

Stock Price Prediction using LSTM Networks and Financial News Sentiment Analysis

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Abstract—This project explores stock price prediction for Apple Inc. [finance:Apple Inc.] using Long Short-Term Memory (LSTM) neural networks and sentiment features extracted from historical financial news headlines. We aggregate daily sentiment scores using FinBERT transformer models and merge them with adjusted closing price and trading volume data. Experimental results demonstrate that incorporating sentiment signals from news headlines yields improved predictive performance compared to price-only baselines.

I. INTRODUCTION

Stock price prediction is a challenging time series problem due to market non-stationarity and the influence of external factors such as news, sentiment, and investor behavior. Recent advances in deep learning and NLP have enabled sophisticated modeling strategies combining price and alternative signals such as sentiment.

II. DATASET AND PREPROCESSING

We use a large corpus of financial news headlines for Apple [finance:Apple Inc.] spanning 1999–2020. Sentiment scores are computed using the FinBERT transformer model. Daily sentiment is aggregated and merged with historical price, volume, open, high, and low values sourced via Yahoo Finance API.

A. Features

- **Price Features:** Close, Open, High, Low, Volume
- **Sentiment Feature:** Daily average sentiment score from news headlines

All features are normalized via MinMaxScaler for model compatibility.

III. METHODOLOGY

A. LSTM Model Architecture

We use a multi-layer Sequential LSTM network:

- Input: $N = 100$ days sliding window, each with 4 features (Close, Sentiment, Open, Volume)
- Layer 1: LSTM (50 units, returns sequences)
- Dropout (20%)
- Layer 2: LSTM (50 units, final)
- Dropout (20%)
- Dense (output layer, 1 neuron)

Trained with Adam optimizer and mean squared error loss.

B. Sentiment Analysis

Sentiment is computed using the FinBERT model as:

$$\text{Sentiment} = \begin{cases} +\text{score}, & \text{if label=positive} \\ -\text{score}, & \text{if label=negative} \\ 0, & \text{otherwise} \end{cases}$$

IV. EXPERIMENTS AND RESULTS

The merged dataset was split into 80% training and 20% test sets. The final model was trained for 20 epochs.

A. Metrics

Performance is evaluated using Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

B. Results

Comparison of true and predicted closing prices is visualized below:

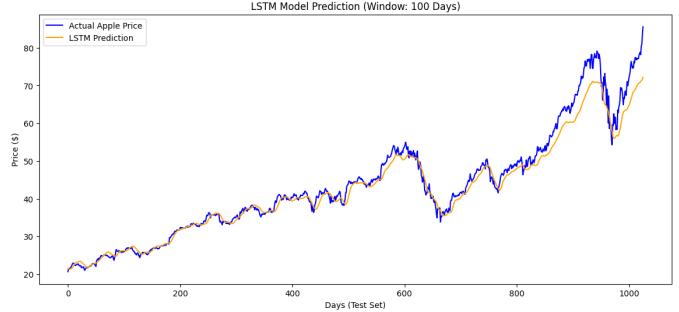


Fig. 1. Actual vs. Predicted Apple [finance:Apple Inc.] Stock Price (Test Set)

Sentiment bars overlayed on price chart:

V. DISCUSSION

The inclusion of sentiment scores improved prediction quality for market jumps associated with major headline events. Limitations include noisy sentiment signals and temporal alignment issues.

VI. CONCLUSION

Integrating financial news sentiment into deep learning models can enhance stock price prediction. Future work can explore news-specific embeddings, multi-stock learning, and alternative sentiment models.

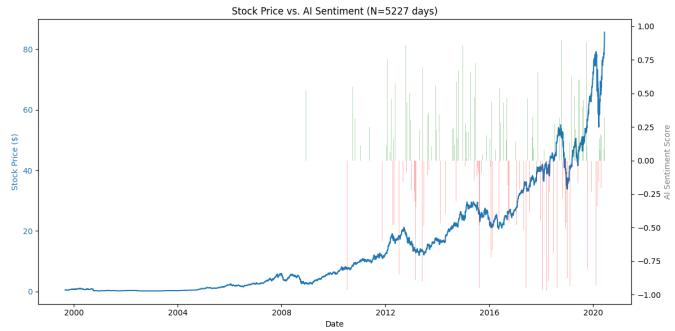


Fig. 2. Daily Sentiment vs. Stock Price

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REFERENCES

- FinBERT: Financial Sentiment Analysis with Pre-trained Language Models.
- https://www.researchgate.net/publication/388883177_Multimodal_Stock_Price_Prediction