ABSTRACT

Artificial Intelligence (AI) has transformed financial market analysis through the use of machine learning, deep learning, and natural language processing (NLP) for enhanced trading strategies and risk management. Sentiment analysis models such as FinBERT and LLaMA analyze financial news, while predictive models such as LSTMs, Facebook Prophet, and Transformers improve stock price prediction. AI-based algorithmic trading executes trades and identifies patterns automatically.

In spite of these improvements, challenges still exist, such as high computational expense, overfitting in RL, financial text misinterpretation, and the black-box nature of AI models. Hybrid AI methods incorporating Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), and machine learning provide enhanced data retrieval, explainability, and flexibility to overcome these. Hybrid AI also improves financial decision-making and predictive accuracy through sentiment-aware trading strategies and effective risk management.

KEYWORDS: Artificial Intelligence (AI), Financial Market Analysis, Machine Learning (ML), Deep Learning, Natural Language Processing (NLP), Sentiment Analysis, Algorithmic Trading, Predictive Analytics, Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), Risk Management.

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ABBREVIATIONS

LLM	Large Language Model
RAG	Retrieval Augmented Generation
FAISS	Facebook AI Similarity Search
TF-IDF	Term frequency-inverse document frequency

CHAPTER 1

INTRODUCTION

1.1 Background

Financial markets are complex, data-driven ecosystems influenced by numerous factors such as corporate earnings, economic indicators, and investor sentiment. Traditionally, traders have relied on manual technical and fundamental analysis for decision-making. However, the growing volume and velocity of financial data require automated tools that can analyze real-time information, extract insights, and assist in forecasting market behavior.

Recent advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have enabled the development of systems capable of performing sentiment analysis, semantic search, and predictive analytics. This project leverages such techniques to build a hybrid AI-powered financial assistant tailored for the Indian stock market.

The assistant combines:

- **Real-time and historical stock data retrieval** using Yahoo Finance APIs.
- **News aggregation** through NewsAPI for tracking financial sentiment.
- **Sentiment scoring** based on keyword-based analysis of news headlines.
- **Knowledge retrieval** via FAISS-based vector search from financial documents.
- **Stock price forecasting** using Prophet for time series prediction.
- **Interactive user experience** through a Streamlit-based chatbot interface.

1.2 Financial Decision-Making with AI

AI plays a growing role in financial analysis by enabling automated pattern recognition, news understanding, and price trend forecasting. In this project, financial decision support is implemented through a combination of rule-based methods and data-driven models integrated into a single assistant.

Key AI-driven components include:

- **Data Collection:** Yahoo Finance for stock data and NewsAPI for live market news.
- **Sentiment Analysis:** News content is scored using keyword-based sentiment rules, with special weighting for ticker-specific context.
- **Retrieval-Augmented Generation (RAG):** A FAISS-based index enables semantic search over financial documents, including PDFs.
- **Predictive Analytics:** Facebook Prophet is used to forecast future stock prices based on historical data.
- **Rule-Based Trading Signals:** Indicators such as moving averages and RSI generate Buy/Hold/Sell signals for selected stocks.

This system does not execute real trades but provides analytics and recommendations that can assist human investors in understanding stock behavior.

1.3 Problem Statement and Motivation

Individual investors experience difficulties in interpreting massive volumes of financial data and making real-time, well-informed decisions. Manual analysis is hard, can lead to errors, and usually not consistent. Most platforms provide stock information, but not a single, intelligent assistant that can pull out related insights, analyze sentiment, forecast trends, and provide decisions in a readable format.

This project addresses the following problem: **To design and implement a hybrid AI-based financial assistant capable of analyzing real-time stock data, retrieving contextual knowledge, performing sentiment analysis, and generating predictive insights through an interactive interface.**

The key motivations include:

- Reducing the time and effort needed to analyze Indian equities.
- Making financial information more accessible via conversational queries.
- Enhancing interpretability of financial trends using visualizations and scoring.

1.4 Objectives

The project aims to make:

- Streamlit-based AI financial assistant interface with chat UI.
- Shows recent market news and market indices in sidebar.
- Fetches live stock prices and day-wise stats.
- Gives investment recommendations using technical, sentiment, and prediction analysis.
- Compares multiple stocks side by side with visual performance charts.
- RAG system retrieves relevant PDF content using FAISS + Sentence Transformers for GPT-2 based answers

By focusing on usability, modularity, and integration of practical AI tools, the assistant serves as a foundation for more advanced financial analysis systems.

CHAPTER 2

LITERATURE SURVEY

2.1 Artificial Intelligence in Financial Market Analysis

Artificial Intelligence (AI) has significantly enhanced financial market analysis through technologies like machine learning, natural language processing (NLP), and predictive analytics. These tools improve decision-making by processing vast financial datasets, identifying patterns, and generating actionable insights [1].

2.1.1 Applications of AI in Finance

Key applications of AI in financial markets include:

- AI processes large volumes of structured and unstructured market data, enabling real-time trend detection, stock price forecasting, and economic indicator analysis [2].
- AI-powered sentiment analysis assesses market sentiment by analyzing news articles, financial reports, and social media content to predict price movements and market behavior [3].
- AI models simulate market scenarios and identify potential risks using predictive analytics, enhancing risk assessment and management strategies [4].
- Automation of repetitive financial processes like reporting, monitoring, and data handling improves operational speed and accuracy [1].

2.2 Technical Challenges in AI-Based Financial Systems

Despite its advantages, implementing AI in finance involves several technical challenges:

- The reliability of AI outcomes depends heavily on the accuracy and completeness of financial datasets [4].
- Financial markets are dynamic and unpredictable, making it difficult for AI models based on historical data to consistently predict future outcomes [2].

2.3 Emerging AI Trends in Financial Services

AI-driven financial services continue to evolve, with emerging trends including:

- AI enables customized investment advice and product recommendations based on client profiles [4].
- AI systems employ anomaly detection and pattern recognition to identify and prevent fraudulent transactions [1].
- AI is being combined with blockchain, IoT, and cloud platforms to improve financial system efficiency and transparency [4].
- AI systems are increasingly designed to learn continuously from new data, enhancing their ability to respond to changing market conditions [5, 6].

2.4 Summary

AI has transformed financial market analysis through improved data processing, forecasting, sentiment analysis, and operational automation. While challenges like data quality and market unpredictability remain, AI continues to evolve, offering more advanced, adaptable, and data-driven financial solutions.

CHAPTER 3

SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 Overview of Hybrid Approach

This project adopts a hybrid AI-based approach that combines Retrieval-Augmented Generation (RAG), rule-based analytics, and predictive modeling to deliver intelligent financial market analysis. The system integrates multiple components such as real-time stock data retrieval, sentiment scoring, vector-based knowledge retrieval, and time series forecasting into a single interactive platform. The assistant is specifically designed for Indian equity markets and provides users with contextual recommendations, sentiment insights, technical signals, and trend forecasts via a chatbot-style interface.

The modular nature of the architecture ensures that each functionality retrieval, prediction, sentiment, and technical analysis can operate independently or together, depending on the nature of the user query.

3.1.1 Role of RAG, Rule-Based AI, and Predictive Analytics

- **RAG (Retrieval-Augmented Generation):** FAISS is used to build a vector index of financial documents (e.g., PDFs, news headlines). This enables semantic search to retrieve the most relevant pieces of information based on user queries.
- **Rule-Based Analytics:** Sentiment scoring, technical signal generation, and decision synthesis are implemented using deterministic logic and heuristics for interpretability and speed.
- **Predictive Modeling:** Time series forecasting with Prophet is used to project stock price trends based on two years of historical data.

The combined use of semantic search, structured analysis, and forecasting ensures both breadth and depth in market intelligence.

3.2 Data Collection and Sources

3.2.1 Yahoo Finance API (Historical & Real-Time Stock Data)

Stock market data is obtained using the `yfinance` Python library, which allows retrieval of:

- Real-time stock prices, volume, and price change percentages.
- Historical stock data for intervals like 1 day, 5 days, 1 month, or 2 years.
- Company metadata such as market cap, industry, P/E ratio, and EPS.

To improve performance, a caching mechanism is implemented using Streamlit's session state. This avoids redundant API calls and ensures a responsive user experience.

3.2.2 NewsAPI (Market News Retrieval)

Financial news is fetched using the NewsAPI, filtered for relevance to Indian markets using queries such as "stocks+finance+market+india." Each article's title, description, source, timestamp, and URL are extracted. Short or low-content articles are filtered out.

The top articles are periodically refreshed in a background thread to ensure up-to-date news for sentiment and RAG modules.

3.2.3 NSE Equity Dataset

To identify valid stock tickers from user queries, the system uses the official NSE equity list in CSV format. This allows robust ticker matching against both stock symbols (e.g., "INFY") and company names (e.g., "Infosys Limited") using fuzzy logic and regex patterns.

3.3 Sentiment Analysis Module

Sentiment analysis is performed using a keyword-based scoring system rather than pretrained language models. This approach allows for:

- Interpretability and rule transparency.
- Fast execution with no dependency on external language models.
- Context-specific weighting of sentiment near ticker mentions.

3.3.1 Keyword-Based Sentiment Scoring

The system uses curated lists of positive and negative financial keywords (e.g., “rally”, “upgrade”, “decline”, “risk”) and counts their occurrences in retrieved news articles. Sentiment around the company name or ticker is given additional weight.

A normalized score between 0 (very negative) and 1 (very positive) is calculated to quantify sentiment, enabling downstream integration with the decision engine.

3.4 Retrieval-Augmented Generation (RAG) Module

This module helps extract semantically relevant content from financial documents to provide context-aware answers.

3.4.1 FAISS for Financial Knowledge Retrieval

- The system loads PDFs (e.g., `Market_reference.pdf`) and splits them into searchable text chunks.
- SentenceTransformers generate vector embeddings (`all-MiniLM-L6-v2`) for each chunk.
- FAISS is used to build a vector index for efficient similarity search.
- At runtime, a user query is embedded and compared to the index to retrieve the top-k relevant documents.

3.4.2 Contextual Document Store

Both static documents (like PDFs) and dynamic content (e.g., news articles) are added to a centralized document store. This allows the assistant to use RAG for both long-term knowledge and real-time updates.

3.5 Predictive Analytics Module

The system includes a time series forecasting module using Prophet to predict the future closing prices of stocks.

3.5.1 Prophet for Time Series Forecasting

- Historical stock data for the past two years is used.
- The data is converted to the Prophet-compatible format (`ds`, `y`).
- The model is trained and a 30-day forecast is generated.
- Forecast results include upper/lower bounds and trend estimates.

Forecasts are displayed alongside the latest closing price, expected percentage change, and a confidence interval. These are used as one of the decision-making components.

3.6 Trade Signal Generation

This module synthesizes signals from sentiment analysis, technical indicators, and price forecasting to generate a final recommendation: `Buy`, `Sell`, `Hold`, etc.

3.6.1 Technical Indicators and Rule-Based Logic

The system uses the following technical indicators:

- **SMA-20 / SMA-50 Crossovers:** Detects bullish or bearish crossover patterns.
- **RSI (Relative Strength Index):** Determines overbought/oversold conditions.
- **Momentum:** Simple rate of return over short windows.

These signals are combined using a weighted scoring system to assess technical strength.

3.6.2 Decision Engine

The final recommendation is based on a weighted average of four components:

- Sentiment Score (25%)
- Technical Score (35%)
- Prophet Forecast Component (25%)
- Market Index Movement (15%)

Thresholds on the final score determine the recommendation:

- Score 0.7: Strong Buy
- Score 0.6: Buy
- Score 0.4: Hold / Sell

3.7 User Interface Module

3.7.1 Streamlit-Powered Financial Assistant

The front-end is built using Streamlit and designed for real-time interaction. Key features include:

- Chat-based input interface for querying the system.
- Support for multiple intents (e.g., prediction, comparison, sentiment, price lookup).
- Visualizations of forecast data, comparison charts, and technical analysis.
- Side panel with live news and market indices (e.g., NIFTY, SENSEX).
- Dynamic caching and background threads for responsiveness.

The interface allows both casual investors and advanced users to interact with the assistant naturally, making financial insights more accessible and actionable.

3.8 System Architecture Workflow

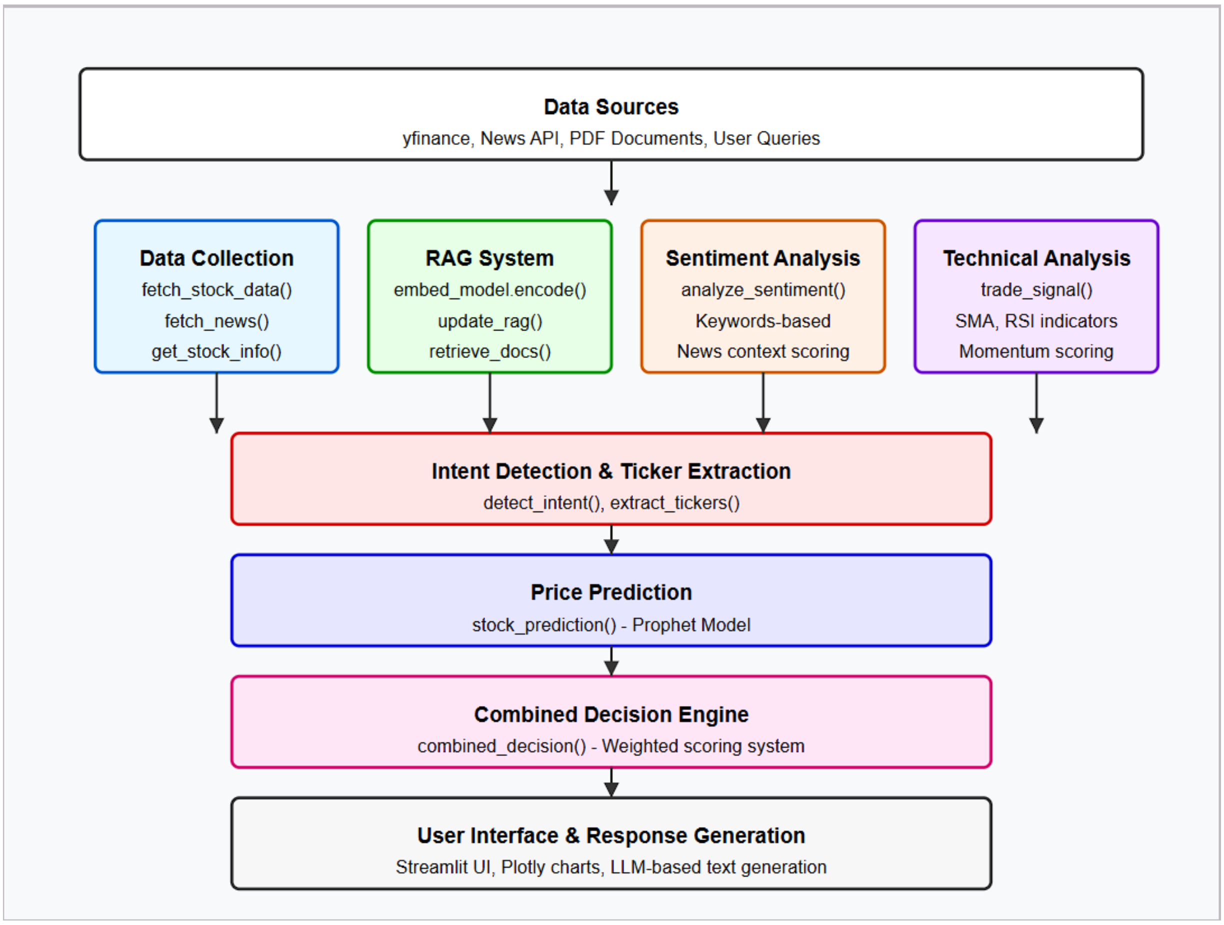

Figure 3.1: Architecture Workflow

CHAPTER 4

RESULTS

4.1 System Landing Page Overview

The chatbot's landing page provides a clear and intuitive interface that serves as the central hub for user interaction. It offers a concise overview of the system's capabilities, including real-time stock price lookups, short-term price forecasts, comparative stock analysis, sentiment-driven investment recommendations, and market news summarization. Each feature is visually represented with distinct icons and examples, making it easy for users to understand how to interact with the assistant.

The sidebar displays the latest financial news headlines, sourced from integrated APIs such as NewsAPI and Yahoo Finance, helping users stay informed on market-moving developments. The main panel welcomes users with a brief introduction and encourages natural language queries, supporting both novice and advanced investors. Additionally, the structured layout ensures a seamless user experience, enabling quick access to actionable insights and improving the usability of AI-generated market intelligence.

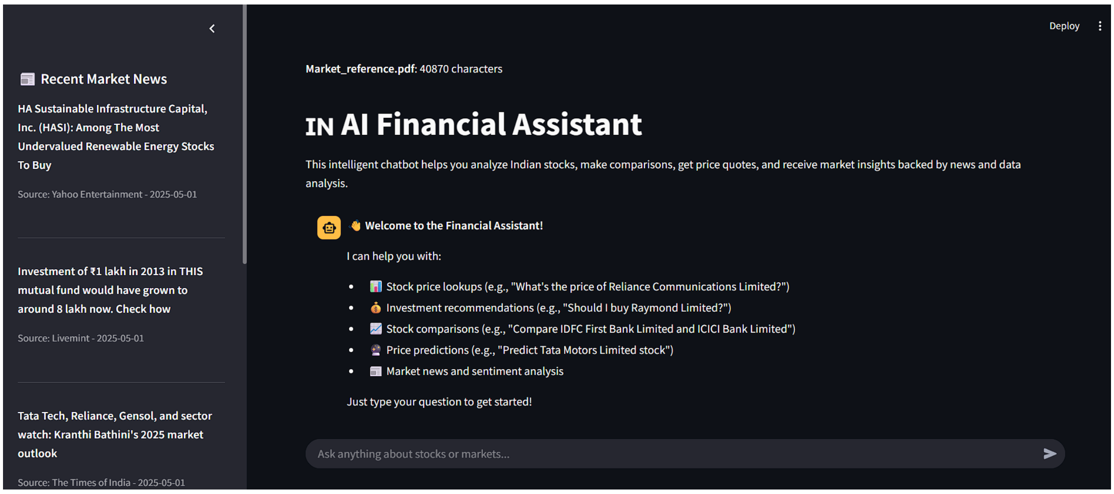

Figure 4.1: Main Interface of the AI Financial Assistant

Observation: The interface is user-friendly, guiding the user through its features using icons, categories, and examples.

4.2 Sentiment Analysis and Investment Recommendation

This section highlights the assistant's sentiment-based decision-making capability. It breaks down the analysis into components such as technical indicators, news sentiment, forecast score, and market conditions.

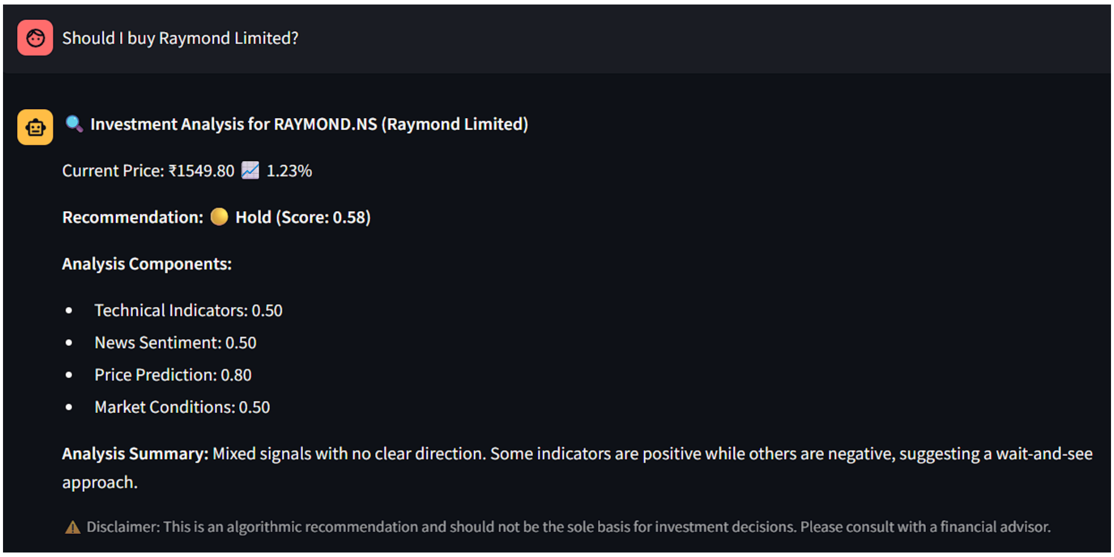

Figure 4.2: Investment Recommendation for RAYMOND.NS

Observation: A score of 0.58 led to a Hold recommendation for Raymond Ltd., with a strong price prediction component (0.80) balanced by neutral sentiment and technical signals.

4.3 Predictive Analytics Forecast Visualization

The system performs stock forecasting using historical data and outputs the expected future trend along with a confidence interval.

Figure 4.3: Price Forecast for TATAMOTORS.NS

Observation: The model predicts a 21.70% decline in Tata Motors stock price over the next 30 days, indicating a bearish signal with high confidence.

4.4 Price Query and Real-Time Updates

The assistant provides current stock price and market movement on demand, including high/low range and update timestamp.

Figure 4.4: Real-Time Price Query for RELIANCE.NS

Observation: The assistant returns accurate, timestamped market prices using Yahoo Finance API integration.

4.5 Stock Comparison and Performance Evaluation

A multi-stock comparison example shows comparative price returns and system-generated scoring across multiple dimensions to help the user identify the better investment.

Figure 4.5: Stock Comparison between IDFC First Bank and ICICI Bank

Observation: ICICI Bank is recommended as the better option with a higher composite score (0.47) and better overall return trend.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Summary of Findings

This project introduces the creation of a hybrid AI-based financial assistant that combines real-time data fetching, sentiment analysis, document fetching through FAISS, and predictive analytics using Prophet. The system is intended to facilitate retail-level financial decision-making with interactive, explainable insights into Indian stock market behavior.

This system shows the potential of combining Retrieval-Augmented Generation, rule-based score functions, and time series modeling to generate valid trading recommendations. The modular structure of the chatbot facilitates flexible handling of queries, giving tailored responses for use in trend prediction, technical analysis, sentiment analysis, and comparison of stock understanding.

5.2 Future Enhancements and Scalability

To make the chatbot into a more service-providing financial analysis platform, several improvements can be made, they are:

- Integrate transformer-based models such as GPT or LLaMA for more contextual sentiment classification and document summarization.
- Implement user user-friendly interface which includes services like user profile management, portfolio tracking, and custom watchlists.
- Wrap the whole system into a package and deploy it in the cloud or Hugging Face, which provides an API to get decisions made by the system.
- To make the system automate the trade executions, explore connections with brokerage APIs (e.g., Zerodha Kite, Alpaca) while enforcing strong risk controls.

These enhancements will make the assistant more robust, user-adaptive, and scalable, bridging the gap between experimental research and real-world financial advisory systems.

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