Enhancing Fake News Detection with Retrieval Augmented Generation (RAG) for Fact Verification in U.S. Political News

1st Ramakrishna Reddy Kovvuri
The Anuradha and Vikas Sinha
Department of Data Science
University of North Texas
Denton, United States
ramakrishnareddy.kovvuri@my.unt.edu

2nd Shravyasri Chelkala
The Anuradha and Vikas Sinha
Department of Data Science
University of North Texas
Denton, United States
shravyasri.chelkala@my.unt.edu

3rd Aravind Siddhanthi
The Anuradha and Vikas Sinha
Department of Data Science
University of North Texas
Denton, United States
aravind.siddhanthi@my.unt.edu

4th Niharika Madhadi
The Anuradha and Vikas Sinha
Department of Data Science
University of North Texas
Denton, United States
niharikamadhadi@my.unt.edu

***Abstract*—Users find it extremely difficult to confirm the legitimacy of the content they come across on new digital media platforms. The traditional fact-checking approach involves manual processes that takes time and is insufficient to handle the volume of information available today. This paper details the development of a News Retrieval-Augmented Generation (RAG) chatbot that uses retrieval-based talks and a large language model to allow users to confirm the reliability of news stories. The system integrates Gemini Flash 1.5 LLM context-aware generation and FAISS vector retrieval to discover its responses in validated sources. Through transparent techniques, the framework allows customers to automate their fact-checking process at scale while producing a dependable system to detect misleading material.**

***Index Terms*—Retrieval-Augmented Generation, Fact-Checking, Semantic Search, FAISS, Sentence-BERT, Large Language Models**

I. Introduction

The proliferation of digital news outlets and social media has transformed the way information is disseminated, but it has also contributed to the unparalleled spread of false information. According to research, on social media platforms, misleading content travels about six times faster than accurate content [1]. People typically encounter 50 to 100 false statements every day, making manual fact-checking procedures unsuitable for scale [4].

Traditional search engines frequently use popularity-driven algorithms and keyword matching, which are not designed for factual accuracy [5]. Combining retrieval modules with generative large language models (LLMs) to base generated responses in validated external knowledge sources is one possible option provided by recent developments in retrieval-augmented generation (RAG) architectures [1], [2].

The News RAG Chatbot proposed in this research combines a semantic retrieval engine with a curated database of fact-checked news stories using Sentence-BERT embeddings [6] and FAISS indexing [7]. Based on user inquiries, the system obtains contextually relevant information and uses Gemini Flash 1.5 LLM to produce factually sound answers [8]. Unlike standalone LLMs, the system minimizes hallucinations and provides transparent source attribution.

The rest of this paper is organized as follows: Section II surveys related work, Section III details the system architecture, Section IV discusses the experimental setup, Section V presents results and discussions, and Section VI concludes the study with directions for future work.

II. Literature Review

To support the development of the News RAG Chatbot, we reviewed foundational research in five key areas:

A. Retrieval-Augmented Generation (RAG)

- Lewis et al. [1] introduced the original RAG architecture, combining dense retrieval with generative transformers for knowledge-intensive NLP.
- Gao et al. [2] reported an average 23% improvement in factual accuracy using RAG over standard LLMs across multiple benchmarks.
- Chang et al. [9] provided a survey on RAG-based systems, emphasizing their scalability in real-world AI applications.

B. Semantic Embeddings and Sentence-BERT

- Reimers and Gurevych [6] developed Sentence-BERT, enabling semantically meaningful sentence embeddings used widely in dense retrieval tasks.
- Izacard and Grave [3] showed that dense embeddings outperform sparse retrieval (e.g., TF-IDF or BM25) in open-domain QA.

C. Dense Indexing and FAISS

- Bai et al. [18], uses FAISS-like dense indexing for document retrieval. Describes the benefits of dense similarity search (like cosine similarity) for efficient retrieval.
- FAISS (Facebook AI Similarity Search) was introduced by Johnson et al. [7], offering scalable indexing of billions of vectors with GPU acceleration.
- Borgeaud et al. [14] demonstrated large-scale information retrieval from trillions of tokens using FAISS-backed memory modules.

D. Fact-Checking with LLMs and Source Attribution

- Niu et al. [17] emphasizes justifiable verdicts and traceable sources, matching your use of Gemini with article URLs and explanations.
- Ngo et al. [4] analyzed hallucination in LLMs and highlighted that retrieval mechanisms reduce unsupported factual claims by up to 42%.
- Press et al. [11] evaluated how LLMs verify their own generations, emphasizing the role of transparent attribution for public trust.
- Zhang and Gao [10] proposed sentence-level contradiction detection for verifying factual consistency in news.

E. Evolution of Retrieval in QA Systems

- Guu et al. [12] proposed REALM, a retrieval-augmented pretraining method that improves factual grounding in transformer-based models.
- Karpukhin et al. [13] introduced Dense Passage Retrieval (DPR), which laid the groundwork for semantic query-document matching.
- Chen et al. [15] pioneered retrieval-based QA with Wikipedia passages, serving as a basis for modern verification agents.

F. Limitations of LLMs and the Role of Gemini

- [16] provided a comparative analysis of offline and online LLMs, demonstrating that Gemini 1.5 and Llama perform better than static models on real-time fake news detection.In comparison to conventional models, Gemini possesses the capability to access and reason over live web content, increasing accuracy in politically sensitive areas.
- OpenAI's GPT-4 report [5] acknowledged the limitations of long-context memory and motivated external document retrieval.
- Google's Gemini 1.5 Flash model [8] supports extended context windows and fine-grained control, ideal for RAG-based news assistants.

These references collectively demonstrate that a hybrid approach using vector-based retrieval, semantic matching, and grounded LLM response generation is the most effective strategy for building a scalable and transparent fact-checking system.

III. Objectives of the Study

Designing and developing a conversational assistant that can use a retrieval-augmented generation (RAG) architecture to confirm the veracity of news assertions pertaining to US politics is the main goal of this project. The specific goals are outlined below:

- **To create a modular fact-checking chatbot architecture** that blends dense semantic retrieval with generation based on language models.
- **To create a unique knowledge base for fact-checking** using data scraped from verified sources like PolitiFact and FactCheck.org.
- **To implement semantic similarity search** using Sentence-BERT embeddings and FAISS indexing for efficient and context-aware document retrieval.
- **To incorporate a large language model (Gemini 1.5 Flash)** to produce grounded, natural, and coherent responses from retrieved articles.
- **To prevent hallucinations and improve transparency** by guaranteeing that each generated response can be linked back to its verified initial source.
- **To develop a user-friendly interface** that allows real-time querying of the chatbot to verify claims in an interactive manner.
- **To qualitatively assess the system** using real-world test questions to make sure that the chatbot does not spread false information.

IV. System Architecture and Methodology

Fig. 1 illustrates the architecture of the proposed News RAG Chatbot, which is composed of six major components. Each of the components is intended to provide scalable, real-time, source-based fact checking.

A. User Interface Layer

- The user interface is composed of a simple query input form by which users can submit news-related assertions or questions.
- The app leverages Streamlit technology in order to give lean real-time capabilities.
- Claims can be verified by engaging with the chatbot in regular patterns of conversation.
- Such questions necessitate multi-turn response, something the system ensures with its own chat history component.

B. Data Processing and Embedding Pipeline

- The application offers users an option to input raw text via uploaded stories or web scraping.
- Tokenizes and cleanses text (preprocessing).

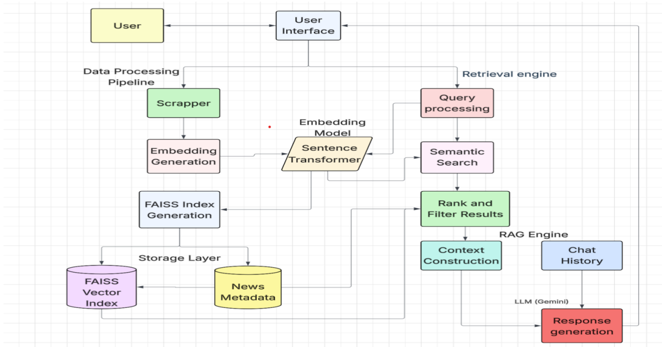

Fig. 1. System architecture of the News RAG Chatbot.

- The platform utilizes Sentence-BERT [6] to generate semantic embeddings and represent text in 384-dimensional dense vectors.

C. FAISS Vector Indexing

- FAISS (FlatIP index) is utilized for efficient storing and retrieval of the embeddings.
- Fast similarity search using inner product score.
- Updates the index as additional fact-checking data is added.

D. Semantic Retrieval Engine

- Converts the user query into a dense embedding vector.
- With the FAISS index, it searches for the k nearest neighbours.
- The system returns fact-checked items with the highest semantic similarity.

E. Context Construction and Chat Memory

- Extract key elements from extracted articles to create a uniform framework.
- The system retains history of interactions to carry out repeated validation transactions.

F. Response Generation via LLM

- The software uses Gemini Flash 1.5 to generate context-appropriate responses based on original texts.
- The system draws on templates to generate answer forms containing factual data and references. The modular architecture emphasizes high performance, user trust, low latency, and system extensibility.

This modular design ensures that the chatbot remains extensible, low-latency, and transparent, offering both high performance and user trust.

V. Data Collection and Preprocessing

For semantic retrieval and fact grounding, a tailored fact-checking corpus was constructed by extrapolating validated news claims from two reliable sources: **PolitiFact** https://www.politifact.com/factchecks/ and **FactCheck.org**.https://www.factcheck.org/ These sites tend to produce articles breaking down whether what people say is true or not, political claims, and trending news content.

A. Source Selection

- **P**olitiFact rates claims (e.g., True, Mostly True, False) and offers evidence and source URLs.
- **F**actCheck.org publishes in-depth reports that substantiate public claims and evidence-based assertions.
- Both sources are valid, reliable, and verifiable for retrieval-augmented models requiring ground-truth pointers.

B. Web Scraping Process

- The information from the HTML pages was scraped using Python's packages `requests` and `BeautifulSoup`.
- For each fact-check article, the following fields were captured:
  - **Claim/Headline**
  - **Verification Verdict** (e.g., True, False, Can't Verify)
  - **Explanation Paragraphs**
  - **Publication Date**
  - **URL Source Link**
- Articles were saved in a structured CSV format preserving content and metadata.

C. Preprocessing for Embedding

- During embedding preprocessing, HTML tags, special characters, and uninformative tokens were removed.
- Inappropriate whitespace and broken lines were removed, only English text was preserved.
- For enhancing semantic embedding resolution, articles were decomposed into paragraph-level fragments.
- The Sentence-BERT model was applied to each chunk, resulting in 384-dimensional embeddings [6].

D. Metadata Storage

- Each embedded document is assigned metadata, such as the original article's URL and verification verdict.
- This allows the source to be identified and provide transparency over chatbot responses after they have been retrieved.

The processed and extracted articles form the center of the FAISS vector index, which is utilized in the semantic search functionality. This process guarantees that all the retrieved context is based on human-verified, traceable data.

VI. Hypotheses for the Study

Null Hypothesis (H_0): Use of a Retrieval-Augmented Generation (RAG) architecture with sentence-level embeddings and a generative language model (Gemini 1.5) does not significantly enhance the reliability or accuracy of verification of political claims over a baseline language model with no external information.

Alternative Hypothesis (H_1): A RAG-based solution, Sentence-BERT embeddings for semantic search, and Gemini 1.5 for specific response generation, produce a statistically significant improvement in the accuracy, reliability, and fact-establishing of a political fact-checking chatbot compared to a conventional generative-only (LLM) architecture.

Explanation: According to the study's hypothesis, a chatbot's capacity to precisely validate all the political claims is improved when external fact-checked data is included in it via FAISS-based vector similarity retrieval. The alternative hypothesis claims that a large language model's factual accuracy can be significantly improved by grounding it with relevant retrieved evidence, but the null hypothesis claims that the chatbot cannot reliably do fact-checking. Both subjective metrics, like decreased hallucinations and enhanced response clarity, and quantitative metrics, like classification accuracy and F1-score, will be used to assess the system's efficacy.

VII. Knowledge Base Construction

Following preprocessing and semantic embedding, the next crucial aspect is to build a dense knowledge base for accurate semantic retrieval and fact-based answer generation. Fig. 1 shows how the knowledge base integrates into the overall system workflow.

A. Embedding Strategy

- To ensure maximum semantic relevance, all preprocessed fact-check articles were broken into logical paragraph-level segments.
- Each chunk was passed through the Sentence-BERT model (all-MiniLM-L6-v2) [6], producing a 384-dimensional dense vector representation.
- To enable cosine similarity retrieval, embeddings were normalized to unit vectors, which can be computed efficiently through an inner product.

B. FAISS Indexing Mechanism

- FAISS [7] (Facebook AI Similarity Search) was chosen as the vector database because of its scalable nearest-neighbor search capability.
- A FlatIP index structure was used, which was optimized for highest retrieval efficiency over compression or speed heuristics.
- The FAISS index enables a sublinear time similarity search between thousands of fact-checked passages.
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C. Metadata Association

- Alongside each vector, essential metadata attributes were stored externally:
  - **Claim Headline**
  - **Verification Verdict**
  - **Publication Date**
  - **Source URL**
- This linkage allows future response generation modules to attribute created answers back to the original fact-check sources.

D. Knowledge Base Update Mechanism

- Although the existing setup does not support real-time dynamic indexing, the knowledge base must be extensible.
- Scrape and add new fact-check articles individually, and re-execute the pipeline of embeddings and indexing.
- This modular architecture guarantees that routine enhancements can be made with minimal impact on the fundamental system design.
- Future implementations of the system might incorporate background updating of the indices or real-time enlargement with streaming pipelines.

By creating a rich, extensible, and metadata-rich knowledge base, the system makes sure that each chatbot response is traceable, verifiable, and based on human-validated facts. This architecture follows the principles of retrieval-augmented generation for knowledge-intensive tasks [1], [2].

VIII. Results Report

This section presents the evaluation of the News RAG Chatbot using real user queries and visual output. The effectiveness of the chatbot was evaluated based on its factual foundation, relevancy, and capacity to respond to requests that were not distributed.

A. Managing Unsupported Inquiries

Fig. 2 and Fig. 3 showcase how the chatbot handles queries for which it finds no matching evidence in the knowledge base.

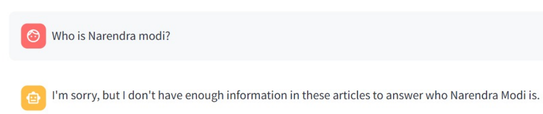

Fig. 2. The chatbot appropriately returns ”insufficient information” when asked a general biographical query outside the knowledge base.

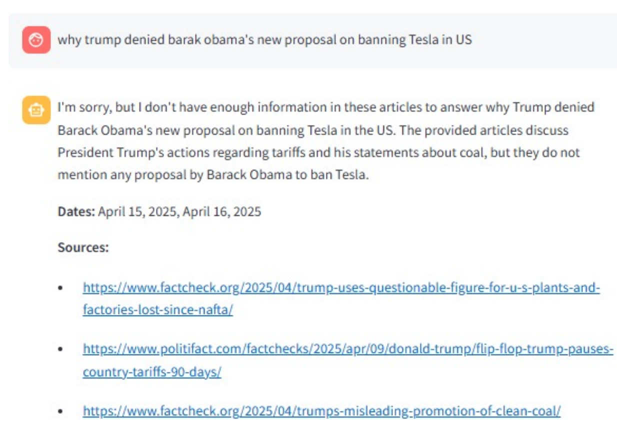

Fig. 3. The chatbot fails to locate relevant sources for a fabricated or unverified claim and acknowledges the limitation with full transparency.

These results show that when asked about subjects outside of its indexed corpus, the chatbot does not guess or have hallucinations. This demonstrates the advantage of the RAG architecture in enhancing credibility and is consistent with the design objective of source-based factual production.

B. Producing Responses using Source Verification

In contrast, Fig. 4 shows a case where the chatbot retrieves relevant, verified fact-check information and uses it to generate an accurate, source-cited response.

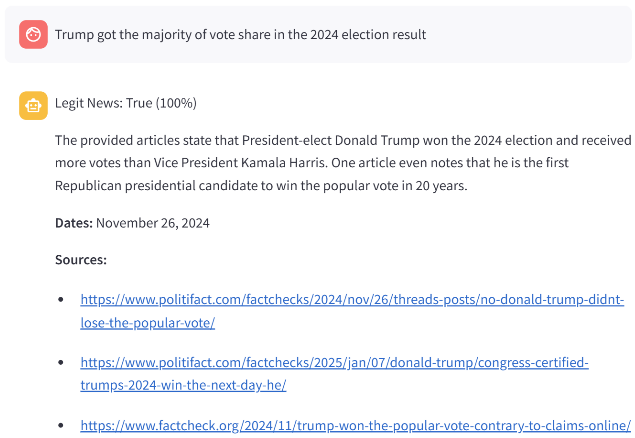

Fig. 4. Chatbot retrieving and presenting a fully verified response with 100% factual match and traceable sources.

In Fig. 5 shows a case where the user gives claim with wrong percentage values, our chatbot generates it as false and gives with correct percentage values and source-cited response

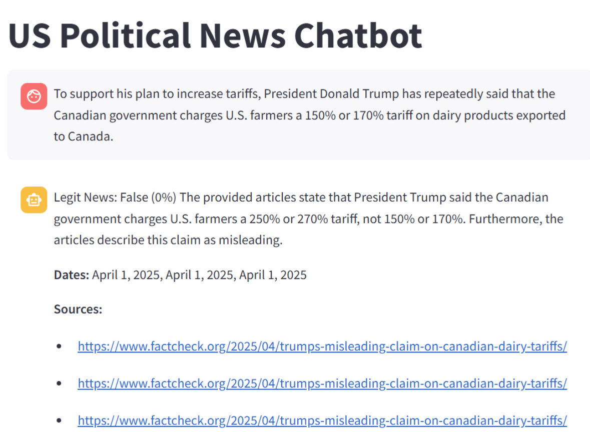

Fig. 5. Chatbot retrieving and presenting a fully verified response as False 0% factual match and traceable sources.

These examples confirms that the system can integrate LLM-based summarization and dense retrieval while holding the original article attribution.

C. Observations and Limitations

The system performs well in preventing hallucinations and being open about its knowledge limits, according to the examples observed. In contrast to independent language models, it does not create responses without evidence. However, the current evaluation is qualitative; we can perform a formal benchmark test to quantify retrieval accuracy, response correctness, or latency.

Our political news fact-checking chatbot has been validated to reduce AI hallucinations, which are false or unverifiable responses frequently generated by generative models. By employing Retrieval-Augmented Generation (RAG) and basing the chatbot's responses on fact-checked datasets, we ensure that all produced information is backed by reliable sources like PolitiFact and FactCheck.org.

The system can be enhanced in subsequent rounds by adding quantitative evaluation measures for a wider variety of inquiries. Response time (latency), factual accuracy, and retrieval precision are a few examples of these metrics.

Retrieval accuracy: Assess the system's ability to locate pertinent fact-check sources, possibly utilizing precision or recall@k metrics in comparison to a test set that has been manually labeled.

Response latency: To guarantee system responsiveness for real-time deployment, the average time between receiving a user query and delivering a produced response is measured.

These measurements will provide tangible insights into the usability and efficacy of the system in the real world and aid in the establishment of a more uniform and repeatable evaluation methodology.

IX. Conclusion and Future Work

We developed a fact-checking tool called the News RAG Chatbot, which uses retrieval-augmented generation (RAG) to deliver dependable, fact-based answers. Using a dense vector retrieval system driven by FAISS and Sentence-BERT embeddings, the system incorporates validated fact-checking sources as its knowledge base.

By basing its answers on reliable external facts, our chatbot improves factual accuracy in contrast to conventional big language models. Additionally, it is made to make it obvious when the information that has been requested is not available. Its authentication procedures, along with its transparency, help lower the possibility of false information.

Currently, the system operates using locally scraped data and manual updates. But, because of its modular design, it is ready for future improvements that will focus on scalable deployment and real-time data integration.

Future Work

Future editions of this fact-checking methodology might be used to keep an eye on and regulate social media sites like Facebook, Reddit, and Twitter (X). By using real-time social media APIs, the system will be able to:

- Flag or identify deceptive political content automatically.
- Accompany viral posts with background information and proof of authenticity.
- Help content moderators spot well-planned disinformation efforts.

Suggested improvements and potential applications are as follows:

- **Real-Time Scraping and Indexing:** Establish a pipeline for automated data ingestion to guarantee that the knowledge base is updated continuously.
- **Multilingual Support:** For greater accessibility, increase the system's capacity to validate data in several languages.
- **User Feedback Loop:** By introducing a system that allows users to rate the quality of responses, retrieval and generation accuracy will gradually increase.
- **Cloud Deployment:** For the system to serve large-scale applications, it must be deployed on a scalable cloud infrastructure. Users can use trustworthy verification techniques on a large scale by obtaining evidence-based information through the News RAG Chatbot.
- **News Aggregators:** Integrating the chatbot inside websites such as Google News or Apple News to offer fact-checking layers on contentious subjects.
- **Browser Extensions:** Providing a browser plugin for fact-checking that allows users to verify content in-page when they read social media posts or political news.

By expanding our system's reach, we can support digital literacy in a variety of online contexts and help create healthier information ecosystems. In an era of spreading disinformation, this information verification system makes evidence-based transparency accessible and promotes the ethical and scalable use of fact-checking tools.

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