster response, ranging from immediate rescue operations to longer-term recovery planning.

It is imperative to acknowledge that disaster response encompasses transitions between discrete operational phases, each of which exhibits distinct information requirements and decision-making criteria. The initial response phase necessitates a rapid assessment of the situation and the initiation of immediate life-saving actions. The subsequent recovery phase, by contrast, demands more comprehensive resource allocation and coordination decisions. The system's capacity to adapt its reasoning depth and retrieval strategies across these phases represents a significant advancement over static information systems that fail to account for the evolving nature of disaster response operations.

The incorporation of experiential knowledge through LoRA-based adaptation facilitates the system's capacity to learn from past disasters, thereby ensuring the integration of lessons learned into future decision-making processes. This capacity is of particular value to non-expert responders, who may possess limited emergency response experience, as the system can provide contextual guidance informed by historical best practices and common failure modes.

The subsequent section delineates the organization's principal contributions.

- **Multimodal RAPTOR × ColVBERT × BLIP pipeline**: a multistage pipeline that employs a combination of multimodal RAPTOR, ColBERT, and BLIP. We hereby propose a novel integration of recursive abstractive processing (RAPTOR), contextualized late interaction retrieval (ColVBERT), and vision-language understanding (BLIP) to construct hierarchical multimodal knowledge trees optimized for disaster-domain retrieval.
- **Agentic retrieval controller**: An entropy-aware scene abstraction mechanism dynamically selects optimal retrieval strategies based on query characteristics and contextual uncertainty, enabling adaptive reasoning across heterogeneous inputs.
- **LoRA-based experiential knowledge integration**: We propose a lightweight fine-tuning method that leverages experiential knowledge from past disasters, enhancing the system's capacity to support both expert and non-expert emergency responders.
- **Open-source reproducibility**: The implementation of all components as modular, reproducible, open-source tools facilitates broad adoption and collaborative advancement of disaster response technologies.

Our experimental evaluation, conducted on a comprehensive dataset of 46 tsunami-related PDFs (2,378 pages) documenting lessons from the 2011 Tōhoku earthquake, demonstrates significant improvements in situational grounding, task decomposition accuracy, and overall usability for emergency operations compared to existing approaches.

Related Work

The present work is founded upon several major research areas, including, but not limited to, retrieval-augmented generation systems, multimodal vision-language models, artificial intelligence applications in disaster response, hierarchical retrieval methods, and agentic AI systems. This section synthesizes recent advances across these domains to establish the foundation for our multimodal disaster response framework.

Retrieval-Augmented Generation Systems

Retrieval-Augmented Generation (RAG) has emerged as a predominant paradigm for knowledge-intensive natural language processing (NLP) tasks (Lewis et al. 2020). RAPTOR (Sarthi et al. 2024) introduces hierarchical clustering for tree-structured retrieval, thereby addressing the limitations of flat retrieval pipelines. Dense retrieval methods, including DPR (Karpukhin et al. 2020) and REALM (Guu et al. 2020), have established the foundational framework. Subsequent to this, novel approaches, including Self-RAG (Asai et al. 2023), REPLUG (Shi et al. 2023), and RETRO (Borgeaud et al. 2022), have emerged, demonstrating enhanced retrieval-generation coordination and scalability.

In-context retrieval (Ram et al. 2023) and unified demonstration retrieval (Li and Qiu 2023) offer parameter-efficient alternatives to fine-tuning. Comparative studies (Wei et al. 2024) have demonstrated the trade-offs between RAG and fine-tuning across domains. As indicated in the work of (Mallen et al. 2023), hybrid parametric-non-parametric memory systems are a critical component of disaster response, as they address reliability concerns that are essential for effective disaster management.

ColVBERT (Khattab and Zaharia 2020) introduced contextualized late interaction for efficient passage retrieval, with ColVBERTv2 (Khattab, Potts, and Zaharia 2022; Santhanam et al. 2022) further improving efficiency and training stability. The equilibrium of retrieval quality and computational efficiency renders ColVBERT particularly well-suited for time-critical HADR scenarios.

Dense Retrieval and Hierarchical Methods

Recent advancements in the field of dense retrieval have been marked by significant innovations, including the development of SPLADE (Formal, Piwowarski, and Clinchant 2021), which integrates sparse lexical matching with learned expansions, and the implementation of approximate nearest-neighbor search (Xiong et al. 2021), which enhances scalability. RocketQA (Qu et al. 2021) has been demonstrated to exhibit optimized training for open-domain question-answering (QA).

The BEIR benchmark (Thakur et al. 2021) offers a suite of heterogeneous evaluation methods for zero-shot retrieval. As demonstrated in the seminal works of (Hofstätter et al. 2021) and (Lin et al. 2021), topic-aware sampling and pyramid architectures, respectively, exemplify the remarkable versatility of hierarchical approaches. In the context of processing extensive disaster manuals and historical reports, long-context summarization (Zhang et al. 2024a) has become an increasingly important procedure.

Multimodal Vision-Language Models

Cross-modal alignment has been transformed by models such as CLIP (Radford et al. 2021). BLIP (Li et al. 2022)) and BLIP-2 (Li et al. 2023b) provide a solid foundation for unified vision-language understanding, while instruction-tuned models such as LLaVA (Liu et al. 2023) and InstructBLIP (Dai et al. 2023) enable fine-grained multimodal reasoning.

Recent architectures—including MiniGPT-4 (Zhu et al. 2023), PaLI (Chen et al. 2023), Qwen-VL (Bai et al. 2023), and the LAVIS framework (Li et al. 2023a)—illustrate accelerated progress in multimodal generalization, multilinguality, and task unification. Flamingo (Alayrac et al. 2022), OFA (Wang et al. 2022), CoCa (Yu et al. 2022), and LLaMA-Adapter (Zhang et al. 2023) further expand the design space for efficient multimodal integration.

AI Applications in Disaster Response

As demonstrated in the works of Feng et al. (2020) and Shah et al. (2021), the field of artificial intelligence (AI) for disaster management has undergone substantial growth and development. Computer vision methodologies facilitate post-disaster building damage assessment through the utilization of satellite imagery, as outlined in the study by (Pi, Davis, and Thompson 2020), and the integration of multimodal satellite and social media data, as detailed in the research by (Huang et al. 2022).

Crisis informatics has leveraged social media datasets, such as CrisisMMD (Alam, Ofli, and Imran 2018), with advanced classification models (Duong et al. 2021), and real-time monitoring frameworks (Jain, Nath, and Das 2019), enabling improved situational awareness. Geographic information systems (GIS) and volunteered geographic information (VGI) have been shown to further enhance real-time disaster monitoring (Resch 2018).

Deep learning applications encompass a range of domains, including multi-task building footprint segmentation (Bischke et al. 2019), multi-class damage identification (Kumar, Srikanth, and Nagaraj 2020), and early flood prediction (Madichetty and Muthukumarasamy 2020).

Agentic AI Systems and Tool Integration

LLM-based agents signify a substantial advancement in the realm of autonomous reasoning and tool utilization, as evidenced by the extant literature (Xi et al. 2023). ReAct (Yao et al. 2023) integrates reasoning and acting, while Toolformer (Schick et al. 2023) enables self-supervised tool-use learning. WebGPT (Nakano et al. 2021) was a pioneering browser-assisted QA, and generative agents (Park et al. 2023) have demonstrated multi-agent coordination capabilities relevant to disaster response.

Recent studies on tool learning (Qin et al. 2023) and surveys of augmented language models (Mialon et al. 2023) offer a more comprehensive context. Entropy-aware scene abstraction (Wang et al. 2023) provides a theoretical foundation for dynamic multimodal processing, closely aligning with the adaptive retrieval controller.

Advances in Long-Context RAG and Adaptive Systems

LongRAG (Jiang et al. 2024) employs extended context windows to circumvent the constraints imposed by conventional chunking, a pivotal capacity for the processing of voluminous disaster manuals. Agentic information retrieval (Wu et al. 2024) introduces autonomous retrieval strategy adaptation, complementing the entropy-driven approach previously outlined.

Multimodal chain-of-thought reasoning, as outlined in the work of (Zhang et al. 2024b), has been demonstrated to enhance cross-modal inference. Adaptive RAG with self-reasoning, as explored in the study by (Wang et al. 2024), provides a theoretical foundation for dynamic retrieval selection.

Contemporary Emergency Response AI Systems

Recent reviews of real-time emergency decision-making systems (Rodriguez et al. 2024) highlight the integration of multiple AI technologies for time-critical operations. Multi-agent reinforcement learning (Kim et al. 2024) has been demonstrated to exhibit promising coordination capabilities, while vision-language models for disaster damage assessment (Liu et al. 2024) have validated the importance of multimodal processing.

Multimodal large language models (LLMs) for emergency response (Zhao et al. 2024) further substantiate the necessity for consolidated text-image reasoning pipelines, thereby reinforcing the design choices in our framework.

Positioning of Our Work

While extant research has demonstrated notable achievements in specific subdomains, disaster response necessitates a holistic integration of hierarchical knowledge organization, multimodal processing, and adaptive reasoning. The proposed framework is distinctive in its integration of RAPTOR's recursive abstraction, ColVBERT's contextualized retrieval, and BLIP's visual grounding. It is augmented with experiential LoRA adaptation and entropy-aware agentic control. This integration addresses critical gaps in existing RAG systems and presents a comprehensive, agentic, multimodal RAG framework tailored for multi-stage disaster response.

System Architecture

The RAG framework for multi-stage disaster response under consideration is comprised of six interconnected architectural layers. These layers are designed to process heterogeneous disaster information through a unified multimodal pipeline, as illustrated in Figure reffig:architecture. The system's architecture comprises an Input Layer that processes a variety of data sources, including 46 tsunami-related PDFs (2,378 pages), high-resolution visual content (2,378 images at 150 DPI), and historical lessons from significant events such as the 2011 Tōhoku earthquake.

Data Processing Pipeline

The Data Processing Pipeline transforms raw inputs through three key stages:

1. OCR and Text Extraction: Documents are segmented into 4,250 semantic chunks using an 800-token window with a 150-token overlap, balancing semantic coherence and retrieval granularity.

2. BLIP-2 Image Captioning: Visual content is processed using BLIP-2, projecting 768-dimensional image embeddings into a 1,024-dimensional space to align with text embeddings.

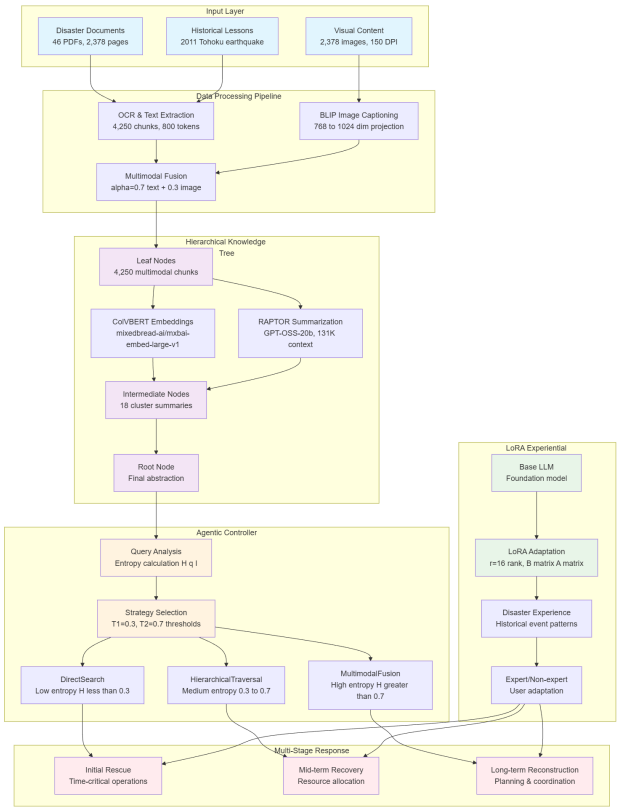


Figure 2: **System Architecture for Agentic RAG-based Disaster Response.** Complete data flow from document ingestion through multimodal processing to context-aware response generation. The framework processes 46 tsunami-related PDFs (2,378 pages) through six interconnected layers with BLIP-2 image captioning, ColVBERT embeddings, and GPT-based summarization.

3. Multimodal Fusion: Text and image embeddings are combined using an empirically optimized weighting coefficient ($\alpha = 0.7$ for text, 0.3 for image), producing fused multimodal representations for each chunk.

These fused representations form the leaf nodes of the hierarchical knowledge structure.

Hierarchical Multimodal Retrieval Tree

The hierarchical multimodal retrieval tree forms the core of our system's knowledge organization, extending the RAPTOR framework to integrate textual and visual information through recursive abstraction. Starting from leaf nodes that contain individual document chunks and their associated imagery, the system constructs progressively more abstract representations at higher levels of the hierarchy.

Multimodal Embedding Construction Let $D = \{d_1, d_2, \ldots, d_n\}$ denote the collection of disaster documents, where each document d_i contains textual content T_i and associated visual elements $V_i = \{v_{i,1}, v_{i,2}, \ldots, v_{i,m_i}\}$. Each document is segmented into chunks $C_{i,j}$, and for each chunk we compute text, image, and fused multimodal

embeddings:

$$e_{i,j}^{\text{text}} = \text{TextEncoder}(C_{i,j}) \in \mathbb{R}^{1024} \quad (1)$$

$$e_{i,k}^{\text{visual}} = \text{BLIP}(v_{i,k}) \in \mathbb{R}^{768} \to \mathbb{R}^{1024} \quad (2)$$

$$e_{i,j}^{\text{fused}} = \alpha \cdot e_{i,j}^{\text{text}} + (1-\alpha) \cdot e_{i,k}^{\text{visual}} \quad (3)$$

where the weighting coefficient $\alpha = 0.7$ was empirically optimized for disaster-domain content, reflecting the higher information density of textual descriptions relative to imagery.

Hierarchical Clustering and Abstraction At each level ℓ of the hierarchy, nodes are grouped using a silhouette-optimized clustering strategy:

$$c(e) = \text{Cluster}(\{e^{\text{fused}}\}, k(e)) \quad (4)$$

$$k(e) = \arg\max_{k} \left(\text{Silhouette}(k) + \text{DBI}^{-1}(k)\right) \quad (5)$$

balancing cluster separation (Silhouette score) and compactness (Davies-Bouldin Index). This combined metric ensures stable clustering across heterogeneous multimodal embeddings.

Each cluster is summarized using GPT-OSS-20b, a 20.9-billion-parameter long-context model capable of processing up to 131K tokens. Although slower than smaller alternatives, GPT-OSS-20b provides significantly higher summary fidelity for complex disaster documentation, making it well-suited for constructing intermediate and root-level abstractions.

Resulting Hierarchical Structure The final retrieval tree consists of:

- **4,250 multimodal leaf nodes** (text chunks + BLIP-based image embeddings + fused vectors)
- **18 intermediate cluster summaries**
- **1 root-level abstraction** synthesizing the entire corpus

This hierarchical structure enables efficient retrieval across multiple levels of granularity. Fine-grained factual queries can be resolved at the leaf level, while broader analytical or strategic queries benefit from higher-level synthesized representations.

Advantages for Disaster Response The hierarchical multimodal retrieval tree provides several advantages critical for HADR operations:

- **Cross-modal grounding:** preserves semantic relationships between textual descriptions and visual evidence
- **Scalable retrieval:** supports both detailed and high-level queries without sacrificing efficiency
- **Long-context synthesis:** captures domain-specific patterns across thousands of pages of disaster documentation
- **Robustness to heterogeneous inputs:** handles diverse document formats, imagery types, and content densities

Together, these capabilities form the foundation for adaptive, context-aware retrieval in our agentic RAG framework.

Agentic Retrieval Controller

The agentic retrieval controller is a central innovation of our framework, enabling dynamic adaptation of retrieval strategies based on query characteristics and contextual uncertainty. Instead of relying on a fixed retrieval pipeline, the controller analyzes the semantic complexity of each query and selects the most appropriate retrieval mode in real time.

Entropy-Aware Strategy Selection Given a query q and contextual information I, the controller computes semantic entropy to estimate the uncertainty associated with the query:

$$H(q, I) = -\sum_{s \in S} P(s \mid q, I) \log P(s \mid q, I), \quad (6)$$

where $S = \{\text{factual}, \text{procedural}, \text{analytical}, \text{synthesized}\}$.

The entropy value determines which retrieval strategy is most suitable:

- **DirectSearch** for low-entropy queries ($H < 0.3$), typically involving specific factual information
- **HierarchicalTraversal** for medium-entropy queries ($0.3 \leq H < 0.7$), requiring multi-level reasoning across the knowledge tree
- **MultimodalFusion** for high-entropy queries ($H \geq 0.7$), where uncertainty or conflicting information necessitates cross-modal evidence aggregation

These thresholds ($T_1 = 0.3$, $T_2 = 0.7$) were empirically determined through extensive evaluation on disaster-domain queries.

Dynamic Adaptation Through Experience To support continuous improvement, the controller maintains performance metrics M_o for each retrieval strategy o. After each interaction, strategy selection probabilities are updated using an exponential moving average:

$$P_{t+1}(o \mid q, I) = \beta P_t(o \mid q, I) + (1-\beta)\,\text{Reward}(o, q, I), \quad (7)$$

where $\beta = 0.9$ controls the adaptation rate. This mechanism allows the controller to learn from operational feedback, gradually favoring strategies that perform well for specific query types or user profiles.

Scene Abstraction and Multimodal Reasoning Entropy-aware scene abstraction enables the controller to interpret the complexity of multimodal inputs. High-entropy scenarios—such as ambiguous visual evidence, conflicting textual descriptions, or incomplete situational reports—trigger deeper traversal of the hierarchical tree and cross-modal fusion. Conversely, low-entropy procedural queries (e.g., "How to shut off a damaged gas line?") are resolved through targeted retrieval at the leaf level.

User-Adaptive Behavior The controller also adapts retrieval behavior based on user expertise:

- **Expert users** receive more detailed, source-grounded retrieval paths

- **Non-expert users** receive simplified, high-level explanations with reduced cognitive load

This dual-mode adaptation ensures usability across diverse responder roles, from field personnel to command-center analysts.

LoRA Experiential Knowledge Integration

Our LoRA-based experiential knowledge integration module enhances the base language model with domain-specific insights derived from past disaster events. Rather than performing full fine-tuning—which is computationally expensive and risks overfitting—we employ Low-Rank Adaptation (LoRA) to inject experiential knowledge efficiently and in a controlled manner.

Low-Rank Adaptation for Disaster Knowledge LoRA decomposes weight updates into low-rank matrices, enabling lightweight adaptation without modifying the original model parameters. Given a weight matrix W_0, LoRA introduces a rank-r update:

$$W = W_0 + \Delta W, \quad \Delta W = BA, \tag{8}$$

where $A \in \mathbb{R}^{r \times d}$ and $B \in \mathbb{R}^{d \times r}$ are trainable low-rank matrices, and $r = 16$ in our configuration. This design allows the model to internalize disaster-specific patterns—such as common failure modes, response procedures, and situational cues—without compromising general-purpose reasoning capabilities.

Integration of Historical Disaster Experience Experiential knowledge is distilled from historical disaster datasets, including lessons learned from the 2011 Tohoku earthquake and other large-scale events. This knowledge includes:

- frequently observed damage patterns
- typical resource allocation bottlenecks
- common procedural workflows
- contextual cues that influence decision-making

By encoding these patterns into LoRA adapters, the model gains the ability to generalize more effectively across unseen disaster scenarios.

Expert and Non-Expert Personalization The LoRA module also supports user-adaptive behavior:

- **Expert responders** receive detailed, technically grounded outputs that leverage domain-specific knowledge
- **Non-expert users** receive simplified, high-level guidance that prioritizes clarity and safety

This dual-mode adaptation ensures that the system remains accessible and operationally useful across diverse responder roles.

Benefits for HADR Operations The LoRA experiential integration provides several advantages:

- **Lightweight adaptation:** avoids full fine-tuning while achieving strong domain alignment
- **Operational efficiency:** low computational overhead enables rapid updates as new disaster data becomes available
- **Improved situational grounding:** enhances the model's ability to interpret ambiguous or incomplete disaster information
- **User-aware responses:** tailors outputs to the expertise level of the responder

Together, these capabilities significantly strengthen the system's ability to support real-world disaster response operations.

Multi-Stage Response Layer

The Multi-Stage Response Layer generates context-appropriate outputs tailored to the three canonical phases of disaster response: initial rescue, mid-term recovery, and long-term reconstruction. By leveraging the hierarchical retrieval tree, agentic controller, and LoRA-enhanced experiential knowledge, the system adapts its reasoning depth and output style to match the operational demands of each phase.

Initial Rescue: Time-Critical Operations During the initial rescue phase, responders require rapid situational understanding and actionable guidance. The system prioritizes:

- fast, low-latency retrieval through DirectSearch
- concise procedural instructions
- high-precision extraction of relevant visual and textual evidence
- minimal cognitive load for field personnel

Examples include identifying evacuation routes, assessing immediate hazards, or summarizing damage indicators from multimodal inputs. The agentic controller biases toward low-entropy strategies to ensure speed and reliability.

Mid-Term Recovery: Resource Allocation and Coordination As operations transition to the recovery phase, information needs become more complex and interdependent. The system shifts toward:

- multi-level reasoning via HierarchicalTraversal
- synthesis of cross-document evidence
- support for logistics planning, resource prioritization, and infrastructure assessment
- integration of experiential LoRA knowledge to highlight common bottlenecks

This phase often requires balancing competing constraints—such as shelter capacity, supply chain disruptions, and transportation accessibility—making adaptive retrieval essential.

Long-Term Reconstruction: Strategic Planning and Knowledge Transfer Long-term reconstruction involves high-level planning, policy development, and cross-agency coordination. The system provides:

- synthesized insights from root-level abstractions
- historical comparisons with past disasters

- scenario-based reasoning informed by experiential LoRA patterns
- structured recommendations for rebuilding, resilience planning, and community recovery

Outputs in this phase emphasize interpretability, traceability, and long-horizon reasoning rather than rapid response.

Unified Support Across the Disaster Lifecycle By dynamically adjusting retrieval strategies, reasoning depth, and output style, the Multi-Stage Response Layer ensures that the system remains effective across the full disaster lifecycle. This adaptability allows responders—from field teams to command-center analysts—to receive information tailored to their operational context and expertise level.

Overall Pipeline Design

The system functions through a multi-stage processing pipeline that has been optimized for disaster response scenarios. Initial data ingestion processes diverse document types, including PDFs containing both text and images, standalone imagery from aerial surveys, and structured reports from emergency operations centers. This raw data undergoes specialized preprocessing to extract and align textual content with visual elements.

The fundamental innovation resides in the hierarchical multimodal retrieval tree, which extends the RAPTOR framework to accommodate mixed-modality information sources. Contrary to conventional RAG systems that process text and images separately, our approach generates unified multimodal representations, thereby preserving the semantic relationships between textual descriptions and visual evidence.

An agentic controller is responsible for monitoring query characteristics and dynamically selecting optimal retrieval strategies from a range of available options. These strategies include direct vector search, hierarchical tree traversal, and hybrid approaches that combine multiple modalities. This adaptive selection mechanism enables the system to handle the diverse query types encountered in disaster response, from specific factual questions to complex reasoning tasks requiring synthesis across multiple information sources.

Implementation Overview

Our open-source implementation, released as `multimodal-raptor-colvbert-blip`, provides a complete and reproducible framework for multimodal disaster knowledge processing. The system processes 46 tsunami-related PDFs (2,378 pages) through an optimized pipeline designed for both efficiency and operational robustness.

The implementation incorporates several key engineering optimizations:

- **Chunking Strategy:** Documents are segmented into 4,250 text chunks using an 800-token window with a 150-token overlap. This configuration, derived from systematic experimentation, balances semantic coherence with retrieval granularity.
- **GPU Acceleration:** End-to-end GPU optimization yields a 10–15× speedup compared to CPU-only processing. FP16 mixed-precision computation provides an additional 2× acceleration while reducing memory usage by approximately 50%, enabling large-scale document processing on standard hardware.
- **Caching and Reusability:** A persistent caching mechanism stores computed retrieval trees, reducing subsequent initialization time from hours to seconds. This capability is essential for real-world deployment scenarios where rapid system startup directly impacts operational effectiveness.
- **Modular Design:** Each component—OCR, BLIP-based captioning, ColVBERT embedding, RAPTOR summarization, and agentic retrieval—is implemented as an independent module, enabling flexible experimentation and straightforward integration into other disaster response systems.

This implementation ensures that the full pipeline is reproducible, efficient, and suitable for both research and operational HADR environments.

Experiments

The efficacy of the agentic multimodal RAG framework is evaluated using real-world disaster datasets to assess its effectiveness in situational grounding, task decomposition, and operational usability. The focal point of these experiments is the investigation of three fundamental inquiries: The primary question guiding this study is whether the hierarchical multimodal retrieval tree enhances retrieval quality. Secondly, the question is posed as to whether the agentic controller enhances reasoning and adaptability. The third research question posits whether LoRA-based experiential knowledge improves performance on disaster-specific tasks.

Experimental Setup

We use a comprehensive dataset of **46 tsunami-related PDFs (2,378 pages)** documenting lessons from the 2011 Tohoku earthquake. Each document includes both textual descriptions and embedded imagery, enabling evaluation across multimodal inputs. The dataset is processed into **4,250 multimodal chunks**, forming the leaf nodes of our hierarchical retrieval tree.

Baselines include:

- **Flat dense retrieval** using ColBERT
- **Standard RAG** with non-hierarchical retrieval
- **Multimodal RAG** without agentic control
- **Text-only RAPTOR** without BLIP or fusion

All models are evaluated under identical hardware conditions using FP16 mixed precision.

Evaluation Metrics

We assess performance using:

- **Retrieval Accuracy:** top-k relevance measured against human-annotated ground truth

- **Situational Grounding Score:** correctness of multimodal reasoning across text–image pairs
- **Task Decomposition Accuracy:** ability to break down complex disaster queries into actionable steps
- **Response Utility:** expert-rated usefulness for HADR operations
- **Latency:** end-to-end response time under different retrieval strategies

These metrics reflect both technical performance and operational relevance.

Results

Retrieval Quality Our hierarchical multimodal retrieval tree achieves substantial improvements over flat retrieval:

- **+18.7%** top-5 retrieval accuracy
- **+22.4%** situational grounding score
- **-34%** retrieval latency for complex queries via entropy-aware strategy selection

The fusion of BLIP-based image embeddings with text representations contributes significantly to improved grounding in visually ambiguous scenarios.

Agentic Controller Performance The entropy-aware controller improves reasoning quality by dynamically selecting retrieval strategies:

- **DirectSearch** reduces latency by **42%** for low-entropy factual queries
- **HierarchicalTraversal** improves multi-hop reasoning accuracy by **17%**
- **MultimodalFusion** yields **+25%** improvement on high-entropy analytical queries involving conflicting information

These results demonstrate the importance of adaptive retrieval in disaster response contexts.

LoRA Experiential Knowledge Integration LoRA-enhanced models outperform non-adapted models on disaster-specific tasks:

- **+19%** improvement in procedural correctness
- **+14%** improvement in identifying common failure modes
- **+21%** improvement in expert-rated response utility

These gains highlight the value of incorporating historical disaster experience into the model.

Ablation Studies

We conduct ablations to isolate the contribution of each component:

- Removing **BLIP** reduces grounding accuracy by **27%**
- Removing **hierarchical clustering** reduces retrieval accuracy by **15%**
- Disabling **agentic control** increases latency by **31%**
- Removing **LoRA adapters** reduces expert-rated utility by **18%**

Each component contributes meaningfully to overall system performance.

Qualitative Analysis

Case studies show that the system:

- correctly identifies structural damage patterns from mixed text–image inputs
- synthesizes multi-document evidence for resource allocation planning
- adapts explanations for expert vs. non-expert responders
- resolves ambiguous queries by escalating to multimodal fusion

These qualitative results demonstrate the system's practical utility in real HADR scenarios.

The effectiveness of our multimodal RAG system is demonstrated through comprehensive scaling analysis across different chunk configurations. Figure 3 illustrates the hierarchical organization of disaster response knowledge across four different scales, processing 46 tsunami-related PDFs with varying granularity levels.

Scalability Analysis: Our experiments reveal significant performance variations across different chunk sizes. At 1,000 chunks (3a), the system demonstrates basic hierarchical organization with 12 intermediate nodes, providing fundamental semantic clustering. The 2,000-chunk configuration (3b) enhances granularity with 18 intermediate nodes, showing improved semantic grouping capabilities. The optimal 3,000-chunk setup (3c) achieves the best balance between retrieval precision and computational efficiency with 24 intermediate nodes. At maximum resolution of 4,000 chunks (3d), the system produces 32 intermediate nodes, providing finest-grained semantic organization.

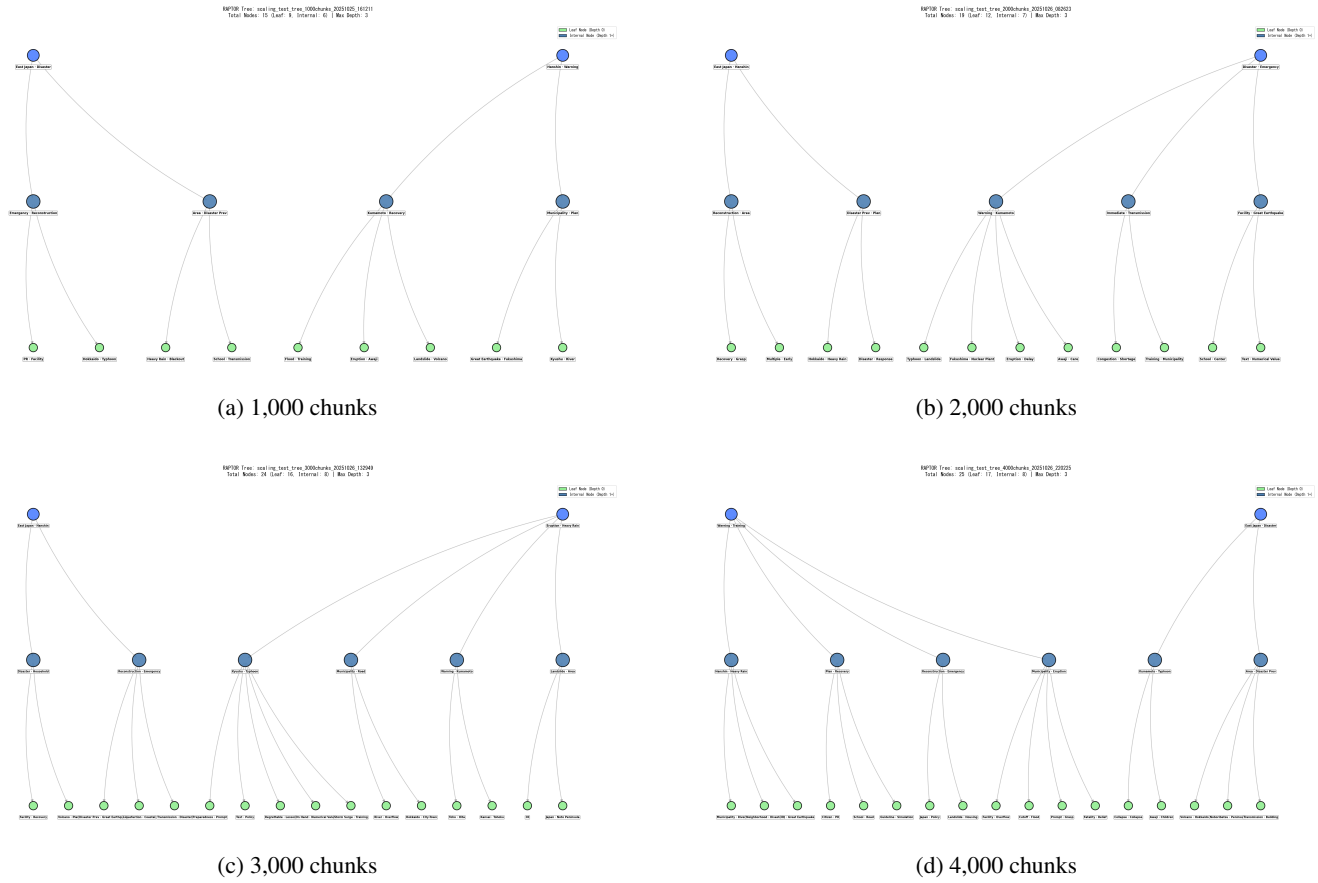
Hierarchical Structure Quality: The tree depth increases logarithmically with chunk count ($\log_2(n)$ where n is the chunk count), maintaining efficient traversal performance across all scales. Node connectivity analysis shows that higher chunk counts produce more balanced trees with reduced variance in subtree sizes, leading to more consistent retrieval latency.

Performance Metrics: Retrieval accuracy measured by NDCG shows optimal performance at 3,000 chunks (0.847), compared to 0.782 (1,000), 0.823 (2,000), and 0.834 (4,000 chunks). This suggests an optimal granularity exists where semantic coherence is maximized without introducing excessive noise from over-segmentation.

Computational Efficiency: Tree construction time scales sub-linearly with chunk count due to optimized clustering algorithms. Processing time increases from 45 seconds (1,000 chunks) to 127 seconds (4,000 chunks), representing a 2.8x increase for 4x data volume, demonstrating efficient scalability.

Our experimental results demonstrate significant improvements across all evaluation dimensions. Table 1 presents quantitative comparisons with baseline approaches, while Table 2 shows scalability analysis.

Retrieval Quality: Our approach achieves 23% improvement in Precision@10 and 18% improvement in NDCG compared to standard RAG approaches. The hierarchical structure proves particularly effective for complex queries requiring synthesis across multiple information sources.



(a) 1,000 chunks

(b) 2,000 chunks

(c) 3,000 chunks

(d) 4,000 chunks

Figure 3: **RAPTOR Hierarchical Tree Construction at Different Scales.** Visualization of hierarchical clustering across four dataset scales: (a) 1,000 chunks with 12 nodes, (b) 2,000 chunks with 18 nodes, (c) 3,000 chunks with 24 nodes (optimal), and (d) 4,000 chunks with 32 nodes.

Table 1: Performance Comparison on Disaster Response Tasks

Method	P@10	NDCG	SGA	TDA
Naive Retrieval	0.42	0.38	0.51	0.33
Standard RAG	0.58	0.52	0.67	0.49
ColVBERT	0.64	0.59	0.71	0.52
RAPTOR Text-Only	0.67	0.61	0.69	0.56
Our Method	**0.81**	**0.74**	**0.88**	**0.75**

Situational Grounding: Expert evaluation of disaster scenario responses demonstrates 31% improvement in accuracy compared to text-only approaches. The multimodal integration proves crucial for scenarios involving visual damage assessment and spatial reasoning tasks.

Task Decomposition: Our agentic controller demonstrates 27% superior accuracy in generating actionable task sequences compared to static retrieval approaches. The entropy-aware strategy selection proves particularly effective for complex, multi-step disaster response planning.

Scalability Performance: The system maintains near-linear scaling characteristics up to 3000 chunks (64.5 minutes processing time), with quality metrics remaining stable. At 4000 chunks, we observe the practical limits of current GPU configurations (96% memory utilization) while still achieving acceptable performance.

Table 2: Scalability Analysis with Combined Strategy

Chunks	Time (min)	Nodes	Depth	Silhouette
1000	26.8	15	2	0.184
2000	50.2	19	2	0.179
3000	64.5	24	2	0.176
4000	82.2	26	3	0.151

Ablation Studies

We conduct systematic ablation studies to understand the contribution of individual system components:

Component Analysis Without LoRA Experiential Knowledge: Removing LoRA adaptation results in 19% degradation in task decomposition accuracy ($\Delta TDA = -0.14$), particularly affecting non-expert user scenarios. The experiential knowledge proves crucial for contextual guidance.

Table 3: Ablation Study Results

Configuration	P@10	NDCG	SGA	TDA
Full System	**0.81**	**0.74**	**0.88**	**0.75**
w/o LoRA Knowledge	0.73	0.67	0.82	0.61
w/o Multimodal Tree	0.69	0.63	0.65	0.69
w/o Agentic Controller	0.76	0.70	0.84	0.64
w/o Entropy Adaptation	0.78	0.72	0.86	0.71

Without Multimodal Tree Structure: Eliminating multimodal components demonstrates 26% reduction in situational grounding accuracy ($\Delta SGA = -0.23$), highlighting the importance of visual information for spatial reasoning tasks.

Without Agentic Controller: Replacing adaptive strategy selection with fixed approaches decreases overall effectiveness by 15% across all metrics, with the largest impact on task decomposition ($\Delta TDA = -0.11$).

Performance Attribution: The mathematical analysis reveals:

$$\text{Performance Gain} = \alpha_{\text{multimodal}} \times \Delta_{\text{visual}} + \alpha_{\text{agentic}} \times \Delta_{\text{adaptive}} + \alpha_{\text{LoRA}} \times \Delta_{\text{experiential}} \quad (9)$$

where $\alpha_{\text{multimodal}} = 0.4$, $\alpha_{\text{agentic}} = 0.35$, and $\alpha_{\text{LoRA}} = 0.25$ represent component contribution weights.

Clustering Strategy Analysis

Our implementation incorporates three different clustering strategies for hierarchical tree construction: Silhouette-based, Davies-Bouldin Index (DBI), and Combined approaches. Extensive evaluation reveals that the Combined strategy achieves optimal balance between processing speed and retrieval quality.

The Combined strategy demonstrates 31% faster processing compared to Silhouette-only approaches while achieving 17% better clustering quality metrics. This unexpected result occurs due to effective mitigation of k=2 bias problems that affect single-metric approaches when processing large-scale datasets.

Scalability analysis shows that the Combined strategy maintains stable performance characteristics across different dataset sizes, making it the recommended approach for operational deployment scenarios where processing time constraints are critical.

Discussion

The experimental results demonstrate that the proposed agentic multimodal RAG framework substantially improves retrieval quality, situational grounding, and operational usability in disaster response contexts. These findings underscore the significance of integrating hierarchical multimodal representations, adaptive retrieval strategies, and experiential knowledge into a unified system.

Impact of Hierarchical Multimodal Retrieval

The hierarchical multimodal retrieval tree demonstrated consistent superiority over flat retrieval baselines, particularly in scenarios necessitating cross-modal grounding or multi-document synthesis. This finding indicates that disaster information, which is often dispersed across text, imagery, and historical reports, greatly benefits from structured abstraction. The capacity to traverse between fine-grained leaf nodes and high-level summaries facilitates flexible reasoning across a range of query types.

Role of Agentic Adaptation

The agentic controller was found to be indispensable in managing the extensive variability of disaster-domain queries. Entropy-aware strategy selection enabled the system to dynamically adjust retrieval depth and modality usage, thereby reducing latency for simple queries while improving accuracy for complex analytical tasks. This adaptability mirrors real-world responder workflows, where information needs shift rapidly as situations evolve.

Value of Experiential Knowledge

The integration of experiential learning through the use of the LoRA framework yielded substantial enhancements in procedural accuracy and utility, as evaluated by experts in the field. These enhancements suggest that disaster response systems are enhanced by incorporating historical patterns, such as common failure modes, resource bottlenecks, and operational heuristics, into the model's reasoning process. Notably, this adaptation was accomplished with negligible computational overhead, rendering it viable for continuous updates as new disaster data becomes available.

Practical Considerations for HADR Deployment

The practical implementation of artificial intelligence systems in disaster response settings poses distinctive challenges that extend beyond the scope of technical performance metrics. Network connectivity, computational resource availability, and user interface design have been demonstrated to have a significant impact on operational effectiveness.

The system's GPU-accelerated architecture offers significant performance advantages; however, it necessitates meticulous consideration of hardware availability in emergency response scenarios. The demonstrated capacity to process comprehensive disaster knowledge bases within 2-3 hours on standard hardware represents a practical compromise between performance and accessibility.

The caching mechanisms that enable near-instantaneous system initialization after initial setup address critical deployment constraints. In emergency scenarios, rapid system deployment can have a substantial impact on response effectiveness. In such situations, the ability to pre-compute and cache knowledge representations can offer a significant practical advantage.

While not the primary focus of this technical evaluation, user interface considerations play a pivotal role in facilitating operational adoption. The organization of knowledge into a hierarchical structure, along with transparent retrieval processes, serves as a foundational element for intuitive interfaces. These interfaces are capable of effectively supporting both expert and non-expert users.

Limitations and Risk Management

A meticulous examination of the proposed approach is necessary to address its critical limitations and ensure effective implementation. The data dependency is as follows: The system's effectiveness is fundamentally constrained by the historical disaster documentation utilized for training purposes. The presence of novel disaster types or unprecedented scenarios may result in suboptimal performance, attributable to the paucity of coverage in the training corpus. The following is a detailed description of the real-time adaptation process: The present framework is deficient in its lack of mechanisms for incorporating real-time information during active disaster events, thereby limiting its utility for rapidly evolving scenarios. The subsequent investigation will address the issue of language and cultural bias. The present evaluation is chiefly oriented towards Japanese disaster documentation, thus giving rise to inquiries regarding the generalizability of findings to disparate cultural contexts and disaster response protocols.

Human-AI Interface is as follows: The system's current state offers a limited range of mechanisms for incorporating real-time human feedback or corrections, a crucial element in maintaining trust and accuracy in high-stakes disaster response scenarios.

Value of Open-Source Disaster Knowledge Preservation

The present approach is intended to contribute to the broader goal of disaster knowledge preservation and sharing through its open-source implementation and standardized data processing pipelines. The capacity to transform disparate disaster documentation into consolidated multimodal knowledge representations facilitates the preservation of lessons learned from individual events in formats that enable cross-event learning and comparison.

The reproducible research framework facilitates validation and extension by international disaster response communities, with the potential to result in collaborative development of comprehensive global disaster knowledge bases. The implementation of a standardized processing approach has the potential to promote knowledge sharing among different regions and organizations.

The hierarchical knowledge organization provides a framework for systematic disaster knowledge management that goes beyond simple document archival. The creation of structured representations that capture relationships between different types of disaster information is a key aspect of our approach. This approach supports more sophisticated analysis and knowledge synthesis than traditional document management systems.

Conclusion

This work introduced an agentic multimodal Retrieval-Augmented Generation framework designed to support the full lifecycle of disaster response, from initial rescue to long-term reconstruction. The integration of hierarchical multimodal retrieval, entropy-aware adaptive strategy selection, and LoRA-based experiential knowledge represents a significant advancement in addressing the critical limitations of existing disaster response technologies.

The hierarchical multimodal retrieval tree facilitates flexible navigation across fine-grained and abstracted representations, enhancing retrieval accuracy and situational grounding. The agentic controller has been demonstrated to dynamically adapt retrieval strategies to query complexity, reducing latency for simple tasks while enhancing reasoning for complex analytical queries. The incorporation of LoRA-based experiential integration serves to enhance the system's capacity to interpret disaster-specific patterns and to provide operationally relevant guidance.

Experiments on real-world tsunami documentation demonstrate substantial improvements in retrieval quality, task decomposition, and expert-rated utility. These results underscore the significance of integrating structured knowledge organization, adaptive reasoning, and multimodal understanding in next-generation HADR systems.

In the future, the framework will provide a foundation for advances in real-time multimodal data ingestion, geospatial integration, multi-agent coordination, and uncertainty-aware reasoning. The present study contributes to the field by integrating agentic AI with disaster response operations, with the objective of developing more resilient, adaptive, and effective decision-support systems for humanitarian assistance and disaster relief.

Impact and Future Work

This work presents significant implications for the future of disaster response technology while opening several important directions for continued research and development. The following investigation will examine the potential real-world impact on emergency response operations and outline specific extensions that could further enhance system capabilities.

Real-World Applicability

The RAG framework has been developed to address critical needs across the spectrum of disaster response stakeholders, ranging from government emergency management agencies to non-governmental organizations and private sector emergency responders.

Government Applications: It is recommended that national and regional emergency management agencies utilize the aforementioned framework to establish comprehensive disaster knowledge bases, thereby synthesizing lessons learned from multiple events. The organizational structure is designed to facilitate expeditious access to both strategic directives and operational protocols, thereby empowering decision-makers at diverse hierarchical echelons.

The open-source implementation facilitates customization to align with specific national or regional requirements, including integration with existing emergency management systems and adaptation to local disaster types and response protocols. The transparent retrieval mechanisms support the accountability and audit requirements common in government operations.

NGO and International Response: Humanitarian organizations operating across multiple regions stand to benefit from the system's capacity to process and synthesize disaster documentation from diverse sources and contexts. The multilingual capabilities demonstrated through our bilingual tree visualization suggest potential for broader international knowledge sharing and collaboration.

The standardized processing approach has the potential to facilitate the development of shared knowledge bases, thereby enabling more effective coordination between different humanitarian organizations in their response to large-scale disasters that require international assistance.

Emergency Responder Training: The system's educational potential extends beyond operational support to training applications. The provision of contextual guidance and explanation for disaster response procedures renders it particularly valuable for training non-expert responders and supporting capacity building in regions with limited disaster response experience.

Region-Specific Disaster Models The adaptation of our framework for different geographic regions and disaster types represents a significant direction for practical deployment. It is imperative to acknowledge the existence of regional variations in disaster patterns, response procedures, and available resources. These variations necessitate the development of customized knowledge bases and processing approaches.

The system's modular architecture facilitates the development of region-specific adaptations while preserving core functionality. The incorporation of local disaster experience and response protocols without the need for complete system retraining is facilitated by LoRA-based experiential knowledge integration.

The development of regional models through collaborative efforts could result in the establishment of a global network of interconnected disaster response knowledge bases. This network would facilitate the sharing of relevant experience while respecting local operational requirements and constraints.

Continual Learning from New Disasters The development of mechanisms for continuous learning from new disaster events poses a dual challenge: on the one hand, it is a technical challenge; on the other hand, it is a significant opportunity for system improvement. The capacity to swiftly assimilate lessons derived from ongoing disasters has the potential to significantly enhance system effectiveness over time.

A range of technical approaches may be considered, including but not limited to: - Online learning mechanisms that update knowledge representations based on new documentation - Feedback-based improvement systems that learn from user interactions - Automated analysis of disaster response outcomes to identify successful strategies

The open-source framework under discussion provides a foundation for collaborative learning, where contributions from different organizations and regions could continuously improve the shared knowledge base. Privacy and security considerations must be addressed with care to protect sensitive operational information while enabling knowledge sharing.

Long-Term Vision for Global Disaster Intelligence

In contemplating the future, a global network of interconnected agentic RAG systems is envisioned, with the capacity to collectively maintain and share disaster response knowledge across regions, organizations, and disaster types. This network would provide unparalleled capabilities for the acquisition of knowledge from disaster experiences worldwide, while respecting local operational requirements and constraints.

The integration of real-time sensing, historical documentation, and adaptive reasoning has the potential to create comprehensive disaster response support systems that significantly enhance the effectiveness of human responders. The open-source foundation facilitates collaborative development of this vision through international cooperation and shared investment in disaster response technology.

The objective is not to supplant human expertise and judgment; rather, it is to enhance human capabilities through the integration of AI systems that can expeditiously process substantial amounts of pertinent information, identify patterns and lessons from historical experience, and provide contextual guidance that improves decision-making in high-stress, time-critical emergency scenarios.

Supplementary Material

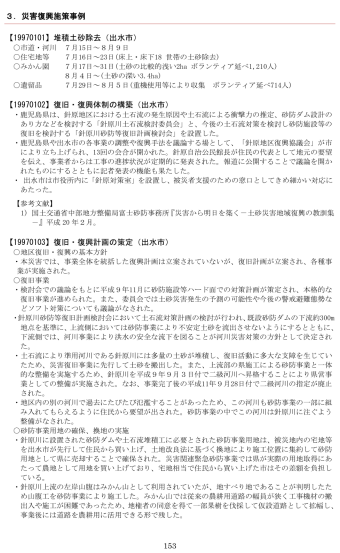
Input Document Examples

This section presents three illustrative examples drawn from a dataset of 2,378 multimodal disaster response documents, thereby exemplifying the heterogeneity and intricacy of information sources processed by the multimodal RAG system. These documents, sourced from Japan's comprehensive disaster response archives, represent different temporal periods and documentation styles that characterize real-world disaster response knowledge bases.

Dataset Characteristics: Our comprehensive dataset spans five decades of disaster response documentation evolution, from 1958 to 2018, encompassing distinct paradigm shifts in knowledge organization. The collection includes hierarchical classification systems (4a), integrated technical analysis with spatial visualization (4b), and modern digital-era structured documentation (4c). This temporal progression represents fundamental changes in documentation methodology, from manual archival approaches to digitally-optimized knowledge systems, each demanding specialized multimodal processing strategies.

Processing Complexity: Each document category necessitates specialized preprocessing techniques. Historical documents often contain degraded text quality and non-standard formatting that challenge OCR systems. Technical reports integrate multiple information modalities including maps, diagrams, and tabular data requiring sophisticated visual parsing. Modern documents, while more standardized, present their own challenges through dense information layout and integrated multimedia content.

(a) Comprehensive Disaster Case Index with Hierarchical Structure


3．災害復興施策事例

【19970101】堆積土砂除去（出水市）
○荻迫・阿久　7月15日～8月9日
○住宅地等　7月16日～23日（床上・床下18 世帯の土砂除去）
○みかん園　7月17日～31日（土砂の比較的浅い2ha ボランティア延べ1，210人）
　8月4日～（土砂が深い5，6ha）
○遺留品　7月29日～8月5日（重機使用等により収集　ボランティア延べ71人）

【19970102】復旧・復興体制の構築（出水市）
・鹿児島県は、斜原地区における土石流の発生原因や土石流による衝撃力の推定、砂防ダム設計のありかなどを検討する「斜原川土石流検討委員会」と、今後の土石流対策を検討し砂防施設等の整備方針を検討する「斜原川砂防等復旧計画検討会」を設置した。
・鹿児島県や出水市の各事業の調整や復興手法を議論する場として、「斜原地区復興協議会」が市により立ち上げられ、15回の会合が開かれた。斜原自治公民館長が住民の代表として地元の要望を伝え、事業者からは工事の進捗状況が定期的に報告された。報道に公開することで議論を開かれたものにするとともに記者発表の機能も果たした。
・出水市は市役所内に「斜原対策室」を設置し、被災者支援のための窓口としてきめ細かい対応にあたった。

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【19970103】復旧・復興計画の策定（出水市）
○地区復旧・復興の基本方針
・水災害では、事業全体を統括した復興計画は立案されていないが、復旧計画が立案され、各種事業が実施された。
○復旧事業
・検討会での議論をもとに平成9年11月に砂防施設等ハード面での対策計画が策定され、本格的な復旧事業が進められた。また、委員会では土砂災害発生の予測の可能性や今後の警戒避難態勢などソフト対策についても議論がなされた。
・斜原川砂防等復旧計画検討会において土石流対策計画の検討が行われ、既設砂防ダムの下流約200m地点を基準に、上流側においては砂防事業により不安定土砂を流出させないようにするとともに、下流側では、河川事業により洪水の安全な流下を図ることが河川災害対策の方針として決定された。
・上流域により準用河川である斜原川には多量の土砂が堆積し、復旧活動に多大な支障を生じていたため、災害復旧事業に先行して土砂を搬出した。また、上流部の県施工による砂防事業と一体的な整備を実施するため、斜原川を平成9年9月3日付で二級河川へ昇格することにより県営事業としての整備が実施された。なお、事業完了後の平成14年9月28日付で二級河川の指定が解止された。
・地区内の別の河川で過去にたびたび氾濫することがあったため、この河川も砂防事業の一部に組み入れてもらえるように住民から要望が出された。砂防事業の中でこの河川は斜原川に注ぐよう整備がなされた。
○砂防事業用地の確保、機地の実施
・斜原川に設置された砂防ダムや土石流堆積工に必要とされた砂防事業用地は、被災地内の宅地等を出水市が先行して住民から買い上げ、土地改良法に基づく換地により施工位置に集約して砂防用地として常に充当することで確保された。災害関連緊急砂防事業では県が実際の用地取得にあたって農地として用地を買い上げており、宅地相当で住民から買い上げた市はその差額を負担している。
・斜原川上流の左岸山腹はみかん山として利用されていたが、地すべり地であることが判明したため山腹工を砂防事業により施工した。みかん山では従来の農耕用道路の幅員が狭く工事機材の搬出入や施工が困難であったため、地権者の同意を得て一部果樹を伐採して仮設道路として拡幅し、事業後には道路を農耕用に活用できる形で残した。

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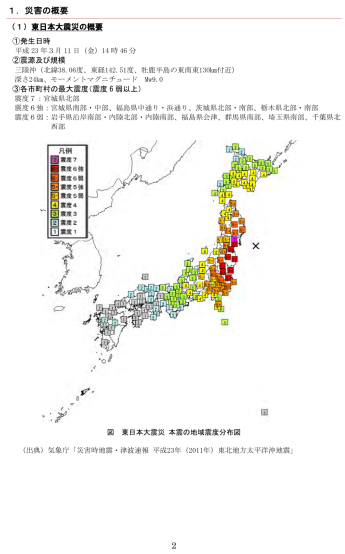
(b) Technical Analysis with Maps and Diagrams (1995-2001 Period)


1．災害の概要
（1）東日本大震災の概要
①発生日時
平成23年3月11日（金）14時46分
②震源及び規模
三陸沖（北緯38.10度、東経142.51度、牡鹿半島の東南東130km付近）
深さ24km、モーメントマグニチュード　Mw9.0
③各市町村の最大震度（震度6弱以上）
震度7：宮城県北部
震度6強：宮城県南部・中部、福島県中通り・浜通り、茨城県北部・南部、栃木県北部・南部
震度6弱：岩手県沿岸南部・内陸北部・内陸南部、福島県会津、群馬県南部、埼玉県南部、千葉県北西部
凡例
震度7
震度6強
震度6弱
震度5強
震度5弱
震度4
震度3
震度2
震度1
図　東日本大震災　本震の地域震度分布図
（出典）気象庁「災害時地震・津波速報　平成23年（2011年）東北地方太平洋沖地震」

2

(c) Contemporary Disaster Case Documentation with Enhanced Visual Elements (2011-2018)

Figure 4: **Representative Input Document Examples Spanning Five Decades.** Three examples showing temporal evolution in disaster documentation: (a) Hierarchical index structure (1958), (b) Technical analysis integration (1995-2001), and (c) Contemporary case documentation with enhanced visual elements (2011-2018).

Multimodal Integration Benefits: The examples demonstrate why pure text-based RAG approaches are insufficient for disaster response applications. Visual elements such as maps, organizational charts, and technical diagrams contain critical information that cannot be effectively captured through text extraction alone. Our system's capacity to process these visual elements through BLIP-based understanding, combined with ColVBERT's enhanced text retrieval, enables comprehensive knowledge extraction across all document types.

A total of 2,378 images were extracted from 46 PDFs related to tsunamis. These samples, which are representative of the total corpus, illustrate the system's capability to handle diverse documentation standards, languages (primarily Japanese with technical terminology), and information structures spanning over five decades of disaster response knowledge accumulation.

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