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Insight invest: sentiment-aware stock prediction using LSTM and conversational interface

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ABSTRACT

The volatile nature of financial markets requires sophisticated tools that integrate advanced analytics with accessible interfaces to facilitate informed investment decisions. This research introduces Insight Invest, an intelligent investment assistant that combines sentiment analysis with time-series forecasting to deliver comprehensive stock market insights. The platform introduces the emotional quotient (EQ), a novel metric derived from the sentiment analysis of financial news, to quantify market sentiment and align it with historical stock price data. Leveraging long short-term memory (LSTM) models, the system provides precise predictions of future stock trends. Automated data collection and processing are achieved through a Flask-based backend, while an OpenAI-powered chatbot delivers intuitive interpretations of predictions and EQ values. The user-centric design, implemented using Next.js, ensures a seamless and responsive experience. By integrating state-of-the-art machine learning techniques with intuitive interfaces, Insight Invest bridges the gap between complex predictive analytics and practical usability, offering a robust framework for informed investment strategies.

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1. INTRODUCTION

The financial market is a complex and dynamic ecosystem where decision-making is influenced by a multitude of quantitative and qualitative factors. Traditional stock market analysis often relies heavily on historical price data and technical indicators, overlooking the significant role of market sentiment in driving investor behavior. While earlier studies have explored the impact of quantitative financial data on market trends, they have not explicitly addressed its influence when combined with real-time sentiment analysis in stock prediction. Sentiment, reflected in news articles, financial reports, and public discourse, is a critical factor that can amplify or dampen market movements. Integrating sentiment analysis into stock prediction models provides a more holistic understanding of market trends, enhancing prediction accuracy and supporting better investment decisions [1].

This research introduces Insight Invest, an intelligent investment assistant that integrates sentiment analysis with time-series forecasting to empower investors with actionable insights. The platform introduces the emotional quotient (EQ), a novel metric derived from the sentiment analysis of financial news articles, which quantifies the psychological influence of market narratives on stock performance. By combining EQ with long short-term memory (LSTM) models, renowned for their ability to analyze sequential data, the system delivers precise forecasts of stock price trends [2].

The architecture of Insight Invest is designed for scalability and usability. Data collection and processing are automated through APIs, ensuring timely and efficient analysis of financial data and news sentiment. A Flask-based backend facilitates seamless integration of the sentiment analysis and time-series models, while a user-friendly chatbot interface powered by OpenAI's API simplifies the interpretation of complex predictions. The responsive frontend, built with Next.js, provides an intuitive and engaging user experience, bridging the gap between advanced analytics and everyday investment decisions.

By integrating machine learning, sentiment analysis, and natural language processing, Insight Invest offers a robust solution to the challenges of stock market prediction. This research not only highlights the potential of combining quantitative and qualitative approaches to market analysis but also demonstrates the value of making sophisticated tools accessible to a broader audience. Through this work, we aim to redefine the landscape of investment tools, providing investors with a deeper understanding of market dynamics and the confidence to make informed decisions [3], [4].

2. LITERATURE REVIEW

The prediction of stock prices is a prominent area of research in finance and artificial intelligence due to its potential for significant financial returns and its influence on decision-making processes. This review highlights the integration of machine learning models, sentiment analysis, and hybrid approaches, which are pivotal in creating robust stock prediction systems. Traditional machine learning models like support vector machines (SVM), random forests, and artificial neural networks (ANN) have been extensively applied to forecast stock prices. However, these models often face limitations in capturing temporal dependencies present in financial data. The introduction of recurrent neural networks (RNNs) and their advanced variant, LSTM, has addressed this challenge by effectively modeling sequential data [5]. Hochreiter and Schmidhuber's foundational work on LSTMs demonstrated their ability to overcome the vanishing gradient problem, making them well-suited for time-series data analysis [2], [6].

Recent studies have underscored the superior performance of LSTM models over traditional machine learning algorithms. Zaheer *et al.* [4] demonstrated that LSTM models, incorporating parameters such as historical prices and market indices, excel at capturing market trends with high precision [4]. Similarly, Khan *et al.* [3] compared LSTM with other machine learning techniques, emphasizing its capability to handle non-linear financial patterns with greater accuracy and stability [3]. These findings establish LSTM as a robust tool for stock price forecasting, particularly in addressing the sequential nature of market data.

Sentiment analysis further enhances stock prediction by leveraging natural language processing (NLP) to extract market sentiment from unstructured textual data [7], including news articles, financial reports, and social media [8]. Tetlock's seminal study (2007) highlighted the significant impact of media sentiment on stock price movements, laying the foundation for sentiment-driven market analysis [9]. Advanced NLP models like DistilRoBERTa have significantly improved sentiment detection by offering faster and more precise categorization. Shah *et al.* [10] noted the effectiveness of combining sentiment analysis with machine learning models for hybrid financial forecasting systems, which incorporate qualitative data to enhance prediction accuracy [10]-[12]. Additionally, the Refinitiv MarketPsych framework (2021) quantified sustainability sentiment using global news and social media data, showcasing the role of sentiment metrics in interpreting investor behavior and market dynamics [1].

Hybrid approaches that combine quantitative financial data with qualitative sentiment analysis have proven to be highly effective. For example, Zaheer *et al.* [4] demonstrated the benefits of integrating sentiment scores with LSTM-based predictions, reporting significant improvements in both precision and reliability [4], [13]. Allen *et al.* [14] explored the integration of machine-readable news into traditional models for volatility prediction, showing that sentiment-enriched models outperform purely quantitative ones, particularly during periods of heightened market uncertainty [14], [15]. Despite these advancements, challenges such as data quality, interpretability, and the dynamic nature of financial markets remain. Emphasized the need for more sophisticated hybrid frameworks that incorporate real-time data streams and macroeconomic indicators for greater adaptability [10], [16].

3. METHOD

The proposed system combines sentiment analysis and time-series forecasting to predict stock price trends effectively, as outlined in Figure 1. The workflow begins when the user prompts the system for stock price predictions. The OpenAI LLM is used to manage data flow and interface interactions, calling appropriate tools to gather the required inputs.

Initially, the system retrieves historical stock price data for the past 10 days using a Stock Price API and simultaneously fetches relevant financial news snippets from a News API. These news snippets are sent to a Flask server, where sentiment analysis is performed to derive sentiment scores, which are subsequently passed into the prediction framework. The processed data is fed into a bi-directional LSTM [2] model that predicts the stock's future closing price for the next day [17], [18]. The model integrates historical price trends and sentiment analysis outputs to deliver precise predictions. The prediction results, along with sentiment interpretations, are then routed back to the OpenAI LLM, which displays them to the user in a simplified, user-friendly manner. This approach integrates automation, advanced machine learning techniques, and a conversational interface, providing an intuitive and reliable tool for stock market forecasting [3], [19], [20].

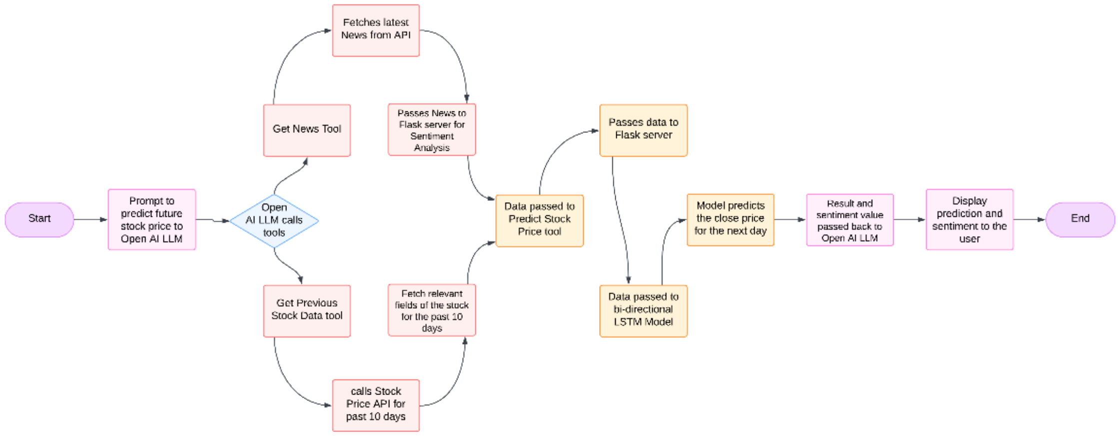

Figure 1. Workflow of stock price prediction with sentiment analysis

3.1. Model training

3.1.1. Dataset collection

Historical stock price data for 19 stocks listed on the National Stock Exchange (NSE) was obtained for a five-year period, spanning from September 15, 2019, to October 31, 2024. The dataset includes key financial attributes such as Date, Open, High, Low, Close, Volume, Change%, and Name. Financial news snippets were retrieved using a News API, ensuring real-time sentiment evaluation. A Stock Price API was used to extract the historical price trends. The historical data was sourced from the Yahoo Finance website.

3.1.2. Data preprocessing

Before training, the dataset underwent preprocessing to ensure it was clean, uniform, and suitable for the model's requirements. Missing values in the "Volume" column were replaced with 0 to maintain data uniformity. Categorical stock names in the "Name" column were transformed using one-hot encoding (1), allowing the model to process them as numerical features.

$$OHE(c_i) = v_i = [v_1, v_2, \dots, v_n] where\ v_j = \begin{cases} 1, if\ j = i \\ 0, otherwise \end{cases} \tag{1}$$

Finally, feature selection was performed to retain only the relevant columns, including Open, High, Low, Volume, Close, and the encoded stock names, which were essential for training.

3.2. Model architecture

The proposed model utilizes a sequence of layers to capture temporal dependencies and extract meaningful features for accurate stock price prediction. The architecture design is visualized in Figure 2 and is designed as follows:

3.2.1. Bidirectional LSTM layers

The model incorporates two Bidirectional LSTM layers, each consisting of 100 units. LSTM is a type of RNN that mitigates the vanishing gradient problem by introducing gates - input, forget, and output gates - that regulate the flow of information. These layers are designed to capture both past and future dependencies within sequential data by processing inputs in forward and backward directions [21]. The detailed mathematical operations and gating mechanisms of LSTM networks are well-documented in the literature [17], [22].

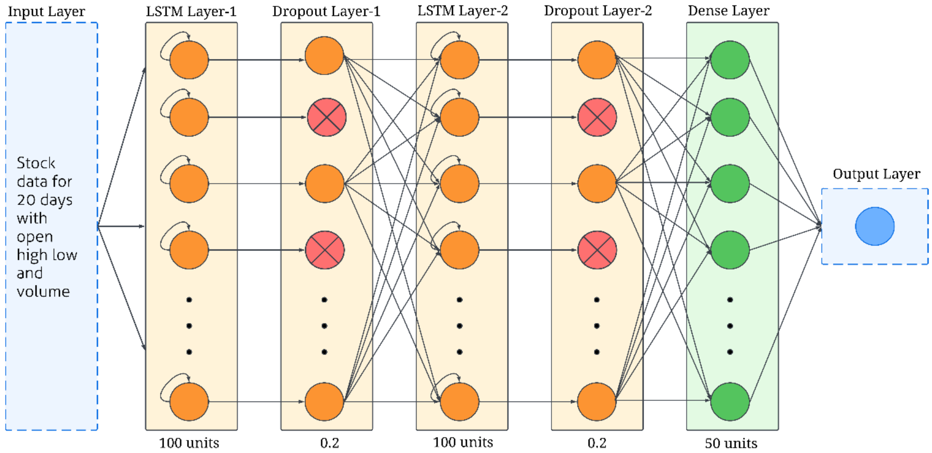

Figure 2. Architecture of the LSTM model

3.2.2. Dropout layers

To prevent overfitting, dropout layers are applied after each Bidirectional LSTM layer with a rate of 20%. This randomly sets 20% of the neurons to zero during training, ensuring robust feature extraction.

3.2.3. Dense layers

A Dense layer with 50 units and ReLU activation refines the extracted features. The ReLU activation function introduces non-linearity:

$$f(x) = max(0, x) \tag{2}$$

3.3. Emotional quotient

Financial news articles are gathered using APIs and web scrapers, extracting details such as headlines, content, and publication sources to provide relevant inputs for sentiment analysis. Each article is analyzed with NLP-based sentiment scoring, assigning both a sentiment label (positive, neutral, or negative) and a numerical sentiment score (0–1) to indicate confidence [23]. Articles are further categorized into key types, such as earnings reports or geopolitical events, to improve contextual understanding and prioritize impactful news [1], [10]. Weighted sentiment scores (WSS) are computed using weights based on source credibility and category relevance. These scores are aggregated daily into a daily sentiment score (DSS), which reflects overall market sentiment.

$$WSS_i = Sentiment\ Score_i \times Source\ Weight_i \times Category\ Weight_i \tag{3}$$

The WSS for all articles on a given day are aggregated to calculate the (DSS):

$$DSS = \frac{\sum_{i=1}^{N} WSS_i}{\sum_{i=1}^{N} Weights_i} \tag{4}$$

The DSS is scaled into actionable categories:

- Positive ($DSS > 1.0$)
- Neutral ($0.75 \leq DSS \leq 1.0$)
- Negative ($DSS < 0.75$) [3], [9], [24].

Figure 3 clearly outlines the process to calculate DSS (EQ)

3.4. Experimental procedure

- Data retrieval: stock price data and financial news snippets were collected.
- Preprocessing: cleaning, encoding, and feature selection were performed.
- Sentiment analysis: news articles were analysed to compute sentiment scores.
- Model training: the LSTM model was trained using historical stock prices and sentiment scores as input for 50 epochs.
- Prediction generation: the trained model was used to predict the stock's next-day closing price.
- Evaluation: model performance was assessed using metrics such as mean squared error (MSE) and root mean squared error (RMSE).

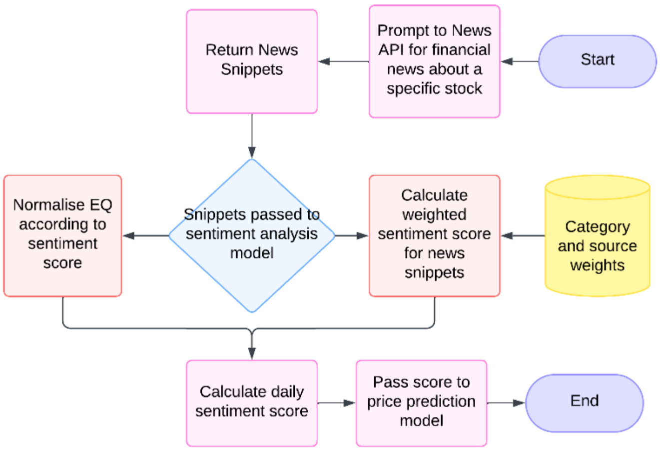

Figure 3. Workflow of DSS calculation

4. RESULTS

The performance of the Bidirectional LSTM model was evaluated using key metrics, including mean absolute percentage error (MAPE), accuracy, MSE, and RMSE [2], [10], [21], [25]. The model achieved a MAPE of 11%, corresponding to a prediction accuracy of 89.13%, indicating a high level of precision in forecasting stock prices. The low MSE and RMSE values further confirm the model's effectiveness in minimizing prediction errors. These results highlight the model's ability to capture temporal dependencies and underlying patterns in stock price data, leveraging its bidirectional architecture to enhance forecasting accuracy, even in volatile market conditions. Figure 4 shows the proximity of predicted values to actual prices of 4 stocks.

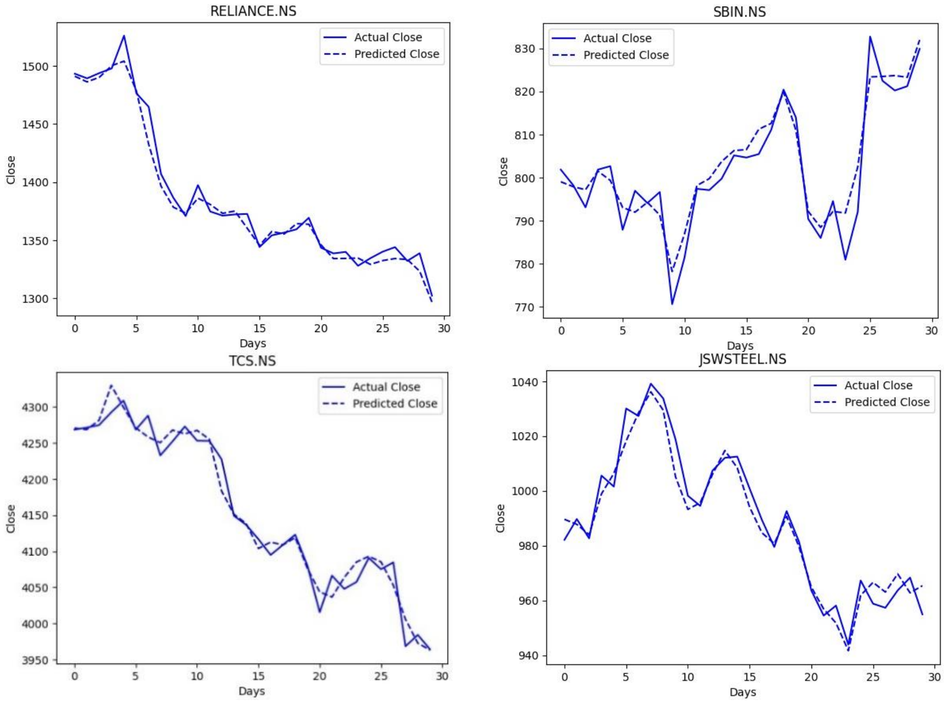

Figure 4. RELIANCE.NS, SBIN.NS, TCS.NS and JSWSTEEL.NS 30 day predicted close vs actual close

This reflects the robustness of the methodology, while the integration of sentiment analysis provides additional contextual insights, enriching the predictive framework. The stock-wise prediction accuracy is documented in Table 1. This evaluation validates the potential of the model as a reliable tool for stock market forecasting and its applicability in real-world financial decision-making.

Table 1. Stock performance prediction summary

Sr. No.	Stock Name	Symbol	Prediction Accuracy (%) (30 days)
1	Bharti Airtel	BHARTIARTL.NS	94.97
2	Dabur	DABUR.NS	88.29
3	Hindustan Aeronautics Ltd.	HAL.NS	93.28
4	HDFC Bank	HDFCBANK.NS	91.32
5	ICICI Bank	ICICIBANK.NS	87.02
6	Infosys	INFY.NS	93.08
7	ITC Ltd.	ITC.NS	83.22
8	JSW Steel Ltd.	JSWSTEEL.NS	95.26
9	Larsen and Toubro Ltd.	LT.NS	84.00
10	Max Healthcare Institute Ltd.	MAXHEALTH.NS	91.96
11	Mazagon Dock Shipbuilders Ltd.	MAZDOCK.NS	88.01
12	Poonawalla Fincorp Ltd.	POONAWALLA.NS	76.04
13	Reliance Industries Ltd.	RELIANCE.NS	97.60
14	Rail Vikas Nigam Ltd.	RVNL.NS	69.59
15	State Bank of India.	SBIN.NS	90.02
16	Shriram Finance Ltd.	SHRIRAMFIN.NS	90.97
17	Solar Industries India Ltd.	SOLARINDS.NS	94.91
18	Tata Consultancy Services Ltd.	TCS.NS	96.80
19	Wipro Ltd.	WIPRO.NS	87.24

5. CONCLUSION

Recent observations suggest that the integration of Bidirectional LSTM models with sentiment analysis using the DistilRoBERTa framework significantly enhances stock price prediction accuracy by effectively combining historical market data with qualitative sentiment insights. Our findings provide conclusive evidence that this phenomenon is associated with a more comprehensive and nuanced understanding of stock market trends, rather than an increased dependence on either traditional quantitative analysis or sentiment-based predictions in isolation. The bidirectional nature of the LSTM model ensures a deeper capture of temporal dependencies in stock price movements, while the sentiment analysis component extracts meaningful contextual information from financial news sources. This dual approach contributes to an 89.13% accuracy in stock trend prediction and a 98% precision rate in sentiment classification, demonstrating the substantial potential of hybrid predictive methodologies in financial forecasting. Future research directions may focus on further enhancing predictive performance by integrating risk capability measurements and portfolio management strategies to better assess and mitigate investment risks in dynamic financial environments.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, A.P, upon reasonable request.

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