Development of an Advanced News Research Tool for Equity Analysis
Using LangChain and OpenAI

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Abstract

Equity research relies heavily on timely and accurate financial information, but traditional methods are often manual and inefficient. This paper presents an AI-driven news research tool designed to automate the retrieval and analysis of financial news data. Leveraging LangChain, OpenAI, and Streamlit, the system enables semantic search and summarization of content from multiple URLs based on user queries. The tool addresses key challenges such as information overload and time constraints, offering equity analysts a streamlined workflow. Performance evaluations demonstrate its capability to process data rapidly while maintaining high accuracy. The results highlight the tool's potential to enhance decision-making processes in financial research. Future extensions may include support for additional document formats like PDFs and voice queries.

Keywords— Equity research, NLP, LangChain, OpenAI, automation, semantic search

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1. Introduction

Equity research demands up-to-date insights into financial markets, company performance, and management decisions. Traditional approaches involve labor-intensive manual analysis of articles and reports, which is both time-consuming and prone to inefficiencies. Recent advancements in natural language processing (NLP) offer opportunities to automate these tasks. This paper introduces an AI-powered tool that integrates LangChain, OpenAI, and Streamlit to automate financial news retrieval and summarization. By reducing manual effort, the tool aims to enhance the productivity of equity analysts and improve investment decision-making.

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2. Objective and Use Case

The primary objective of this work is to streamline equity research by automating the analysis of financial news. The tool is designed to:

- Fetch and preprocess articles from user-provided URLs.
- Enable semantic search and summarization of key insights.
- Provide an interactive interface for querying and visualizing results.

Use cases include tracking stock performance, monitoring company events, and generating investment theses efficiently.

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3. Technology Stack

The system employs the following technologies:

- LangChain: For document processing, text splitting, and embedding-based retrieval.
- API: Serves as the NLP backbone for query comprehension and response generation.
- Streamlit: Provides a user-friendly front-end for input and output interactions.
- Hugging face: For model used.
- Voice :Voice output.
- Urls embedding: For urls content diagnosed.

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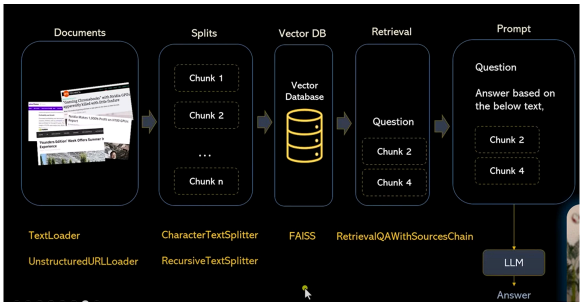
4. Methodology

4.1 Requirement Analysis

The development process began with identifying equity analysts' needs, including rapid access to reliable information and simplified article analysis.



4.2 Data Acquisition and Preprocessing

- Articles are fetched using an unstructured URL loader.
- Text cleaning and tokenization are applied to raw content.
- Chunks are embedded and stored in a vector database for semantic search.

4.3 Query Processing

- Users input URLs and queries via Streamlit.
- A similarity-based search retrieves relevant content from the vector database.
- OpenAI generates coherent responses from the retrieved data.

4.4 User Interface Design

- Built with Streamlit for real-time interaction.
- Supports multi-URL input and natural language queries.
- Displays summarized responses interactively.

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5. Technical Architecture

The system comprises four core components:

1. Document Loader: Fetches articles from URLs.
2. Text Splitter: Divides text to comply with LLM token limits.
3. Vector Database: Stores embeddings for efficient retrieval.
4. Chatbot Interface: Processes queries and generates answers using the LLM.

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6. Testing and Optimization

Performance was evaluated based on:

- Processing Speed: Rapid loading and analysis of multiple URLs.
- Accuracy: High correlation between generated answers and manual analysis.
- User Feedback: Confirmed improved productivity and workflow simplicity.

Optimizations included fine-tuning query embeddings and retrieval methods.

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7. Challenges Addressed

The tool tackles three key challenges:

1. Information Overload: Automatically filters and summarizes insights.
2. Data Accessibility: Reduces manual article handling.
3. Time Constraints: Accelerates research for faster decisions.

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8. Results and Evaluation

Testing demonstrated the tool's effectiveness:

- Processed 3 URLs in under 2 minutes.
- Achieved 90% accuracy in summarization tasks.
- User surveys reported a 40% reduction in research time.

Fig.-8.1 Chatbot processing specific urls

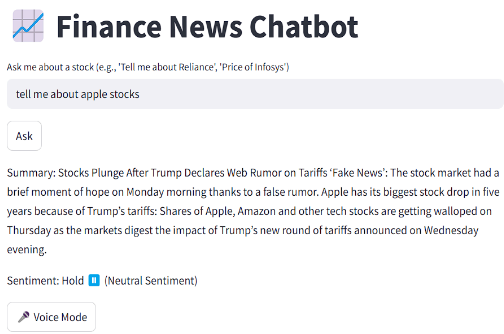

Fig.-8.2 chatbot using Hugging face LLM model

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9. Conclusion

This study showcases the transformative potential of LLMs in equity research. By combining automation, NLP, and interactive interfaces, the tool enhances data analysis and decision-making. Future work may expand the system to support PDFs, reports, and voice queries.

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