Report

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Title

Health Myth Buster Agent using Retrieval-Augmented Generation (RAG)

Introduction

Health misinformation is a growing public concern, especially on social media and informal information channels. Unverified health claims—such as "garlic cures heart attacks" or "vaccines cause autism"—can lead to harmful self-treatment, public panic, and mistrust in science.
This project presents a **RAG-powered AI system** that **scrapes trusted health websites**, indexes the content using embeddings and FAISS, and generates **fact-checked, context-rich responses** via **Google Gemini**. The system aims to provide **clear, authoritative answers** to debunk or verify health-related claims.

Problem Statement

The digital age has amplified the spread of health myths due to:

- Lack of immediate, trustworthy fact-checking tools.
- Difficulty in manually verifying claims from authoritative sources.
- Over-reliance on anecdotal evidence instead of scientific data.

The risks include:

- **Public Health Harm**: People may adopt unsafe practices or avoid legitimate treatments.
- **Erosion of Trust**: Decline in public confidence in health organizations.
- **Information Overload**: Users may find it hard to locate and interpret credible sources.

There is a need for an **automated, domain-restricted fact-checking system** that retrieves evidence from credible health sources and synthesizes accurate, easy-to-understand answers.

Objective

- Scrape and process text from trusted health websites.
- Convert text into vector embeddings for semantic search.
- Retrieve relevant evidence based on a user's health claim.
- Generate accurate, fact-checked responses using an LLM (Gemini).
- Provide an **interactive UI** for ease of use by non-technical users.

Why This Problem Matters?

- **Public Health Safety**: Misinformation can directly harm individuals.
- **Rapid Response**: Users need instant, trustworthy answers.
- **Educational Impact**: Helps in spreading awareness and correcting misconceptions.
- **Scalability**: Can be applied to multiple domains beyond healthcare.

Solution Overview: RAG Workflow

Step 1: Web Scraping

- User enters one or more URLs of trusted health sites.
- Controlled depth (max_depth) and page limit (max_pages) to avoid over-scraping.
- Extracts <p>, <li>, <td>, and <th> content.

Step 2: Text Cleaning & Chunking

- Removes unnecessary whitespace, citation markers, and parentheses.
- Splits long texts into 500-word chunks for better semantic matching.

Step 3: Embedding & Vector Store

- Uses **all-MiniLM-L6-v2** (Sentence Transformers) for embeddings.
- Stores vectors in **FAISS** for fast similarity search.

Step 4: Retrieval

- Given a health claim, retrieves the **top-k most relevant chunks**.
- Ensures only semantically related evidence is considered.

Step 5: LLM Generation

- Sends retrieved chunks + user query to **Gemini 2.5 Flash**.
- Generates a context-aware, scientifically accurate answer.

Step 6: Interactive UI

- Built with **ipywidgets** for seamless Jupyter Notebook interaction.
- Components:
  - URL input area
  - Depth and page limit selectors
  - Health claim query box
  - Buttons for scraping and generating answers
  - Output display with Markdown formatting

System Architecture

User Input → Scraper → Text Cleaning & Chunking → Embedding → FAISS Vector Store

↘ Retrieval (Top-k) → Prompt Construction → Gemini API → Fact-Checked Answer

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Technology Stack

Component	Technology / Library
Scraping	requests, BeautifulSoup4
Text Processing	re, numpy
Embedding	sentence-transformers
Vector Store	faiss-cpu
LLM Generation	google-generativeai
UI	ipywidgets, IPython.display

Outcomes & Impact

- Accurate Fact-Checking: Ensures answers are backed by reliable medical sources.

- User-Friendly Interface: Non-technical users can use it easily.
- Customizable Data Sources: Any trusted domain can be added for scraping.
- Prevents hallucination of made up answers by using RAG architecture.

Limitations

- Depends on the quality and credibility of scraped sources.
- Limited to English content unless multilingual embeddings are used.
- Requires Gemini API access (paid/free quota limitations).

Future Enhancements

- Support multilingual queries and sources.
- Add a citation system with clickable source links.
- Include live dashboards for misinformation trends.
- Cache scraped pages for offline use.

Conclusion

The Health Myth Buster Agent demonstrates how Retrieval-Augmented Generation can be effectively applied to combat health misinformation. By combining web scraping, semantic search, and LLM reasoning, it empowers users to get instant, reliable, and science-backed answers—helping improve public health literacy and trust in credible information sources