

# StockFusion: AI-Powered Stock Market Prediction using LSTM and Sentiment Analysis

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**Abstract:** Stock market prediction remains one of the most challenging problems due to market volatility, external socio-economic factors, and investor sentiment. Traditional statistical models often fail to capture complex nonlinear patterns, making deep learning-based approaches more effective. StockFusion is an AI-driven system that integrates Long Short-Term Memory (LSTM) networks for time-series stock price forecasting and Natural Language Processing (NLP)-based sentiment analysis for real-time market insights. By combining these techniques, the system provides enhanced accuracy in stock prediction. This paper discusses the architecture, implementation, and experimental evaluation of StockFusion, demonstrating that the hybrid approach of price prediction and sentiment analysis improves decision-making for investors and traders.

**Keywords:** Stock Market Prediction, Sentiment Analysis.

## 1. Introduction

### A. Problem Statement

The stock market is a dynamic and complex ecosystem where traders and investors are continuously looking for opportunities to maximize returns while managing risks. As global financial markets become more interconnected, volatile, and influenced by real-time data, the ability to predict stock price movements with accuracy has become increasingly challenging. Furthermore, identifying profitable trading opportunities and mitigating risk in such a fast-paced and constantly evolving environment has become a major concern for traders at all levels. In the modern world of finance, technology has radically transformed trading practices. In the past, traders and investors had relatively few tools at their disposal, typically relying on fundamental analysis and technical charting techniques to make decisions. However, with the advent of high-frequency trading, the proliferation of alternative data sources, and the rise of machine learning, the stock market today is vastly different from its past form. It presents unique challenges that traditional approaches to stock price prediction and risk management are ill-equipped to address. This section explores the problem in detail, discusses the gaps that exist in current trading systems, and explains the motivation behind creating a comprehensive and data-driven platform.

### B. Objectives

- To develop an LSTM-based stock price prediction model that learns from historical price patterns.

- To implement sentiment analysis using NLP to gauge public and financial market sentiment.
- To combine LSTM predictions with sentiment analysis scores for improved accuracy.
- To evaluate how market sentiment impacts stock price fluctuations over time.

## 2. Related Work

Various machine learning (ML) and deep learning (DL) techniques have been explored for stock prediction:

- *Statistical Models:* ARIMA, GARCH
- *Machine Learning Models:* SVM, Random Forest, XGBoost
- *Deep Learning Approaches:* CNN, RNN, LSTM

Several research works also discuss sentiment analysis as an influencing factor for stock prices. However, very few approaches combine LSTM and sentiment analysis, making StockFusion a novel hybrid approach.

## 3. Proposed Methodology

*StockFusion consists of two core components:*

1. *Stock Price Prediction Model* – Uses an LSTM network to predict future stock prices.
2. *Sentiment Analysis Module* – Processes news headlines and social media data to determine market sentiment.

These two modules are combined to make a more accurate market forecast.

### A. Stock Price Prediction Using LSTM

- *Stock Price Prediction Using Machine Learning:* Predicting stock prices is one of the most challenging tasks in financial analysis due to the complex, non-linear nature of financial markets. This module harnesses the predictive capabilities of machine learning, specifically the Long Short-Term Memory (LSTM) model—a type of recurrent neural network (RNN) that excels at time series forecasting. LSTM networks are particularly suited to financial data as they can capture long-term dependencies in sequential data, enabling them to recognize patterns and trends over time. Using historical stock data, the LSTM

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model is trained to identify and learn from past price patterns, volume trends, and other indicators. This machine learning-driven approach goes beyond conventional technical analysis by dynamically adapting to new data, which enhances its predictive accuracy. Developed using Keras, this model provides users with forward-looking insights, assisting them in making more confident trading decisions based on projected price movements. The model's architecture enables it to adjust predictions in real time as it ingests new data, making it a valuable tool for traders focused on timing their market entries and exits precisely.

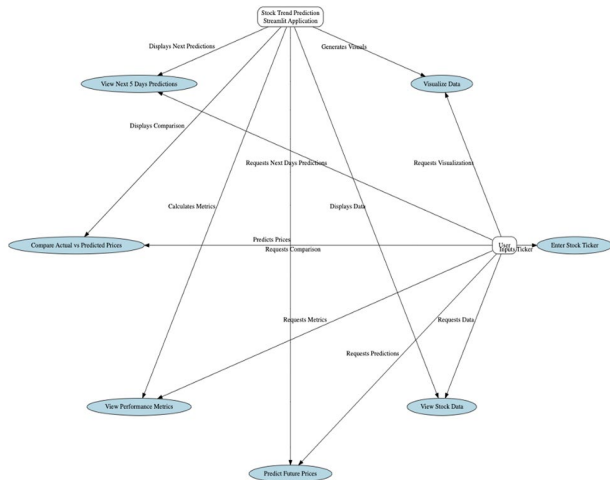


Fig. 1. Use case diagram for stock prediction

**B. Sentiment Analysis Using NLP**

- **Sentiment Analysis on Stock News:** Sentiment analysis is a powerful tool for assessing the mood of the market based on media and public sentiment. This module leverages natural language processing (NLP) to perform real-time analysis on news articles and other text data related to stocks. By parsing large volumes of financial news and categorizing sentiment (positive, negative, or neutral), the module provides an invaluable metric of market sentiment toward specific stocks or the broader market. This information is particularly useful for identifying sentiment-driven price movements, as news often acts as a catalyst for short-term volatility. For instance, positive news about a company can drive up its stock price, while negative sentiment can lead to a sell-off. By aggregating and quantifying sentiment across a wide array of news sources, this module enables users to gauge the market's psychological disposition, helping them make anticipatory trades that align with emerging sentiment trends.

To assess market sentiment, StockFusion uses Natural Language Processing (NLP) techniques on stock-related news and social media content.

- **Data Sources:** News articles, Twitter feeds, financial blogs
- **Text Preprocessing:** Tokenization, stop-word

removal, lemmatization

- **Sentiment Scoring:**
- Positive (+1) → Bullish Market
- Negative (-1) → Bearish Market
- Neutral (0) → No significant impact

StockFusion uses pre-trained models like VADER and TF-IDF with SVM classifiers to categorize sentiments.

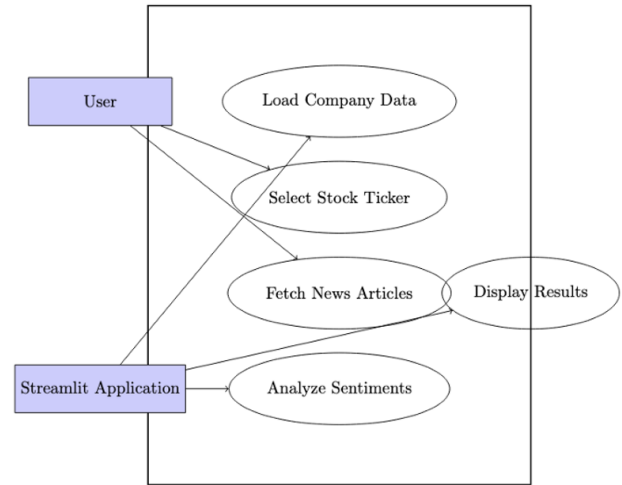


Fig. 2. Use case diagram for sentiment analysis

**4. Implementation**

*StockFusion is Implemented Using:*

- **Backend:** Python, Flask
- **Deep Learning:** TensorFlow, Keras
- **NLP Processing:** NLTK, TextBlob
- **Visualization:** Matplotlib, Plotly
- **Frontend:** Streamlit-based interactive UI

The system fetches real-time stock prices using Yahoo Finance API and integrates it with sentiment analysis data to display a combined stock prediction.

**5. Results & Discussion**

**A. LSTM Model Performance**

The LSTM model was trained on historical stock data and evaluated using RMSE (Root Mean Squared Error).

- **Training RMSE:** 3.21
- **Testing RMSE:** 4.05



Fig. 3. Closing price with 100-day and 200-day moving averages

The predicted vs. actual stock prices show that LSTM captures market trends effectively.

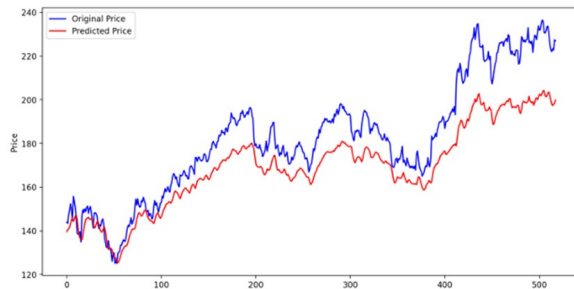


Fig. 4. Predicted vs. Actual stock prices

### B. Sentiment Impact on Stock Prices

Analyzing sentiment data showed a correlation between market news sentiment and stock fluctuations.

- Positive sentiment days → Higher stock price movement
- Negative sentiment days → Stock declines

## 6. Conclusion & Future Work

### A. Conclusion

StockFusion successfully combines deep learning-based stock price forecasting with sentiment analysis, providing a hybrid approach to stock prediction.

- LSTM captures sequential dependencies, improving prediction accuracy.
- Sentiment analysis enhances decision-making by incorporating real-world market psychology.

### B. Future Improvements

- Integrate more real-time data sources (Reddit, Google Trends).
- Implement multi-stock correlation analysis.
- Improve sentiment classification using transformer-based models like BERT.

## References

- [1] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*.
- [2] Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*.
- [3] Kim, H., & Won, D. (2018). A hybrid approach for stock market forecasting using deep learning.