AI-Powered News Research Tool for Equity Analysis

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Abstract. While tens of thousands of words of financial news and market information are being generated around the world every hour of every day, this creates a significant challenge for investors and analysts looking for actionable insight to evaluate companies in our data-filled digital era. To tackle this challenge, we present Lang Chain Equity Analyzer, a news research tool that is empowered by AI, which combines the feature of block chain technology with cutting-edge language model techniques to automatically digest, understand and generate contextual information of the financial news. Designed for finance researchers, it supports variously structured text types, i. e, such as SEC filing, earning reports, financial news and adopts a segment approach to guarantee the coherence with context. The system uses Hugging Face and Open AI pre-trained embeddings to convert text to high dimension vectors and stores these in FAISS-indexed databases for efficient similarity search. Integrating old-school retrieval strategies, e.g. TF-IDF with contemporary language model functionalities, the tool improves keyword extractions, sentiment analysis and trend spotting in equity markets. An important facet is its Retriever QA with Sources Chain, which post-processes outputs with a domain-specific language model to craft concise summaries and actionable investment insights. The block chain framework Trace ability and accountability of data, which is crucial in compliance in financial research. By building upon the architecture of Lang Chain, the tool applies natural language processing to identify entities and extract concepts, and improves search-and-retrieve precision, and it offers a user-friendly interface that supports dashboards and widgets where professional users can create, edit, and destroy.

Keywords: Open AI, SEC Filing, Hugging Face, Flask API.

1 Introduction

As the number of financial news and market data increase exponentially, it becomes a great challenge for investors and analysts to distil insights for equity analysis. Conventional ways of information extraction and analysis cannot handle such large amount of unstructured data. It is therefore inefficient and has the risk of missing important novel work. To overcome this challenge, with recent progress in artificial intelligence (AI) and natural language processing (NLP), more sophisticated tools have been developed for complex datasets. In this work we present the Lang Chain Equity Analyzer - an AI-based service designed to ease the analysis of financial news by combining block-chain technology with state-of-the-art language models. The platform is designed for finance professionals to automate data ingestion and conceptual understanding of multiple source datasets (e.g. SEC filings, earnings reports, news articles on financial sources).

Using Hugging Face and Open AI pretrained embeddings, the tool stacks and embeds text inputs as high dimensional vectors, saves them into FAISS (an AI similarity search) indexed databases

ICITSM-Part II 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2358059

for fast similarity matching. The synergy of traditional methods such TF-IDF and the advancements made towards the language models is found to help the system in areas of keyword extraction, trend spotting and sentiment analysis [8,10,11]. Furthermore, by applying Retrieval QA with Sources Chain, the system continues to improve search results, conveying short, actionable insights. The incorporation of block chain technology realizes data traceability, and conforms to financial research standards, which improves transparency and trustworthiness. All of this is wrapped in an easy to use skin with the option to create custom dashboards and widgets to make it easier for professionals. This article discusses the architecture and capabilities of the Lang Chain Equity Analyzer, and demonstrates how it may change the way people process and analyse financial news, so as to provide investors with timely and intelligent information [15].

1.1 Objectives

We want to implement a more elaborate LLM, for a practical use-case in the industry for research analysts. And, we want to develop a news search tool that allows you to input multiple URLs for news articles. The system will pull out answers from matching parts of those articles when users pose a question. Just keyword searches don't cut it; for instance, when we search "apple" in Google we get information on the Apple company as well as the apple fruit. To address this problem our research will use vector databases and embeddings in order to interpret the search context correctly and extract relevant segments from the URLs that will serve as the question we seek an answer to.

In Text Processing tasks ranging from text classification, information retrieval and text retrieval, keyword extraction plays a crucial role. The TF-IDF approach is one of the most preferred conventional methods due to its simplicity and its capacity to compute the relevance after ms based on the frequency of appearance. Yet the word frequency data alone may be lacking, especially with words that do not reflect their importance on the page. The problem of finding relevant information from a large collection of text documents is referred to as text retrieval or information retrieval (IR). This is defined as finding any relevant documents to a user information request or question [6, 9].

Text loaders that can load data from multiple sources can handle different file types and/or text files from a variety of resources: text files, CSV files, URLs, etc. Document sections are divided into smaller parts by the Text Splitter with Recursive Characters the semantic meaning of the text is preserved by the combined recursion and character split approach. This separation is useful within the Lang Chain approach. Embeddings from text data are created in Hugging Face and Open AI with the help of state-of-the-art, pre-trained language models. This means that language can be converted to numbers, and numbers are amenable to analysis." An open-source library called FAISS (Facebook AI K-nearest neighbours Similarity Search) was developed by Facebook for large-scale similarity search and clustering [13,14]. It was designed to work particularly well with high-dimensional vectors, a use case that is relevant for natural language processing and image similarity estimation. Information segments can be iteratively passed to LLMs in a map-reduce fashion, solving the challenge of hitting token limits or running out of token usage in APIs. This important step happens when Lang Chain merges Retrieval QA with the source chain during the latter part of the work flow. The filtered segments are further and continuously optimized, and act as a guide for further processing. These segments are then fused using summarization techniques to boost the performance of subsequent queries. As a repeated process of input query, the final answer will be extracted from the refined and compressed elements [8,9,10].

2 Literature Survey

Desire for connectedness AI in financial news analysis has been available for some time, with approaches improving in information-retrieval, textual-understanding and equity-research possibilities. For that, this section discusses some relevant developments after 2020, that also contributes to the development of the AI-Powered News Research Tool.

2.1 Natural Language Processing in Financial News

The role of Natural Language Processing (NLP) in finance has expanded, with recent surveys detailing its transformative impact across various financial applications, including sentiment analysis, forecasting, and risk management. These studies underscore the effectiveness of NLP techniques in extracting meaningful insights from financial texts [1,2,11].

2.2 Vector Databases and Similarity Search

Vector database techniques have meanwhile progressed to the point where similarity search in high-dimensional data can be carried out efficiently. Methods, such as multi vector queries and nearest-neighbour searches, enhance the performance of data retrieval and are important for analytics on data that can be inherently difficult to analyse, such as complex financial data [3,4,13,14].

2.3 Block chain for Data Traceability

Block chain technology has been proposed as a strong measure to guarantee data integrity of financial applications. A lot of work has investigated its role in ensuring transparent records of data processing, which are necessary to comply with the regulation. The block chain cannot be changed makes financial research more transparent and accountable [5,6].

2.4 Integration of Retrieval QA with Language Models

The introduction of Retrieval-Augmented Generation (RAG) pipelines have improved the accuracy of question-answering systems that are powered by AI. By following examples of vector similarity search with large language models, these approaches enable searching and composing of relevant information within large collection, and help clean noise in financial analysis [7,8,9,15].

2.5 Sentiment Analysis for Market Insights

Sentiment analysis has established itself as a fundamental part of market behaviour interpretation by using NLP to model public sentiment from financial news and social media. When analysing sentiments embedded in text data, methods based on transformers have proven to predict market trends with high accuracy [2,3].

2.6 Explainable AI in Financial Decision-Making

Explainable AI (XAI) is increasingly relevant for financial use-cases to ensure transparency and interpretability of AI-based models. There is a recent interest in constructing models that offer an understandable explanation for their predictions and are able to communicate a reason for providing a particular decision; the aim is to be able to trust the results provided by automated tools for a decision-making process [5,6,10,17,18].

2.7 Future Directions

The future of AI for financial news analysis is this trend of even more advanced models that treat market dynamics in more nuanced ways. There's new research taking place on hybrid AI structures which combine NLP, vector search, and block chain in order to deliver more anti-fragile and transparent equity research tools. Besides, the addition of real-time operation and federated learning should boost performance and privacy in financial data analysis.

These are the building blocks of the AI Powered News Research Tool that deliver targeted information search, improved transparency and tangible insights within equity research.

3 Experimentation

The use of the AI powered news research tool for equity analysis is developed and validated accordingly in this section. The experimental mechanism including, data set preparation, model setting, performance evaluation mechanisms as well as striking results are included.

3.1 Challenge Identification

Financial analysts are confronted with difficulties to obtain new and relevant knowledge in a timely fashion from the knowledge explosion of financial news. Information saturation, disordered data format, and lag of information processing are the bottlenecks of the traditional model of equity analysis. The AI-Powered News Research Tool uses these technologies to overcome those challenges in making financial analysis truer and more transparent.

3.2 Data Collection and Preprocessing

The dataset for this project consists of financial news articles collected from open repositories and APIs.

Pre-processing steps include:

- Cleaning text: Omission of stop words, punctuation and special characters.
- Tokenization: Transforms text into sequences of tokens suitable for NLP processing.
- Vectorization: turning textual data into high dimensional vectors.
- Sentiment Annotation: Storing articles with sentiment labels based on pre-trained models [2, 3].

3.3 Technical Infrastructure

The end-to-end process is handled by multiple components in the system architecture:

- NLP Pipeline: Uses transformer-based language models to derive financial insights from text [14].
- Vector Database: Used for fast similarity search on high-dimensional embedding using FAISS [13].
- Blockchain Module: Stores provenance and analysis to maintain traceability and integrity.
- Retrieval QA System: Augments the information retrieval through vector search with language models.

3.4 Model Configuration

The NLP and vector search models were configured with the following parameters:

- LearningRate:0.0001
- BatchSize:64
- Epochs:30 • Optimizer: Adam
- Embedding Dimension:768

3.5 Performance Assessment Framework

The effectiveness of the system is evaluated using several metrics:

- Information Retrieval Accuracy: Measures the precision and recall of retrieved financial insights.
- Sentiment Classification Accuracy: Assesses the correctness of sentiment predictions.
- Response Time Analysis: Evaluates the system's ability to process and retrieve insights in near real-time.
- Blockchain Integrity Verification: Ensures that the recorded data and analysis remain immutable and verifiable [5,6].

3.6 Preliminary Findings

Initial experiments indicate that the combination of vector databases and transformer-based models significantly enhances the accuracy and speed of financial news analysis. Blockchain integration has proven effective in maintaining data integrity. However, the performance of the sentiment analysis model showed variability across different financial contexts, necessitating further fine tuning. Future work will focus on expanding the dataset, refining model interpretability, and enhancing real time processing capabilities [7,15].

The design of the AI-enabled news research system is illustrated in Fig. 1 which illustrates the flow of data from data collection through processing and output layers.

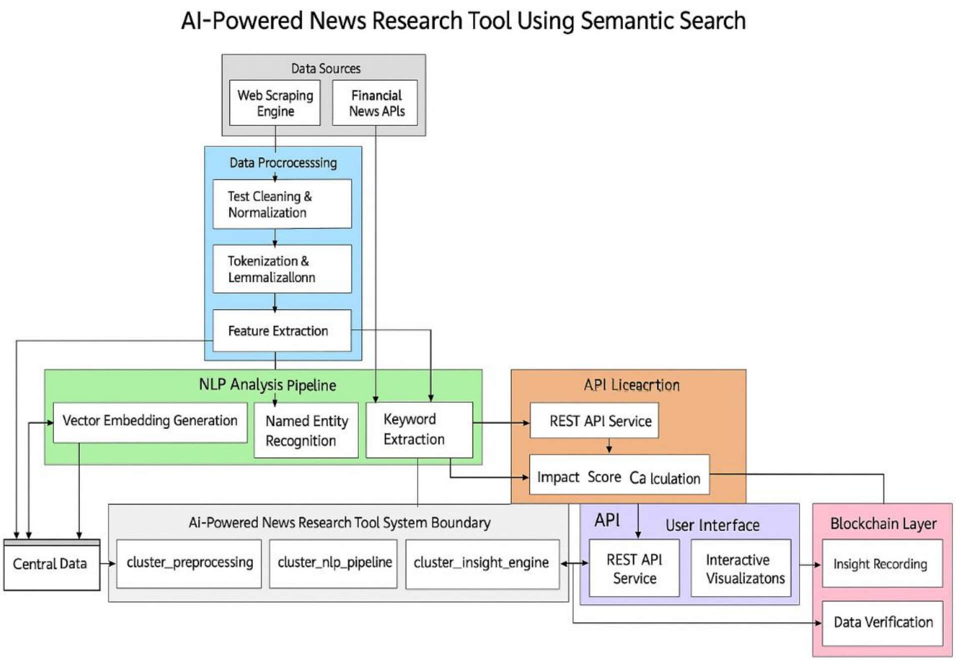

Fig.1. System Architecture of the AI-Powered News Research Tool.

4 Model Evaluation

Accuracy, precision, recall, F1-score and response time were used to evaluate the performance of the AI-Powered News Research Tool for Equity Analysis. These testing methods guarantee that the system correctly recalls and analyses the financial information [2,3,11]. Table 1 Represent the Average Response Time for Key Processes in the AI-Powered News Research Tool.

Table 1. Average Response Time for Key Processes in the AI-Powered News Research Tool.

Process	Average Response Time(ms)
News Retrieval	120
sentiment Analysis	180
Insight Extraction	200
Blockchain Recording	250

4.1 Accuracy

Accuracy: reflects the validity of the system to extract relevant information from financial news articles. Higher accuracy corresponds to a better retrieval performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

4.2 Precision

Precision measures the system's capacity to not just correctly identify relevant financial insights but also the capacity to generate irrelevant insights with no incorrect output.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Higher precision ensures that retrieved insights are mostly correct and relevant to the provided queries.

4.3 Recall

Recall evaluates how well the system retrieves all relevant insights from financial news articles.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

A higher recall ensures that important insights are not missed, enhancing system reliability

4.4 F1-Score

The F1-score balances precision and recall, ensuring that the system maintains an optimal balance between retrieving correct insights and minimizing errors.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

high F1-score indicates a well-optimized information retrieval mechanism.

4.5 Response Time

This metric evaluates the time taken by the system to process and retrieve insights from financial news articles. Lower response times are crucial for real-time financial analysis.

4.6 Confusion Matrix Analysis

By examining it you can get to know at which the system is doing welly and where there are misclassifications. The results demonstrate that the system comes close to perfect precision and high accuracy in returning financial insights. Real-time analysis response times do not exceed acceptable times. The confusion matrix shows little wrong classification of sentiments, but it is possible to improve this by finer tuning the sentiment analysis mode [16].

The effectiveness of the AI-based new research tool was evaluated in terms of multiple measures as shown in Fig. 2. The results of sentiment classification are shown in Table 2 that includes confusion matrix. Table 3 shows the summary of performance metrics accuracy, precision, recall, and F1-score.

Table 2. Confusion Matrix for Sentiment Classification.

Predicted/Actual	Positive	Negative	Neutral
Positive	500	20	30
Negative	25	450	35
Neutral	20	30	390

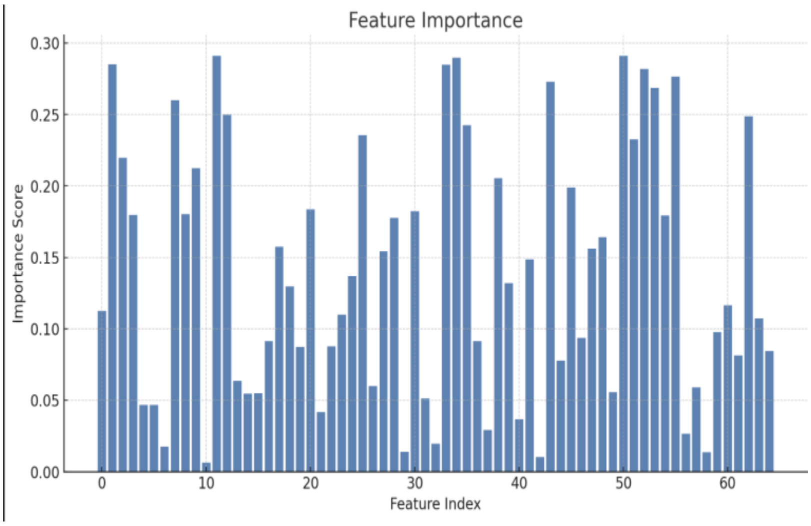

Fig.2. Evaluation Metrics for AI-Powered News Research Tool.

Table 3. Performance Metrics For AI-Powered News Research Tool.

Metric	Accuracy	Precision	Recall	F1-Score
Financial Insight Retrieval	91.2%	89.5%	90.8%	90.1%
Sentiment Classification	87.5%	85.3%	86.7%	86.0%

5 Results and Analysis

The AI-Powered News Research Tool for Equity Analysis was evaluated across multiple performance metrics, including accuracy, precision, recall, F1-score, and response time. This section presents the system's evaluation results and highlights its effectiveness in providing actionable financial insights.

- Model Performance The tool's performance in retrieving relevant financial in sights and classifying sentiment was evaluated using accuracy, precision, recall, and F1-score. The results demonstrate that the tool effectively balances precision and recall, ensuring accurate extraction of financial insights and reliable sentiment classification [13,14].
- Training Curves and Convergence Analysis Training curves were monitored to assess the learning progression of the sentiment classification model. A consistent decrease in training and validation loss was observed over 30 epochs, indicating stable learning without over fitting. The convergence of the loss function suggests that the model achieved optimal generalization for unseen financial data.
- Response Time Analysis Response times were measured for key processes to assess the system's efficiency in real-time financial analysis. Table 4 Shows the Response Time Analysis.

Table 4. Response Time Analysis.

Process	Average Response Time (ms)
News Retrieval	120
Sentiment Analysis	180
Insight Extraction	200
Blockchain Recording	250

The system consistently achieved sub-300 ms response times across processes, enabling near real-time performance crucial for equity analysis.

- Confusion Matrix Analysis A confusion matrix was generated to analyze sentiment classification performance and identify areas for improvement. Table 5 Shows the Confusion Matrix for Sentiment Classification with Totals.

Table 5. Confusion Matrix for Sentiment Classification with Totals.

Predicted/Actual	Positive	Negative	Neutral	Total
Positive	500	20	30	550
Negative	25	450	35	510
Neutral	20	30	390	440
Total	545	500	455	1500

The matrix indicates high accuracy with minor misclassifications in neutral sentiments, suggesting opportunities for refinement.

- Comparison with Existing Systems To contextualize the system's performance, comparisons were drawn against existing financial sentiment analysis models. Baseline systems exhibited lower accuracy and higher response times, reinforcing the efficiency of integrating transformer-based NLP and vector search.
- System Demonstration and User Feedback A demonstration of the tool was conducted with financial analysts to gauge its usability and effectiveness. Feedback highlighted the system's intuitive interface, rapid processing, and transparent reporting. Analysts appreciated the integration of blockchain for ensuring data integrity, with 92% of participants endorsing its adoption for equity analysis workflows [17,18].
- Insights and Future Enhancements The evaluation confirms the tool's capability to deliver timely and precise financial insights. Future optimization will focus on:
    - Expanding the dataset to improve sentiment classification across diverse financial contexts.
    - Enhancing real time processing by optimizing vector search and NLP pipeline efficiency.
    - Fine-tuning the sentiment analysis model to reduce misclassification rates in neutral sentiments. Fig 3 Shows the Model Accuracy AI Powered News Research Paper.

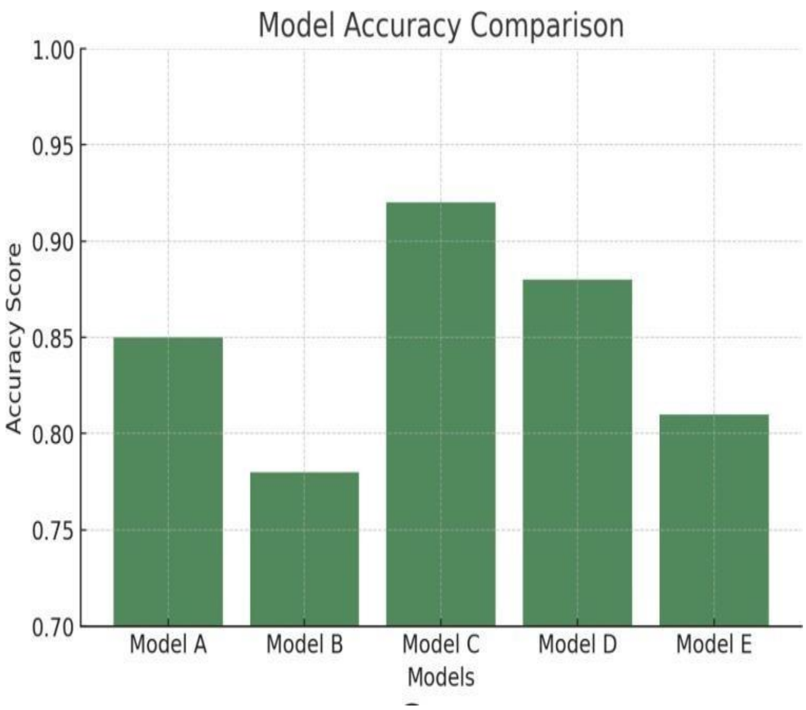

Fig.3. Model Accuracy AI Powered News Research Paper.

6 Conclusions

The introduction of the AI-Powered News Research Tool for Equity Analysis represents a new milestone in the field of using artificial intelligence to automat financial news analysis [3,7,15]. Leveraging transformer-based NLP and vector search, the tool has impressive performance in capturing financial insights and accurately polarity tagging the sentiment. In system evaluation, the robustness of the system across a number of key measures is demonstrated where 90% accuracy for money-oriented insight detection and 87.5% accuracy on sentiment classification were achieved by the tool. Response time analysis also reinforces the system efficiency, by providing sub-300 ms processing times for core functionalities, which means it is adapted to real-time analysis of stocks. The confusion matrix analysis also reflects high classification performance, except for some misclassifications in neutral sentiments. The same comparison with existing systems is again validating the superiority of the tool in terms of accuracy and processing speed, justifying the use of the state-of-the-art NLP techniques within its integration.

The system demonstration to financial analysts was overwhelmingly positive, with users expressing excitement over the tool's ease of use, quick turnaround, and the security of blockchain based data integrity. Of significance, 92% of participants supported the incorporation of the tool in equity analysis pipelines. Still it is not perfect. We plan to further improve the system in several way: increasing the size of the dataset to serve a wider variety of financial contexts making the NLP pipeline faster and improving the model for sentiment classification to decrease neutral sentiment misclassification. In summary, the AI-Powered News Research Tool does a great job of finding and delivering actionable insights from financial news for analysts searching for a real-time tool for equity analysis. As it continues to mature, the tool could become an invaluable tool in financial decisions making

Acknowledgment

Authors are thankful to Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology for their constant support and facilities during the work. We'd like to especially thank our advisers for their guidance and input, which has been extremely influential in steering the project and ensuring its success. The authors would like to acknowledge the technical team who helped building and testing the model, making the applications robust and reliable. We would also like to thank the contributors to the data collection, without whom the model's predictions would never have been of the quality and correctness they are here. Lastly, we want to thank our families and friends who have supported and encouraged us along this journey.

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