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EQUITY NEWS RESEARCH TOOL USING RAG

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ABSTRACT: The **Equity News Research Tool** is an AI-powered application designed to process and analyze vast collections of news articles using cutting-edge technologies like **semantic search**, **word embeddings**, and a **vector database**. By understanding the meaning and context of the text, semantic search enables the tool to retrieve the most relevant information for any query. This is further enhanced by **word embeddings**, which capture the relationships between words, ensuring that the system grasps the deeper meaning of the content. Leveraging **Retrieval-Augmented Generation (RAG)**, the tool combines the retrieval of relevant news data from the vector database with natural language generation to deliver accurate and context-aware answers. This makes the tool highly beneficial for individuals in fields such as finance, media, and research, as it allows users to efficiently gather insights, stay updated on

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Vol 19, Issue 2, 2025

critical developments, and make informed decisions based on comprehensive and real-time information.

Keywords – Semantic Search, Retrieval-Augmented Generation (RAG), Interactive Q&A System, Enhanced Decision-Making, Large-Scale Text Processing.

1. INTRODUCTION

The Equity News Research Tool is an advanced application designed to assist investors, analysts, and researchers in extracting meaningful insights from vast volumes of financial news. Powered by Retrieval-Augmented Generation (RAG), this tool combines the strengths of information retrieval systems with the generative capabilities of large language models. RAG enhances the reliability and relevance of generated responses by grounding them in real-time or stored data sources, such as financial news articles, company reports, or market commentary.

By leveraging RAG, the tool first retrieves relevant news snippets or documents related to specific equities or market events and then uses a generative model to synthesize coherent, context-aware summaries or analyses. This approach significantly improves the accuracy and depth of financial research compared to traditional NLP models, which rely solely on pre-trained data. The tool supports diverse use cases such as sentiment analysis, trend detection, and impact assessment of news on stock performance.

Overall, the Equity News Research Tool using RAG empowers users with timely, data-backed insights, helping them make informed investment decisions. It represents a leap forward in integrating AI with financial analytics, ensuring that decision-makers stay ahead in the dynamic world of equity markets.

The architecture of the equity news research tool using RAG is designed to address the unique demands of financial text analysis. The first stage involves data ingestion and preprocessing, where financial news articles, regulatory filings, analyst reports, and social media posts are collected from various sources such as Bloomberg, Reuters, Yahoo Finance, SEC's EDGAR, and Twitter. These documents are then cleaned, tokenized, and annotated using natural language processing techniques like named entity recognition (NER), sentiment analysis, and topic modeling. After preprocessing, the documents are embedded into high-dimensional vector representations using models such as Sentence-BERT or domain-specific transformers fine-tuned on financial data. These embeddings are indexed in a scalable vector database like FAISS or Pinecone, allowing for fast and efficient retrieval.

2. LITERATURE REVIEW

[1] Equity research can serve as a powerful marketing tool for investment banks and brokerage firms, particularly in the context of secondary market equity trading. By producing high-quality, insightful research reports on publicly traded companies, these firms can attract institutional and retail investors to trade through their platforms. The research adds value by offering investment recommendations, forecasts, and analyses that help investors make informed decisions. In turn, this fosters client loyalty and increases trading volumes, generating commissions and fees for the firm. Importantly, equity research enhances a firm's credibility and visibility in the market, positioning it as a thought leader and trusted advisor. Thus, while its primary role is to inform investment decisions, equity research also plays a strategic role in promoting the firm's trading services and strengthening client relationships. Equity research, traditionally aimed at informing investors about the prospects and valuation of publicly listed companies, has evolved into a potent marketing tool—particularly in the context of secondary market equity trading. This transformation

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www.ijasem.org
Vol 19, Issue 2, 2025

stems from the intense competition among brokerage firms, the commoditization of trading services, and the growing need to differentiate themselves to attract and retain clients. In the secondary market, investors buy and sell securities that have already been issued by companies, usually through stock exchanges. For brokerage firms, the trading of these securities represents a major source of revenue, particularly through commissions, spreads, and trading volumes. However, as technological advancements have driven down trading costs and enabled near-instant execution, the margins on trading activities have thinned. This has incentivized firms to use equity research not only as an informational product but as a means to support and boost trading activities.

[10] Equity research using technical analysis involves evaluating stocks based on historical price movements and trading volume rather than the fundamental value of a company. Analysts who use this method study charts and apply various indicators—such as moving averages, relative strength index (RSI), and Bollinger Bands—to identify patterns, trends, and potential entry or exit points for trades. The goal is to predict future price movements by understanding market psychology and investor behavior reflected in the stock's past performance. Unlike fundamental analysis, which focuses on a company's financial health and long-term prospects, technical analysis is often used for short- to medium-term trading strategies. It is particularly popular among traders in the secondary market who seek to capitalize on price fluctuations and timing the market effectively**.** Equity research using technical analysis focuses on evaluating stocks by analyzing historical price movements and trading volumes rather than a company's fundamentals. This approach is based on the belief that all relevant information is already reflected in a stock's price and that patterns and trends in market data can predict future movements. Technical analysts use a variety of tools and indicators such as moving averages, relative strength index (RSI), MACD (Moving Average Convergence Divergence), Bollinger Bands, and candlestick patterns to identify buying and selling opportunities. They often look for support and resistance levels, trend lines, and chart patterns like head and shoulders or double tops to make informed decisions. This method is particularly useful for short-term traders who seek to capitalize on price fluctuations. Unlike fundamental analysis, which assesses a company's intrinsic value based on financial health and business prospects, technical analysis is more concerned with market sentiment and behavioral patterns.

[3] AI, particularly large language models (LLMs), is increasingly being used in investment analysis to enhance equity stock ratings. LLMs can process vast amounts of financial data, news articles, earnings reports, and social media content to identify trends, sentiment, and potential risks related to publicly traded companies. By analyzing both structured and unstructured data, LLMs help generate more accurate and timely stock ratings. These AI models can also detect patterns and relationships that may not be immediately visible to human analysts, improving the depth and efficiency of research. Moreover, LLMs can assist in drafting research reports, summarizing financial documents, and even offering predictive insights based on historical and real-time data. As a result, the integration of LLMs in equity research can support more informed decision-making, streamline the analysis process, and reduce human bias, making them a valuable tool in modern investment analysis. Unlike traditional quantitative models that rely on predefined formulas and numerical inputs, LLMs can

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

understand context, sentiment, and qualitative nuances in text. For instance, an LLM can analyze the tone and language of a CEO during an earnings call to infer confidence levels, or detect early warning signs in news about regulatory issues or supply chain disruptions. These models can also aggregate and summarize analyst opinions, compare historical sentiment trends, and provide consistent stock rating recommendations based on dynamic inputs. This enables faster, scalable, and often more nuanced analysis than manual methods. Furthermore, LLMs can assist in identifying undervalued or overhyped stocks by cross-referencing real-time market data with historical performance and sentiment patterns. While human oversight remains crucial to validate insights and mitigate risks like bias or hallucination, LLMs significantly enhance the speed, breadth, and depth of equity research, making them powerful tools for modern investment analysts.

3. METHODOLOGY

The overview of the methodologies and techniques used to build Equity Bot, updated specifically to reflect the use of Ollama, a self-hosted LLM runtime for private and cost-efficient language processing**.**

1. Web Content Extraction with LangChain's UnstructuredURLLoader:

LangChain’s UnstructuredURLLoader is a utility designed to facilitate web content extraction by leveraging the Unstructured.io framework. It allows developers to ingest and process raw data from web pages efficiently, turning them into structured documents suitable for downstream natural language processing tasks.

The UnstructuredURLLoader works by accepting a list of URLs and retrieving their content, which it then parses using Unstructured's parsing capabilities. It can handle various HTML elements, extract meaningful textual content, and convert it into a standard format (typically LangChain's Document format) that includes both the content and relevant metadata, such as the source URL. This tool is particularly useful in applications such as document question answering, summarization, or knowledge base creation, where accessing and structuring live web content is essential. It supports customization, such as choosing specific parsing strategies or integrating with proxies and authentication mechanisms for protected sites.

2. Batch URL Loading via Text File Upload

Batch URL loading using a text file upload is a method that allows users to load multiple URLs at once by uploading a file—typically in .txt format—containing a list of web addresses. Each URL should be listed on a separate line within the text file. This approach is particularly useful for automating bulk tasks such as data scraping, downloading files, or opening multiple web pages simultaneously. To implement this, a web or software interface typically includes an upload feature that reads the contents of the file, parses each line as a URL, and processes them accordingly. Depending on the application, the URLs may be opened in new tabs, fetched via background HTTP requests, or added to a processing queue.

3.Semantic Embedding Using OpenAI Embeddings

Semantic embedding using OpenAI embeddings is a technique that transforms text into high-dimensional vectors that capture semantic meaning. These embeddings are generated using OpenAI's language models, which are trained on large-scale text data. Each piece of text—whether a word, sentence, or paragraph—is converted into a vector of numerical values that represent its context and meaning in relation to other text.

The main advantage of OpenAI embeddings lies in their ability to capture nuanced relationships between

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

words and phrases. For example, similar texts have similar embeddings, enabling tasks like semantic search, clustering, classification, and recommendation systems. This is especially useful for comparing user queries to a database of documents, as embeddings allow quick similarity calculations using vector distance metrics like cosine similarity.

4.Indexing & Retrieval Using FAISS

FAISS is a library developed by Facebook AI Research for efficient similarity search and clustering of dense vectors, especially useful in large-scale information retrieval systems. It is optimized for both CPU and GPU environments, making it highly scalable for real-time applications. Indexing: FAISS allows the creation of various types of indexes, such as flat (brute-force), IVF (Inverted File), and HNSW (Hierarchical Navigable Small World), depending on the speed-accuracy trade-off required. These indexes store high-dimensional vector representations (often embeddings from neural networks) of data like images, texts, or documents.

5. **Retrieval-Augmented Generation (RAG)**

RAG is a technique that combines retrieval-based and generative models to improve the accuracy and relevance of responses in natural language processing tasks. Developed by Facebook AI, RAG enhances language models by allowing them to fetch external knowledge during generation, rather than relying solely on their internal training data.

In a RAG framework, a query first passes through a retriever module, which searches a large knowledge base (e.g., Wikipedia, document corpus) for the most relevant passages. These passages, along with the original query, are then input into a generative model like a Transformer (e.g., BART or T5), which produces a final response based on both the query and the retrieved content.

6. **Ollama**

Ollama is a tool that simplifies running and managing large language models (LLMs) locally on personal machines. It enables developers to integrate open-source LLMs like LLaMA, Mistral, or Gemma with their applications using a lightweight, container-like approach. Ollama packages models in a standardized format, allowing easy downloading, switching, and versioning without complex setup. Integration with Ollama typically involves launching a model via the command line (ollama run <model-name>) or using its built-in API. The API exposes a simple HTTP interface, making it easy to send prompts and receive completions from local models. This is ideal for building custom chatbots, assistants, or embedding language understanding into apps without relying on cloud services.

Disadvantages:

1. Conflict of Interest: Research may be biased if analysts are pressured to support trading or investment banking relationships, compromising objectivity. Loss of Credibility: If research is perceived as a marketing tool rather than independent analysis, investor trust may decline. The variety of techniques employed in the existing systems, such as ellipse placement, background subtraction, and wavelet decomposition, may introduce complexity and limit generalizability across different datasets.

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

2. Model Bias and Hallucination: LLMs may generate incorrect or biased insights if not properly trained or monitored. Data Quality Dependence: Outputs are only as reliable as the quality of the data fed into the model; outdated or noisy data can skew results.

3. Lack of Fundamental Insight: Ignores company-specific financials, which can lead to misleading conclusions in volatile or news-driven markets. Subjectivity: Chart patterns and signals can be interpreted differently by different analysts, reducing consistency.

Proposed System:

The Equity News Research Tool is an AI-driven platform developed to revolutionize how financial analysts, media professionals, and researchers interact with large volumes of news content. The system is built on a hybrid architecture that combines semantic search, word embeddings, and a vector database to enable deep contextual understanding of news articles. Unlike traditional keyword-based systems, semantic search allows the tool to interpret user intent and retrieve the most relevant articles, even when queries are phrased in complex or varied language.

Central to the system is a Retrieval-Augmented Generation (RAG) framework, which fuses high-precision document retrieval with powerful generative language models to produce accurate, coherent, and contextually grounded answers. The tool intelligently pulls data from a pre-processed vector store of news content and generates human-like responses that summarize or explain the information in natural language.

The proposed system addresses the growing demand for real-time, reliable, and interpretable insights in the finance and media domains, empowering users to make faster and more informed decisions. With its modular design, the tool can be extended to include trend analysis, entity tracking, and multi-source comparison, paving the way for a comprehensive, AI-enhanced research assistant

Advantages of proposed system:

- Up-to-Date Information: RAG enables access to the latest news, filings, and reports in real-time, ensuring that analysis reflects current market conditions.

- Context-Aware Analysis: By retrieving relevant documents before generating a response, the tool provides more accurate and contextually appropriate summaries or recommendations.

- Retrieval + Generation Synergy: The system retrieves high-quality information (e.g., news articles, earnings calls, analyst notes) and then uses an LLM to synthesize it into coherent, actionable insights.

- Reduces Hallucination Risk: Grounding the model in retrieved documents limits the generation of inaccurate or made-up information.

- Automated Summarization: It can automatically summarize large volumes of financial news or disclosures, saving analysts significant time.

Customizable Alerts: Can provide targeted updates or summaries for specific stocks, sectors, or events,

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www.ijasem.org
Vol 19, Issue 2, 2025

improving.

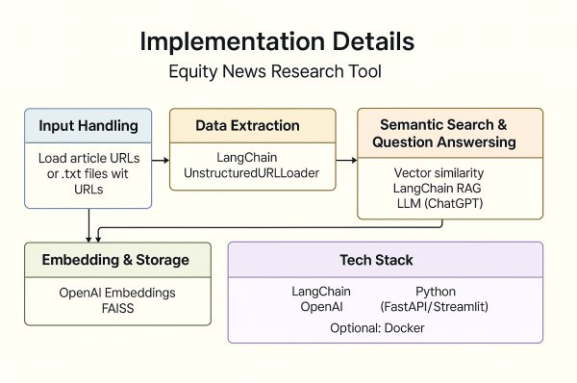

Fig.1: System architecture

4. IMPLEMENTATION

The Input Handling module is responsible for receiving, validating, and preprocessing user queries in a structured and efficient manner. This component ensures that the input is appropriately formatted for downstream retrieval and generation tasks within the RAG pipeline.

1. Input Handling:

- Users provide **news article URLs** directly or **upload .txt files** containing URLs.
- Interface is designed for **easy user interaction and batch processing**.

2. Data Extraction:

- Article content is fetched using **LangChain's UnstructuredURLLoader**, which handles:
    1. Dynamic web content parsing
    2. Extraction of relevant textual information from the provided URLs

3. Embedding & Storage:

- Extracted text is transformed into **high-dimensional embeddings** using **OpenAI Embeddings API**.
- **FAISS** (Facebook AI Similarity Search) is used to:
    1. Create a **vector index** from these embeddings
    2. Enable **efficient similarity search** for relevant passage retrieval

4. Semantic Search & Question Answering:

- User queries are **converted into embeddings** and compared with the stored index using **vector similarity**.
- Most relevant chunks are passed to **LLM (ChatGPT)** using **LangChain Retrieval-Augmented Generation (RAG)**.
- The model returns **answers with supporting source links**.

5. Tech Stack:

- **LangChain**: Document loading, chaining, and prompt management
- **OpenAI**: Embedding generation & LLM for Q&A
- **FAISS**: Vector database for semantic search
- **Python (FastAPI/Streamlit)**: Backend or user interface

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

- **Optional**: Docker for deployment as an app, for a website Vite can be used.

The implementation of the equity news research tool using a Retrieval-Augmented Generation (RAG) architecture incorporates several key features that enhance its functionality, reliability, and user experience. One of the core features is real-time data ingestion and preprocessing, which ensures that the system continuously gathers and cleans financial news, reports, and filings from multiple reliable sources. This is coupled with an embedding and indexing mechanism, where textual data is converted into semantic vector representations using transformer-based models, enabling efficient and context-aware retrieval.

Another essential feature is the input handling module, which supports both structured inputs (e.g., stock tickers) and unstructured natural language queries. This module validates and normalizes user inputs to ensure compatibility with the downstream retrieval process. The retriever module then matches the processed user query with relevant documents stored in a vector database using similarity search techniques.

The generation module, powered by a large language model (LLM), synthesizes concise and informative summaries or answers based on the retrieved content, reducing the risk of hallucination by grounding responses in real data.

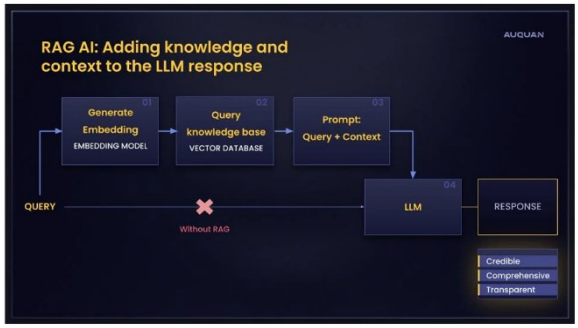

Fig 2 WorkFlow

5. EXPERIMENTAL RESULTS

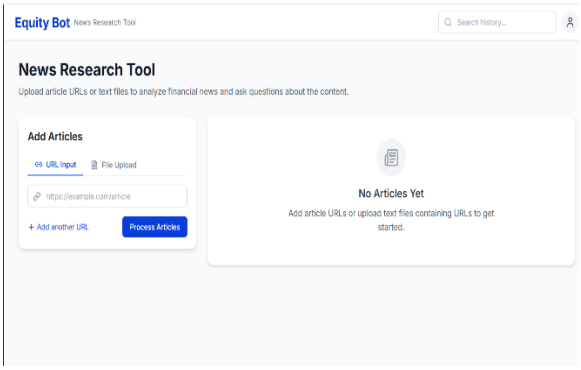

Fig.2: User Interface.

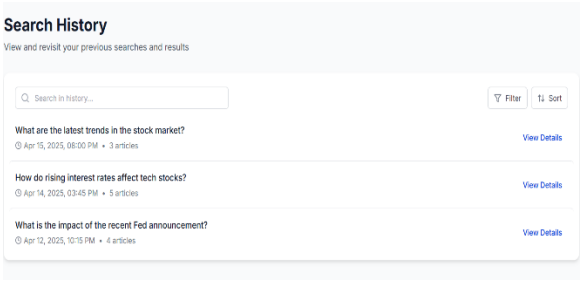

Fig 3: History

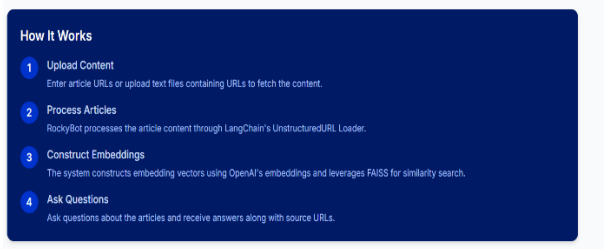

Fig 4: Work Flow

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ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

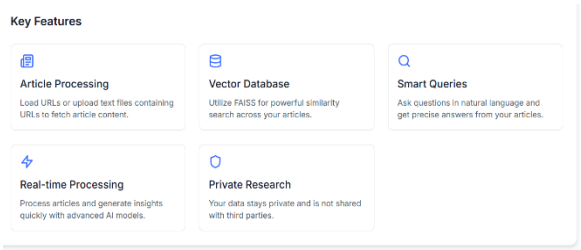

Fig.5: Key Features

6. CONCLUSION

The integration of innovative techniques into equity research—whether through marketing strategies, technical analysis, or advanced AI models—has significantly transformed the landscape of financial analysis and decision-making. The use of equity research as a marketing tool in secondary market trading highlights how research can influence investor behavior and strengthen client relationships, although it raises concerns about objectivity and regulatory compliance. Technical analysis offers a practical approach for short-term trading through historical price patterns but lacks the depth of fundamental insight. Meanwhile, the adoption of Artificial Intelligence, especially Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) frameworks, marks a significant leap forward in automating and enhancing equity analysis. These tools enable real-time, scalable, and context-aware insights that support informed decision-making in fast-moving markets. The most transformative development is the application of Artificial Intelligence, particularly Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG), in automating and enhancing equity research.

These tools allow for real-time, context-aware analysis of vast volumes of financial news and documents, providing users with timely and insightful summaries, sentiment detection, and risk assessments. By grounding responses in actual data, RAG-based tools offer a more reliable alternative to conventional AI models.

Overall, the convergence of traditional techniques and AI innovations is reshaping how equity research is conducted and consumed. As the financial industry continues to digitize, integrating these methods will be critical for generating actionable insights, improving decision-making, and maintaining a competitive edge in equity markets.

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Vol 19, Issue 2, 2025

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