A Hybrid RAG-Based Framework for Real-Time Fact Verification in Social Media Using Knowledge Graphs and Vector Embeddings

By

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Declaration

We certify that this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university, and to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where due reference is made in the text.

Acknowledgement

We would like to express our heartfelt gratitude to all those who supported us throughout the preparation of this research proposal on “A Hybrid RAG-Based Framework for Real-Time Fact Verification in Social Media Using Knowledge Graphs and Vector Embeddings.”

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1. Abstract

Social media has become a powerful tool for information sharing, but it also enables the rapid spread of misinformation. False claims can circulate widely within minutes, leading to confusion, mistrust, and in some cases, serious real-world consequences. Manual fact-checking is valuable but too slow to keep up with the scale and speed of online misinformation. This highlights the need for automated solutions that are accurate, fast, and transparent. Large language models (LLMs) have shown promise for fact-checking, yet they often generate incorrect information, known as hallucinations. Retrieval-Augmented Generation (RAG) offers improvements by connecting LLMs to external knowledge sources, but most existing approaches still struggle with accuracy, scalability, or providing clear explanations of their results.

This project proposes a hybrid RAG-based framework that combines knowledge graphs, vector embeddings, and real-time retrieval. Knowledge graphs provide structured reasoning, vector embeddings support efficient semantic search, and the retrieval pipeline ensures access to the most up-to-date information. Together, these elements aim to reduce errors, improve transparency, and enable real-time verification. The proposed solution has the potential to support journalists, policymakers, and social media users by offering a reliable and explainable fact-checking system. Ultimately, this research contributes both to advancing RAG technology and to promoting trustworthy digital communication.

2. Introduction

2.1 Background and Motivation

Social media platforms have become primary sources of news, but this accessibility has also enabled the rapid spread of misinformation. False health claims during the COVID-19 pandemic and politically motivated fake news illustrate how viral content can create real-world harm. Traditional fact checking is accurate but too slow to match the speed of misinformation. Automated approaches using large language models (LLMs) show promise, but they often generate hallucinations, responses that sound convincing but are factually incorrect. Retrieval Augmented Generation (RAG) addresses this issue by grounding outputs in external knowledge. However, most existing RAG systems still rely only on unstructured text and offer limited transparency. This motivates the need for a hybrid RAG-based framework that combines structured and unstructured knowledge, ensuring both accuracy and explainability in real-time fact verification.

2.2 Problem Statement

Misinformation on social media is no longer limited to harmless rumors it actively shapes public opinion, disrupts democratic processes, and endangers public health. False claims about vaccines during the covid-19 pandemic fueled vaccine hesitancy worldwide, while fabricated political news stories have influenced elections and deepened social polarization. Despite these risks, current verification methods remain inadequate. Human fact checkers cannot scale to the sheer speed and volume of viral content, leaving dangerous falsehoods unchecked until after they have spread widely. Automated systems have improved detection rates but often operate as black boxes, providing little clarity on how conclusions are reached. Others depend heavily on curated datasets, which limits their ability to adapt to breaking events or emerging misinformation trends. These shortcomings reveal a critical gap: there is no existing solution that combines real-time responsiveness with both accuracy and transparency. Without such a framework, misinformation will continue to outpace efforts to counter it, undermining trust in information ecosystems and posing growing risks to society.

2.3 Proposed Solution

To overcome the weaknesses of current fact-checking methods, this project proposes a Hybrid Retrieval-Augmented Generation (RAG) framework tailored for real-time misinformation detection on social media. Existing systems often rely only on unstructured text retrieval, which limits their ability to capture relationships between entities or adapt to fast-changing contexts. Our framework addresses this by combining multiple approaches: knowledge graphs to provide structured and explainable reasoning, vector embeddings to enable semantic matching at scale, and a real-time retrieval pipeline to ensure that the system always works with the most current information.

This hybrid design offers two key advantages. First, it enhances accuracy by leveraging both structured and unstructured knowledge sources to validate claims. Second, it improves trustworthiness by making the verification process transparent, showing users how and why a claim is judged as true or false. Together, these features allow the framework to go beyond detection alone offering an adaptable, explainable, and scalable solution that can keep pace with the viral spread of misinformation across modern social media platforms.

2.4 Aims and Objectives

2.4.1 Main Objective

The main goal of this research is to design and evaluate a hybrid Retrieval-Augmented Generation (RAG) framework that integrates knowledge graphs, vector embeddings, and real-time retrieval pipelines to improve the accuracy, scalability, and transparency of fact verification on social media.

2.4.2 Specific Objectives

- **To enhance the accuracy of fact verification by combining structured and unstructured knowledge sources**

This involves integrating knowledge graphs for relational reasoning and vector embeddings for semantic similarity, ensuring that claims are verified against both structured and large scale unstructured evidence.

- **To provide transparent and explainable fact-checking outcomes**

This objective focuses on designing the system to generate reasoning paths and evidence trails, making it clear to users how each claim is validated and increasing trust in the verification process.

- **To evaluate the performance of the proposed framework against existing models**

This includes measuring accuracy, precision, recall, and latency using benchmark misinformation datasets as well as real-world social media data, to establish improvements over baseline RAG and LLM approaches.

- **To ensure scalability and adaptability for real-time misinformation detection**

This objective examines how the system handles high volume and fast evolving data streams, enabling practical deployment on social media platforms where misinformation spreads rapidly.

- **To explore the potential of multi-agent and collaborative extensions**

Although the core design is hybrid RAG, this objective considers extending the framework with agentic or collaborative modules to enhance robustness in complex misinformation scenarios.

2.5 Significance of the Solution

The rise of misinformation on social media has created serious risks for society, from undermining democratic processes to spreading harmful health related falsehoods. Current fact-checking approaches are either too slow, too narrow in scope, or too opaque to address these challenges at scale. By introducing a hybrid RAG framework that integrates knowledge graphs, vector embeddings, and real-time retrieval, this research directly addresses the urgent need for a solution that is both accurate and transparent. Unlike existing systems that focus only on unstructured retrieval, the proposed model combines structured reasoning and semantic flexibility, offering a more comprehensive approach to claim verification.

The significance of this work extends beyond academic contribution. A reliable and explainable fact-checking framework can be deployed by journalists, policymakers, and social media platforms to counter the viral spread of misinformation. For users, the inclusion of transparent reasoning paths enhances trust, helping them better understand how conclusions are reached. On a broader scale, the project contributes to strengthening digital information ecosystems, reducing the harmful impact of false content, and promoting more informed public discourse.

3. Literature Review

3.1 Introduction to Retrieval Augmented Generation (RAG) and Misinformation Detection

The rapid growth of social media has transformed the way information is created and consumed. While these platforms enable global communication and quick access to news, they have also amplified the spread of misinformation and fake content. Traditional fact checking methods, often manual and human-led, cannot keep up with the speed and scale of viral misinformation. Large language models (LLMs) such as GPT variants show potential for automating this process, but they suffer from significant limitations, including the generation of "hallucinations" outputs that sound plausible but lack factual grounding. To overcome these weaknesses, Retrieval Augmented Generation (RAG) has emerged as a promising paradigm. RAG enhances LLMs by incorporating an external retrieval component, which fetches relevant, up to date documents or structured knowledge to ground the generated response (Kumar et al., n.d.; Nezafat, 2024)

In the context of misinformation detection, RAG provides several benefits. It improves factual accuracy by cross verifying claims with external sources, reduces reliance on outdated training data, and increases transparency by linking generated outputs to verifiable evidence. Broader surveys of misinformation research emphasize the importance of integrating approaches such as knowledge graphs, multimodal analysis, and credibility modeling to strengthen detection systems (Guo et al., 2020). This indicates that while RAG represents a major step forward, it must be combined with other complementary methods such as structured reasoning and trust signals to effectively adapt to the dynamic and adversarial nature of misinformation on platforms like Twitter, Facebook, and Reddit.

3.2 RAG for Fake News and Claim Verification

One of the earliest applications of RAG in misinformation detection was the use of retrieval pipelines to enhance claim verification tasks. For example, the Evidence-Driven Retrieval Augmented Response Generation (RARG) model focuses on grounding generated outputs in verifiable sources. It employs a two stage retrieval and reranking system to ensure that the most relevant evidence is selected before response generation, leading to more accurate and contextually relevant refutations of online misinformation (Yue et al., 2024). Similarly, Fake

News Detection with RAG highlights how adding a retrieval layer to LLMs improves factual accuracy compared to purely generative systems, reducing hallucinations and improving trust in automated verification (Nezafat, 2024).

Beyond single round retrieval, newer approaches emphasize iterative evidence gathering. The Research for the Truth framework demonstrates the effectiveness of multi round retrieval, where the model refines queries across several iterations to disambiguate complex or ambiguous claims. This strategy enables stronger performance in fake news detection tasks compared to one shot retrieval systems (G. Li et al., 2024). Such iterative processes highlight how misinformation detection often requires layered reasoning, where multiple evidence sources are combined to reach a reliable conclusion.

Domain specific adaptations of RAG further underscore its value in fact verification. For instance, VeraCT Scan introduces a two stage pipeline that first extracts factual claims from social media posts, then retrieves external evidence and applies credibility scoring to produce transparent verification outputs(Niu et al., 2024). In the health domain, Use of RAG for COVID-19 Fact Checking integrates biomedical datasets into its retrieval pipeline, achieving higher accuracy and reducing hallucinations when debunking pandemic related misinformation(H. Li et al., 2024) These applications show that while the core principle of RAG remains consistent, tailoring retrieval sources and verification strategies to domain specific contexts greatly enhances effectiveness.

3.3 Multi-Agent and Collaborative Frameworks

While single model RAG pipelines improve factual grounding, they often face challenges in handling diverse input modalities and rapidly evolving misinformation. To address this, researchers have proposed multi-agent frameworks, where specialized agents collaborate across retrieval, reasoning, and verification tasks. The Retrieval Augmented Multi-Agent (RAMA) framework is a good example. It introduces a pipeline where a WebRetriever agent gathers multimodal evidence, multiple Vision Language (VL) Judge agents evaluate consistency between text and images, and a DecisionFuser agent aggregates outputs into a final verdict. This distributed approach significantly outperforms text only models on multimodal misinformation datasets, demonstrating that agent collaboration enhances both accuracy and robustness (Yang et al., 2025).

Beyond multimodal detection, multi-agent systems have been extended to manage the full misinformation lifecycle. A dedicated framework assigns agents to specialized roles such as detection, correction, and source identification, ensuring that misinformation is not only flagged but also contextualized and traced back to its origins(Gautam, 2025). This holistic approach highlights the scalability of agentic collaboration, showing how misinformation can be managed from spread to correction rather than just detected in isolation.

Collaborative multi-agent approaches are also being applied in countering misinformation through evidence based counterspeech. For example, a multi-agent retrieval-augmented system was designed to generate polite, evidence backed responses to health misinformation, making it suitable for real world deployment where user trust and tone are critical (Anik et al., 2025). Together, these works illustrate that agentic frameworks allow for modularity, adaptability, and greater resilience against the complexity of misinformation ecosystems, though they also introduce challenges related to latency and coordination overhead.

3.4 Knowledge Graph and Structured RAG Approaches

A major limitation of standard RAG pipelines is their reliance on unstructured text retrieval, which can lead to shallow reasoning and difficulty in handling entity relations. To address this, researchers have begun to integrate Knowledge Graphs (KGs) into RAG-based systems, providing structured and relational context to retrieved evidence. The Retrieval-Augmented generation Inside Knowledge Graph (RAING) framework exemplifies this trend by embedding RAG directly within KG structures. It employs graph embeddings such as TransE, RotatE, and DistMult to model relationships between entities, enabling the system to verify claims not only through text similarity but also via structured semantic reasoning. By doing so, RAING improves the explainability and precision of fake news detection (Ubaque & Rincon-Yañez, 2024).

Building on this, TrumorGPT demonstrates the value of combining RAG with domain-specific knowledge graphs for fact checking. Designed for health misinformation, TrumorGPT integrates graph-based retrieval with large language models to validate claims against a curated health knowledge base. This structured retrieval enhances both the accuracy of claim verification and the interpretability of outputs by providing explicit relational evidence (Hang et al., 2025). Such work highlights that domain-focused KGs, when paired with vector embeddings for semantic similarity, can significantly strengthen misinformation detection pipelines.

Another study, FactCheck: Knowledge Graph Fact Verification Through Retrieval Augmented Generation Using a Multi Model Ensemble Approach, explores entity-based validation using KGs as the foundation for fact verification. By mapping claims to graph nodes and relationships, the system reduces misinformation propagation by ensuring consistency across retrieved knowledge. Unlike unstructured retrieval approaches, graph-based reasoning makes it possible to trace verification outcomes through explicit entity relations, which improves user trust and interpretability (Shami Stefano Marchesin & Gianmaria Silvello, 2025). Collectively, these works demonstrate that Knowledge Graph-enhanced RAG provides a pathway toward explainable AI for misinformation detection, though challenges remain in terms of scalability, graph construction, and integrating real time updates.

3.5 Credibility and Trust-Driven RAG

While RAG improves factual grounding, it does not inherently distinguish between reliable and unreliable sources. This limitation is critical in misinformation detection, where unverified or low-credibility content can contaminate retrieval pipelines. To address this, researchers have integrated credibility scoring into RAG frameworks. CrediRAG is a key example: it augments the retrieval process with network credibility signals derived from social platforms like Reddit. By weighting evidence according to user trust and source reliability, CrediRAG ensures that retrieved documents are not just relevant but also credible, leading to higher accuracy in misinformation detection (Ram et al., 2024).This credibility aware retrieval marks an important step toward systems that can adapt to the noisy, user driven nature of social media.

Emotional and contextual signals have also been explored as credibility indicators. RAEmoLLM introduces an emotion aware RAG model that uses emotional information as an additional retrieval cue. This design reflects the observation that misinformation often leverages emotional triggers such as fear, anger, or outrage to spread quickly across platforms. By incorporating emotion-based in-context learning into the retrieval process, RAEmoLLM improves cross domain detection, enabling the system to generalize more effectively beyond a single (Liu et al., 2025).This shows how credibility can be framed not only in terms of trustworthiness of sources but also in terms of emotional manipulations embedded in misinformation.

3.6 Comparative Analysis and Research Gaps

The reviewed literature demonstrates that Retrieval-Augmented Generation (RAG) has rapidly evolved into a cornerstone of misinformation detection. Across the studies, three main design choices stand out. First, retrieval strategies vary: some systems emphasize web-scale search to ensure real-time evidence access (e.g., VeraCT Scan, RAMA), while others rely on curated datasets for reliability (e.g., COVID-19 RAG fact-checking). Each choice entails trade-offs between timeliness and credibility. Second, reasoning architectures diverge between single-agent RAG pipelines (RARG, VeraCT) and multi-agent frameworks (RAMA, Misinformation Lifecycle Systems). While the former offer simplicity and speed, the latter enhance robustness and multimodal capability but often at the cost of higher latency and coordination complexity. Third, trust modeling appears inconsistently: systems like CrediRAG and VeraCT integrate credibility signals, while others (e.g: Re-Search for the Truth) focus purely on semantic similarity without weighing source reliability.

Despite these advances, several gaps remain. Most existing frameworks operate within constrained domains (e.g: health misinformation, curated benchmarks) limiting generalizability to the fast moving environment of social media. The integration of knowledge graphs and vector embeddings two complementary retrieval paradigms remains underdeveloped. While RAING and TrumorGPT explore KG-based reasoning, they do not combine it with dense semantic embeddings in a single hybrid loop, which could offer both structural precision and flexible recall. Similarly, while multi-agent approaches improve accuracy, they introduce computational costs and lack real-time adaptability. Few systems are optimized for scalable, real-time detection, leaving a gap between research prototypes and the urgent demands of real-world misinformation control.

These gaps underscore the need for a hybrid RAG framework that unites the strengths of prior work: the factual grounding of RAG pipelines, the structured reasoning of knowledge graphs, the semantic flexibility of vector embeddings, and the transparency of credibility scoring. Such a framework could deliver real-time, explainable, and domain-adaptive fact verification at the scale required by modern social media. By synthesizing these innovations, the proposed research aims to advance both the technical robustness of RAG systems and their societal value in building digital trust.

4. Methodology

4.1 System Overview

The proposed system is a Hybrid Retrieval-Augmented Generation (RAG) pipeline enhanced with Knowledge Graphs (KGs), Vector Databases (VDs), Corrective (agentic) Retrieval, and a Human-in-the-Loop feedback channel to verify the truthfulness of Social media posts. Figure X (System Architecture) depicts eight coordinated

Stages,

(1) Intake

(2) Embedding & Categorization

(3) Retrieval & Ranking

(4) Corrective Retrieval

(5) Evidence Validation

(6) RAG Generation

(7) Delivery & Feedback

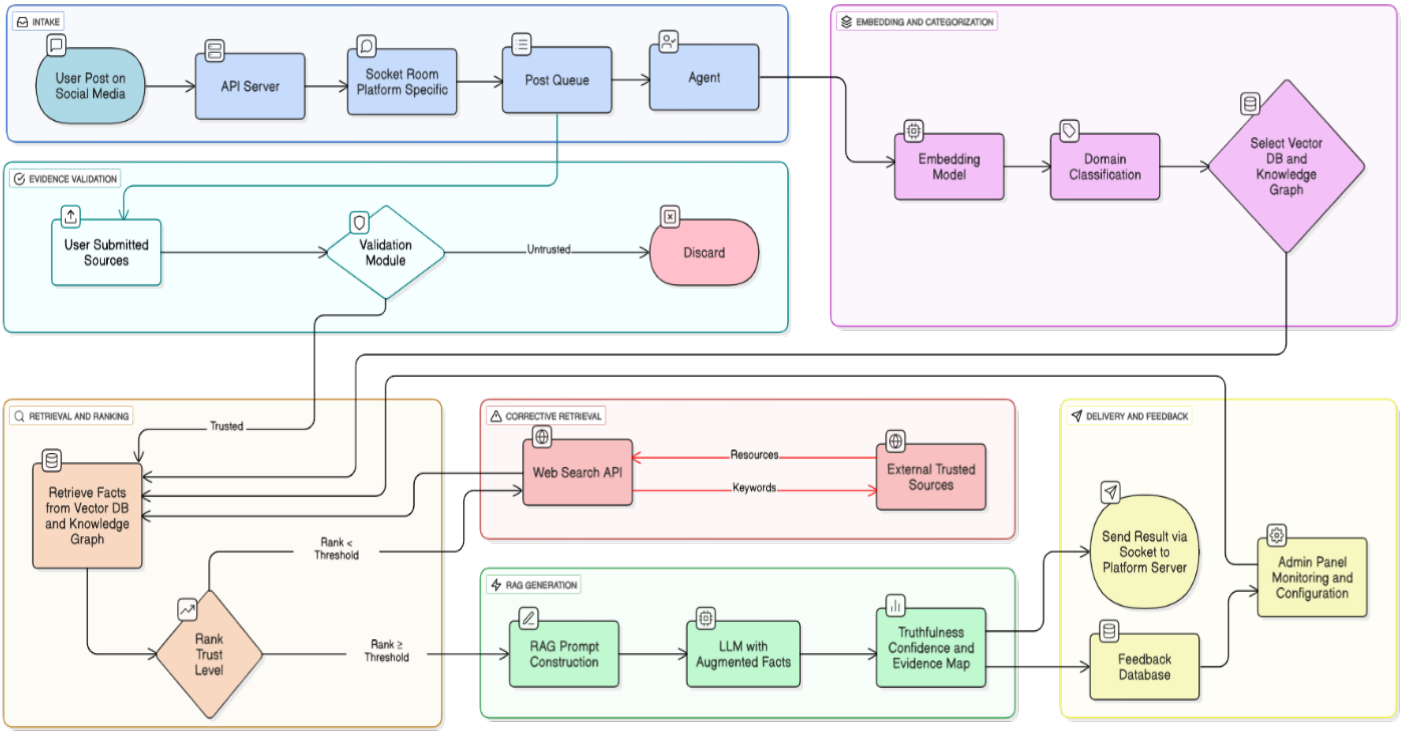

Figure 1: System Architecture for Social media oriented agentic RAG verification.

4.2 Stage 1 – Intake

- User post submission - a post (text + optional links) is submitted on a simulated Facebook-like interface.
- Transport - The UI streams content send the their server (Ex – Facebook server) then retrieve the content to our server via Web Socket, it has a Peer-to-Peer connection
- Socket rooms & queues - posts are routed to platform-specific rooms and enqueued (FIFO).

- Agent pickup - a lightweight Agent service dequeues items for downstream processing and maintains request context (post ID, timestamps, user session hash).

4.3 Stage 2 - Embedding & Categorization

- Semantic embeddings - The post is converted into a semantic embedding using a transformer-based encoder.
- Domain classification - compact classifier assigns domain labels (politics/health/science/economy/environment/general).
- The domain label selects the target evidence indices - a vector index for dense retrieval and a domain-aligned knowledge graph (KG) namespace for structured reasoning.

Output should like,

embedding vector, domain label, target indices.

4.4 Stage 3 - Retrieval & Ranking

- Dual retrieval,
  (1) dense retrieval from the Vector DB using v_post (Top-k_d)
  (2) KG traversal from domain/claim entities (Top-k_k).

- Hybrid re-ranking - results are merged and re-ranked by semantic similarity, source credibility, recency, and domain fit.
- Initial trust rank - compute Trust Grade (A+…F) from similarity, source credibility, recency, and stance consistency.

Decision: if the grade ≥ threshold, the pipeline advances to generation otherwise it triggers corrective retrieval.

4.5 Stage 4 - Corrective Retrieval (Agentic Loop)

- Query reformulation - Agent creates focused searches from failed facets (entities, dates, numbers).
- Web Search API - A web search layer queries external, reputable sources and collects snippets with metadata (title, publisher, date).
- Retrieved items pass a credibility filter (e.g., domain reliability, recency, authorship).
- New evidence is merged and re-ranked with prior candidates; the score is recomputed.
- The loop stops when the threshold is met or a maximum number of rounds is reached.
- All search queries, clicked results and inclusion/exclusion reasons are logged for auditability.

4.6 Stage 5 - Evidence Validation (Human-in-the-Loop)

- User-submitted sources - if any are routed to a validation module.
- The module checks domain trust, security, date/author details and performs claim–evidence entailment tests (entails/contradicts/neutral).
- Trusted items are admitted into the retrieval pool; untrusted ones are discarded (with justification).
- An admin review panel can approve or reject candidate facts for promotion into the vector index or KG so that the knowledge base grows under governance.

4.7 Stage 6 - RAG Generation

- The system constructs a RAG prompt containing: the original post, top-k evidence (deduplicated), domain instructions, and citation requirements.
- LLM inference - outputs like,
  (1) truthfulness estimate,
  (2) confidence score,
  (3) evidence map with citations,
  (4) short explanation (≤120 words).
- Hallucination controls require citations for factual claims and reject unsupported content via self-consistency checks.

4.8 Stage 7 - Delivery & Feedback

- Results (verdict, confidence, citations, short explanation) are delivered back to the platform over the socket.
- A feedback store records user rating (usefulness/clarity) and flags.
- An admin console exposes live metrics (throughput, retrieval hit-rate, domain mix) and allows adjustment of Top-k, thresholds and agent loop depth
- Admins can review user-submitted sources and confirm additions to the knowledge base.

5. System Design

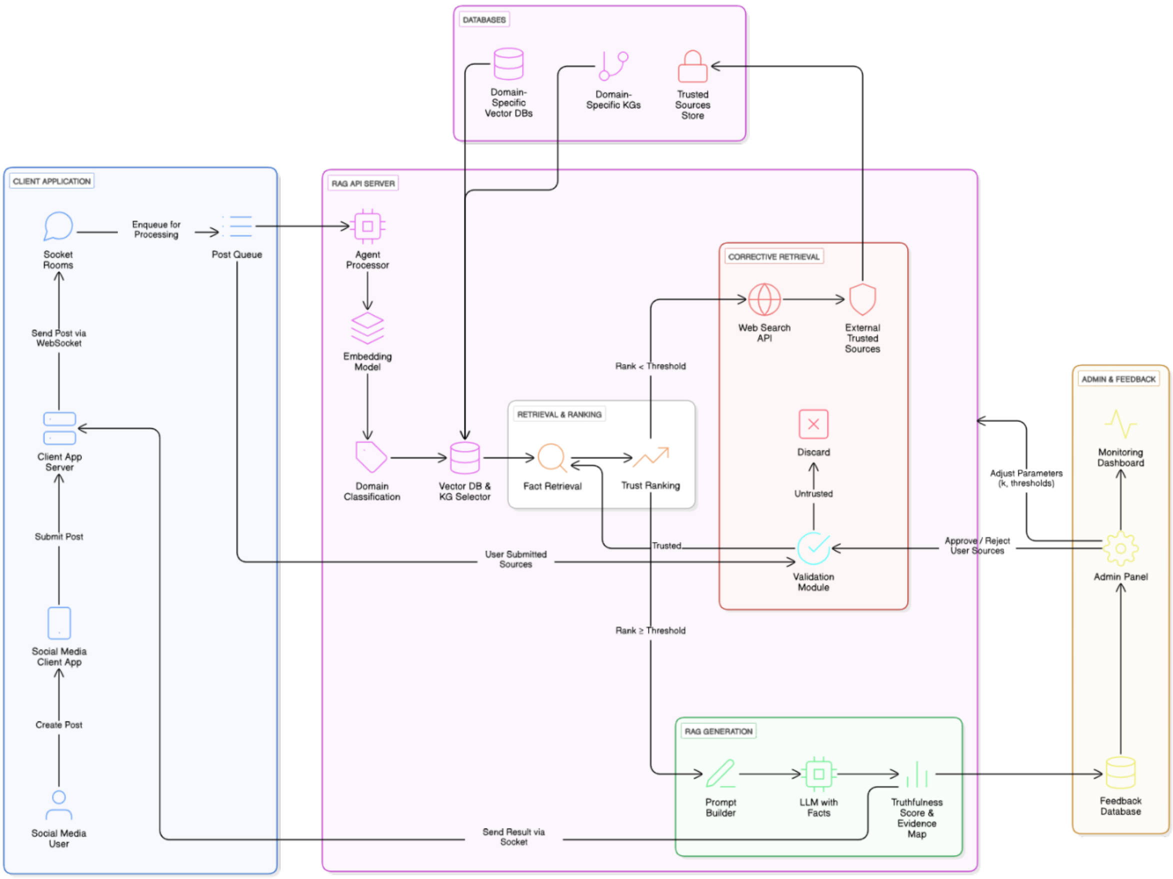

Figure 2: System Design Diagram

6. Timeline

Task Name	Duration	Start	Finish	Predecessors
Project Proposal	10 days	Mon 8/18/25	Fri 8/29/25	
Proposal Preseantation	6 days	Mon 9/1/25	Sun 9/7/25	
Project Design dn Modeling(Design)	11 days	Mon 9/8/25	Sat 9/20/25	
Rag System Development (Development)	79 days	Fri 9/12/25	Wed 12/31/25	
Web Development (Development)	55 days	Tue 9/16/25	Sun 11/30/25	
Testing and Debugging (Development)	102 days	Sat 8/16/25	Sun 1/4/26	
Evaluation (Development)	23 days	Mon 12/1/25	Wed 12/31/25	
Project Thesis	13 days	Thu 1/1/26	Sun 1/18/26	
Individual Report	10 days	Tue 1/6/26	Sun 1/18/26	

Figure 3: Timeline

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