crypto price prediction from sentiments

This project tested whether Twitter sentiment could improve short-term stock price forecasting using a hybrid model

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A multi-head transformer to forecast Bitcoin's hourly price and volatility using comprehensive real-time data.Developed a Transformer model by integrating performer + BiLSTM, effectively capturing long-range dependencies and fine-grained sequential dynamics for enhanced time series forecasting and risk assessment. Use a pre-trained finBERT and fine-tune it for better performance on classifing tweets' sentiments about BTC. The performance will require further evaluation. This part is still in progress

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Will Tweets Sentiment Boost Your Stock Profits?

Testing Hybrid Models on Market Sentiments for Higher Returns

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ABSTRACT

Short-term financial time-series forecasting remains challenging due to market complexity and volatility. Traditional methods primarily rely on historical price data, but investor sentiment from platforms like Twitter can enhance prediction accuracy. This study proposes a hybrid forecasting framework integrating statistical (ARIMA), machine learning (XGBoost), and deep learning (CNN−LSTM) methods, enriched by Twitter sentiment analysis using the transformer-based FinBERT model. Evaluations conducted on Yahoo Finance data demonstrate the effectiveness of sentiment-informed hybrid models for one-day-ahead price prediction, highlighting sentiment's complementary role alongside conventional financial indicators.

METHODOLOGY

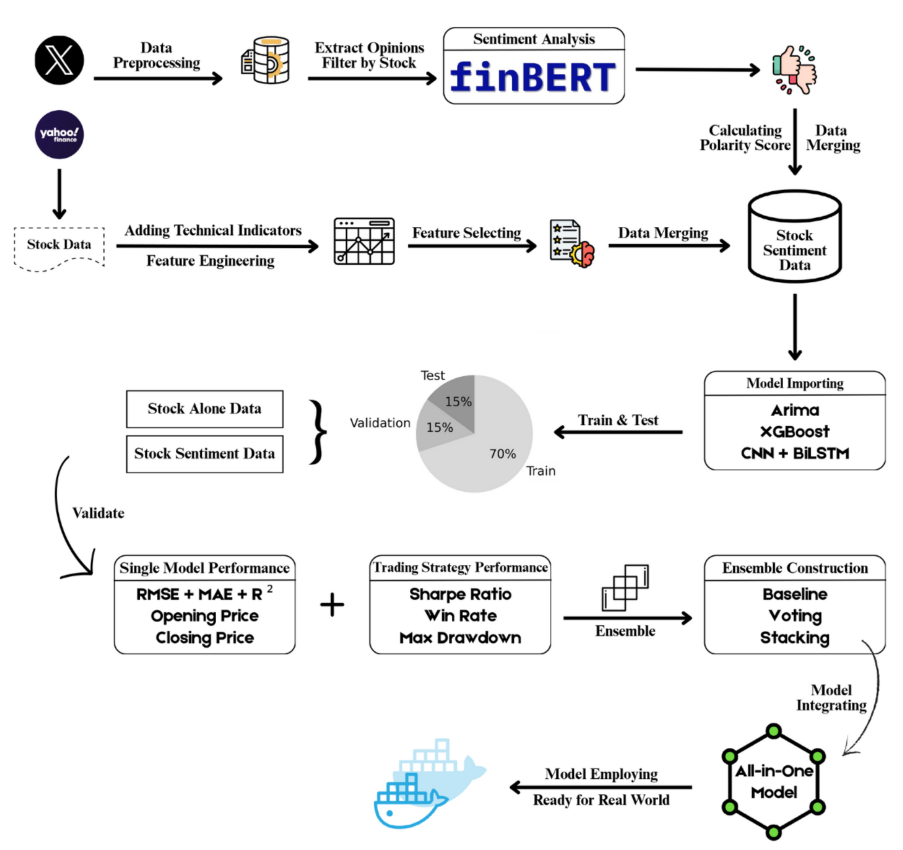

Figure 1.1 *Workflow chart*

This diagram (Figure 1.1) illustrates our full stock prediction pipeline, combining price data, technical indicators, and Twitter sentiment using FinBERT. We tested multiple models—including ARIMA, XGBoost, and CNN+BiLSTM—on both stock-alone and sentiment-enriched data. Among all models, CNN+BiLSTM consistently delivered the best performance in terms of both predictive accuracy and trading metrics, making it the core of our final all-in-one ensemble strategy.

PERFORMANCE

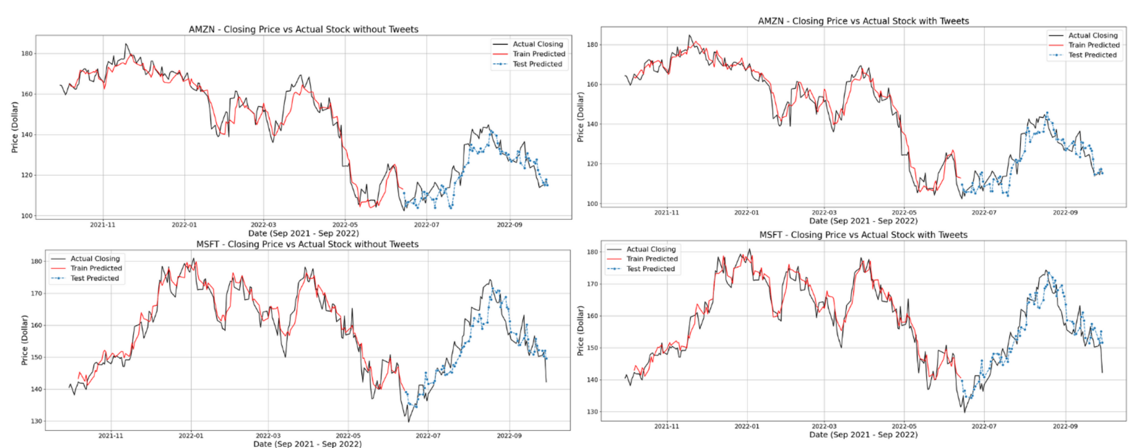

Figure 2.1 *MSFT, AMZN with, without sentiment closing priceprediction. AMZN without(top left), AMZN without(top right), MSFT without(bottom left), MSFT with(bottom right)*

Figure 2.1 presents the comparative performance of stock price predictions for AMZN and MSFT using models trained with and without Twitter sentiment as an additional input. Each subplot overlays the actual closing price with the model's predictions during both the training and testing periods, spanning September 2021 to September 2022.
Visual inspection reveals that the models excluding sentiment (top-left for AMZN and bottom-left for MSFT) exhibit closer alignment with actual closing prices, particularly in the test intervals, indicating more stable and accurate forecasting. In contrast, the sentiment-augmented models (top-right for AMZN and bottom-right for MSFT) display increased volatility and larger deviations from true prices, especially during periods of abrupt market movement.

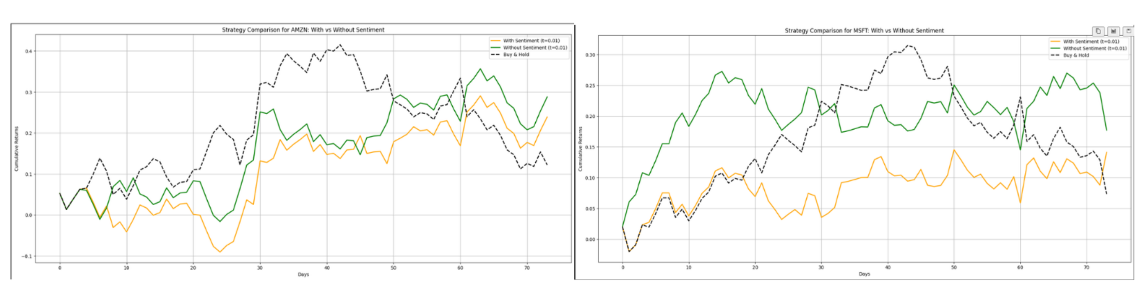

Figure 2.3 AMZN, MSFT total return graph with/without sentiment

In this project, we developed a hybrid forecasting model combining ARIMA, XGBoost, and CNN–LSTM, and tested its performance on MSFT and AMZN stocks with and without Twitter sentiment input. We also applied a 0.01% prediction threshold to filter out low-confidence trades.
The results(Figure 2.3 - 2.5) show that incorporating sentiment consistently reduced returns. For MSFT, the strategy with sentiment achieved a 19.74% return, compared to 22.35% without sentiment—both outperforming the 7.32% Buy & Hold baseline. For AMZN, the effect was even more pronounced: 36.50% with sentiment versus 65.22% without, again both beating the 12.21% Buy & Hold return.

STRATEGY COMPARISON SUMMARY for AMZN:

Strategy	Threshold	Trades	Dir Acc	Return	Sharpe
With Sentiment	0.0100	22	44.59	% 23.87%	1.85
Without Sentiment	0.0100	20	50.00	% 28.76%	2.15
Buy & Hold	-	-	-	12.21%	-

Figure 2.1 AMZN total return stats with/without sentiment

STRATEGY COMPARISON SUMMARY for MSFT:

Strategy	Threshold	Trades	Dir Acc	Return	Sharpe
With Sentiment	0.0100	22	51.35	% 14.12%	1.62
Without Sentiment	0.0100	21	52.70	% 17.71%	1.96
Buy & Hold	-	-	-	7.32%	-

Figure 2.1 MSFT total return stats with/without sentiment

CONCLUSION

In this project, we built a hybrid forecasting model using ARIMA, XGBoost, and CNN–LSTM to predict short-term stock returns, testing whether Twitter sentiment from FinBERT could improve performance. We evaluated the model on AMZN and MSFT stocks, comparing strategies with and without sentiment against a Buy & Hold baseline.
Results show that adding sentiment consistently hurt performance. For AMZN, the return dropped from 28.76% without sentiment to 23.87% with sentiment. MSFT showed a similar pattern, with returns falling from 17.71% to 14.12% when sentiment was added. Sharpe ratios and directional accuracy were also lower with sentiment.
In conclusion, sentiment signals did not improve forecasting and often reduced model effectiveness. Models without sentiment were more accurate and profitable across both stocks.

FUTURE

- Integrate real-time data collection using the X (formerly Twitter) API or web scraping to gather tweets and financial news.
- Develop a dynamic weighting mechanism to assess the influence of each tweet/news item
- Feed the weighted sentiment data into the prediction model for enhanced signal strength.
- Implement and test the model in a simulated trading environment.
- Improve directional forecasting accuracy with a focus on short-term movements.

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