Stock Sentiment Analyzer using AI and NLP for Financial Decision Support

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Abstract:Investor sentiment has emerged as a critical factor in stock market behavior, influencing price fluctuations beyond traditional quantitative indicators. In this research, we propose a lightweight and accessible Stock Sentiment Analyzer that utilizes Artificial Intelligence (AI) and Natural Language Processing (NLP) to classify financial news sentiment in real-time. The system automatically retrieves recent news articles for a selected stock ticker and applies NLP-based sentiment analysis to label them.
Keywords: Stock Market, Sentiment Analysis, Natural Language Processing, Artificial Intelligence, Financial News, Decision Support Systems

I. INTRODUCTION

The stock market is a dynamic ecosystem influenced not only by financial metrics but also by human perception, psychology, and investor sentiment. Reports from financial institutions and the media often shape investor decisions—optimistic earnings coverage may trigger buying pressure, while negative headlines such as fraud allegations may induce panic selling. Traditional models for stock forecasting, including econometric analysis and moving averages, provide valuable insights but often overlook emotional and sentiment-driven fluctuations.

II. LITERATURE REVIEW

Research on sentiment analysis in finance spans multiple dimensions, including textual data mining, market prediction models, and AI-based decision support.

1. Traditional Stock Prediction Models

Quantitative forecasting techniques such as autoregressive integrated moving average (ARIMA) and econometric models have been widely used. While effective for time-series data, these approaches fail to capture emotional and sentiment-driven fluctuations.

2.2 Sentiment Analysis in Financial Markets

Studies have shown that market sentiment can predict short-term trends. Bollen et al. (2011) demonstrated that Twitter mood significantly correlates with market movement. Similarly, Loughran and McDonald (2011) introduced finance-specific sentiment dictionaries, highlighting the importance of domain adaptation.

2.3 AI and NLP Applications

With advances in deep learning, NLP techniques such as word embeddings, transformers, and LSTMs have been applied to financial forecasting. These models analyze news sentiment with high accuracy but often lack interpretability, making them less practical for small investors.

2.4 Research Gap

Most existing tools are either too costly or non-transparent, offering predictions without explanations. There is a need for a system that is free, interpretable, and accessible, while still leveraging modern AI/NLP for sentiment analysis.

III. PROPOSED METHODOLOGY

The methodology for the Stock Sentiment Analyzer is divided into six stages:

3.1 User Input

The user enters a stock ticker symbol (e.g., "AAPL" for Apple, "TATA" for Tata Group).

3.2 Data Collection

The system fetches 10-12 latest financial news articles using NewsAPI, extracting headlines and descriptions.

3.3 Sentiment Analysis

Each article is processed using AI/NLP models (e.g., transformer-based models such as GPT-4). A sentiment score is generated:

3.4 Aggregation

The sentiment scores are averaged:

Where s_{i} is the sentiment score of article i, and n is the number of articles.

3.5 Visualization

* Article cards display sentiment scores with color coding (red, green, yellow).
* A summary panel shows average sentiment and prediction.
* Interactive charts visualize sentiment trends.

3.6 Storage

All searches and sentiment results are logged in MongoDB for future analysis.

IV. SYSTEM DESIGN AND IMPLEMENTATION

The proposed system is built as a full-stack application combining backend APIs, AI models, and an interactive frontend.

4.1 System Architecture

The system consists of:

* Frontend (React.js): For user interaction and visualization.
* Backend (Node.js / Python Flask): Handles news retrieval and AI model inference.
* Database (MongoDB): Stores logs and sentiment scores.
* AI/NLP Models: Performs sentiment classification.

4.2 Workflow

* User enters stock ticker.
* Backend retrieves real-time news.
* AI/NLP model classifies sentiment.
* Results aggregated and visualized.
* Output displayed as "Likely to Rise/Fall/Neutral".

4.3 Advantages of Proposed Design

* Lightweight: No GPU requirement, runs on standard CPUs.
* Transparent: Highlights key words influencing predictions.
* Accessible: Free and academic-friendly.
* Actionable: Provides clear sentiment labels.

V. EXPECTED OUTCOMES AND DISCUSSION

The proposed system is expected to provide:

* Accurate sentiment-driven insights by analyzing real-time news.
* Transparent outputs highlighting sentiment-driving keywords.
* Visual dashboards for intuitive decision support.
* Accessibility for students, researchers, and small investors.

Unlike premium platforms, this tool emphasizes interpretability, cost-effectiveness, and usability. It demonstrates how modern AI/NLP techniques can enhance financial decision-making without requiring expensive infrastructure.

VI. CONCLUSION

The Stock Sentiment Analyzer demonstrates how AI and NLP can be applied to transform unstructured financial news into actionable insights. By combining automated news retrieval, AI-based sentiment classification, aggregation, and visualization, the system offers a free, transparent, and academic-friendly platform. It not only supports quick decision-making but also bridges the gap between academic learning and practical financial applications.

Future work includes integrating deep learning-based transformers (e.g., BERT, FinBERT), adding multilingual support, and expanding to social media sentiment for more comprehensive insights.

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