Predicting NVIDIA stock price trends from market sentiment data

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1 Introduction

Our primary goal through this project is to predict future trends in NVIDIA (NVDA)'s stock prices by leveraging a combination of market sentiment data (e.g., technical indicators such as OBV, AD, ADX, MACD, RSI, and Stoch) and stock historical data (e.g., Open, High, Low, Close Prices, and Trade Volume) since both quantitative and qualitative factors influence stock prices. In doing so, we analyze diverse datasets to identify patterns and relationships that may inform us of credible predictions of future stock. Accurate stock price predictions may assist investors in their trading decisions by informing a more probable outcome based on past data. Incorporating historical data and market sentiment data will better increase understanding of the correlation between market sentiment and NVDA stock price movements, which could be expanded to model the broader financial markets. By applying machine learning techniques such as ARIMA and SVM to a real-world scenario, we also test the utility of these techniques in time series forecasting and non-linear regression.

2 Related Works

Several studies evaluate the efficacy of various machine learning algorithms for stock price prediction. For example, Zhong (16) uses LSTM as the primary algorithm, discussing its strengths and weaknesses alongside other models. Zhang (15) compares SVM, Linear Regression, Logistic Regression, and LSTM, highlighting the data's specificity to the BSE Index. Wang (14) compares Linear Regression, SVM, and Random Forest, which informed our decision to exclude Random Forest. Rahimzad (10) provides insights into Linear Regression, Multilayer Perceptron (MLP), SVM, and LSTM, focusing on streamflow forecasting. Di (3) predicts using time series, incorporating the Tree algorithm for more accurate results than simple SVM.

Other studies incorporate additional factors to enhance prediction accuracy. Shen (11) combines temporal correlation and financial products with SVM, though the second model works best in a rising market. Vijh (13) uses Open, High, Low, and Close prices of stocks as inputs, evaluated using RMSE and MAPE, but relies on too few variables. Kumar (7) employs five supervised learning techniques, revealing a correlation between technical indicators and accuracy. Nabipour (9) implements RNN, ANN, CNN, and LSTM for stock market trends, noting the strength in predicting non-linear relationships despite complexity. Ashok (2) uses ARIMA and LSTM for both long and short-term predictions, covering linear and nonlinear relationships but lacking a numerical summary. Granville(18) provides interpretative explanations for technical indicators we use in the study.

In terms of market sentiment data, Gupta (5) uses Hidden Markov Models to predict stock trends, capturing market volatility effectively but being unsuitable for long-term predictions. Kim (6) uses text data mining to analyze public sentiment for stock market prediction, though it lacks comprehensive factor consideration. Fu (4) combines sentiment analysis and technical indicators to demonstrate superior performance of multi-source sentiment data compared to traditional methods. Mittal (17)

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demonstrates that incorporating technical indicators and stock price data increases prediction accuracy compared to relying solely on raw price data.

3 Dataset and features

3.1 Dataset details

For our project, we used historical stock data for NVIDIA (NVDA). This data was obtained from Yahoo Finance, covering the period from January 1, 2023, to December 31, 2023. The training data was 80% of the data, and the testing data was 20% of the data. We chose this specific time period to avoid the volatility and numerous unknown factors associated with the COVID-19 pandemic, ensuring a more stable and reliable dataset for our analysis.

3.2 Preprocessing steps

We first cleaned the data by dropping any missing values in order to ensure the data was formatted correctly. We also extracted some features from the data to be used in our models, aligning with our proposal. The features were: close prices (the closing prices of NVDA stock each day), high prices (the highest price of the stock each day), low prices (the lowest price of the stock each day), volume (the number of shared traded each day), MACD(Moving Average Convergence Divergence), ADX(Average Direcitonal Index), RSI(Relative Strength Index, Stochastic Oscillator, OBV(On-Balance Volume), and AD(Accumulation/ Distribution). Based on related works, we selected technical indicators of stock price sentiment data. MACD and ADX indicate stock trends; RSI and Stoch indicate stock momentum; OBV and AD indicate stock volume. Combined, these indicators provide a comprehensive approach to market sentiment analysis. ADX measures the strength of stock trend without direction.(17) This accounts for market volatility, which we need in addition to predicting the direction of price movement.(17)(18) MACD measures stock price momentum using two moving averages of prices.(17) This identifies potential buy/sell signals and confirms trend direction. Combined, these two indicators account for market volatility and direction. RSI measures the magnitude of price movements (overbuy/ oversell). Using RSI, out model forecasts potential reversals and predict short term price momentum.(18) Combined with RSI, Stoch allows our model to compare the closing price to historical high/low prices and therefore help the model predict if stock prices will reverse.(17) OBV measures buy/sell pressure based on changes based on changes in volume relative to price movements; inputted into our model, it predicts the direction of prices(up/down).(18) Based on AD, our model identifies divergence between price movement and accumulation trends to designate price reversal.(17)

3.3 Examples from dataset

Table 1: Example of processed data

Date	Adj Close	Close	High	Low	Open	Volume	OBV	AD	ADX	MACD	MACD Signal	MACD Diff	RSI	Stoch_K	Stoch_D
2023-12-22	48.820	48.830	49.383	48.467	49.195	252507000	18459737000	1.016e+10	15.763	0.634	0.564	0.070	55.345	68.946	66.507
2023-12-26	49.268	49.279	49.600	48.960	48.968	244200000	18703937000	1.016e+10	15.998	0.655	0.582	0.073	57.240	77.017	73.118
2023-12-27	49.406	49.417	49.680	49.085	49.511	233648000	18937585000	1.019e+10	16.282	0.675	0.601	0.075	57.832	78.960	74.974
2023-12-28	49.511	49.522	49.884	49.412	49.643	246587000	19184172000	1.005e+10	16.717	0.692	0.619	0.073	58.305	80.209	78.729
2023-12-29	49.511	49.522	49.997	48.751	49.813	389293000	19573465000	1.015e+10	16.292	0.697	0.635	0.063	58.305	80.209	79.793

4 Methods

4.1 Learning pipeline

Our learning pipeline uses various machine learning and deep learning algorithms. Our approach was to preprocess the data, extract relevant information, and apply the models to make predictions, with and without market sentiment analysis data.

4.2 Parameter selection

These technical market sentiment data indicators are derived from historical stock data and were selected after referring to similar stock price prediction research articles.

4.3 SMA model background and usage

The Simple Moving Average model, or SMA model, is a basic method for time series forecasting. It calculates the average of a selected number of past data points to smooth out short-term fluctuations and show longer-term trends. The SMA model is easy to implement and understand. It serves as a helpful benchmark for comparing the performance of more complex forecasting models. By evaluating how well-advanced models perform relative to the SMA, we can measure their effectiveness and potential improvements over this simple approach.

We used the SMA model to smooth out short-term fluctuations and highlight longer-term trends in NVIDIA's stock prices. By calculating the average of the closing prices over a rolling 10-day window, we obtained the SMA, which we then plotted alongside the actual stock prices. The simplicity and ease of implementation of the SMA model made it a helpful baseline method for evaluating the performance of more complex forecasting models.

4.4 ARIMA model background and usage

After preprocessing and feature extraction, as described in the dataset and features section, we used the AutoRegressive Integrated Moving Average (ARIMA) model to predict future stock prices using only historical stock data. We chose this model because it is suited for time series forecasting. To break down the ARIMA model, the 'AR' part of the model explains how the current value of the series is related to its previous values. The 'I' makes the data stationary in order to remove trends or seasons. The 'MA' part models the relationship between the current value and the residual errors from previous values.

We applied two ARIMA models to forecast NVIDIA's stock prices using selected historical data variables and market sentiment data. The first model utilized only historical data, while the second incorporated both historical and market sentiment data to evaluate the impact of sentiment on stock price predictions. We began by downloading historical stock data, focusing on the 'Close,' 'Open,' 'High,' 'Low,' and 'Volume' variables. To prepare for model training, we split the data into training (80%) and testing (20%) sets. Variables ('Open,' 'High,' 'Low,' 'Volume') provided additional context for the first model. For the second model, we included technical indicators such as 'OBV,' 'AD,' 'ADX,' 'MACD,' 'RSI,' and 'Stoch' alongside the original variables. The ARIMA model parameters (5, 1, 0) were selected to include five lag observations, one differencing operation to ensure stationarity, and no moving average component. We based this selection on findings from Adhikari (2024), which indicated that this configuration provided the best balance between model accuracy and computational efficiency (1). Both models were trained on the training data and corresponding exogenous variables, followed by generating forecasts for the test period. We then plotted the training data, actual prices, and forecasted prices to visually assess the performance of each model. This approach allowed us to understand the contribution of market sentiment data in enhancing the accuracy of our stock price predictions.

4.5 SVM model background and usage

Support Vector Machines (SVM) are well-suited for our NVIDIA stock prediction because they handle non-linear relationships through kernel functions, which is useful for capturing complex market patterns. They also help prevent overfitting, ensuring reliable performance on new data. SVMs work well with high-dimensional datasets, which is beneficial given the numerous features in stock market data, such as historical prices and technical indicators. This makes SVM a strong option for accurately predicting stock price movements and trends.

We applied two SVM models to forecast NVIDIA's stock prices using different sets of input features. The first model utilized historical stock data, specifically the 'Open,' 'High,' 'Low,' and 'Volume' variables. We split the data into training (80%) and testing (20%) sets and trained an SVM model using a radial basis function (RBF) kernel on the training data. The choice of the RBF kernel was informed by the findings in "Can stock prices be predicted? A Comparative study of LSTM and SVR for financial market forecast," which demonstrated that the RBF kernel provided superior performance in comparison to other kernels (12). The model generated forecasts for the test period. The second model incorporated additional market sentiment indicators such as 'OBV,' 'AD,' 'ADX,' 'MACD,' 'RSI,' and 'Stoch' along with the historical stock data. We followed the same separation, training, and evaluation process as the first model. This allowed us to assess the impact of market sentiment data on the accuracy of our stock price predictions. Visualizations of the actual and forecasted prices provided insights into the models' performance, highlighting the potential benefits of including sentiment data in stock price forecasting.

5 Experiments/ results

5.1 Results

For each of the models, we used MSE and MAE to evaluate their accuracy with cross-validation. These metrics show the average magnitude of the errors in the predictions and the squared average of these errors, respectively.

5.2 Time series split cross-validation background

TimeSeriesSplit is a cross-validation technique specifically designed for time series data. Unlike traditional k-fold cross-validation, which randomly splits the data into k subsets, TimeSeriesSplit maintains the temporal order of the data. This method divides the dataset into sequential training and test sets by progressively expanding the training set and moving the test set forward. We are using TimeSeriesSplit cross-validation in our project to provide a consistent and realistic evaluation of our ARIMA and SVM models. This method maintains the temporal order of the data, ensuring that each training set precedes its corresponding test set, which mirrors real-world forecasting scenarios. This method is also beneficial for SVM models as it respects the temporal structure of the data, helping to prevent overfitting and ensuring the model's predictions are based on sequential data, which is crucial for time series forecasting.

5.3 SMA historical data model

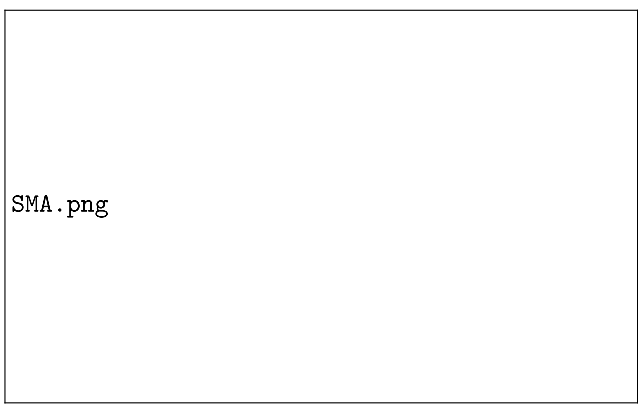

Figure 1: SMA (baseline) method

While the SMA is useful for highlighting general trends, its limitations are evident in Figure 1. The SMA line smooths out the daily price volatility, providing a clearer view of the overall trend. However, this effect means that the SMA reacts slowly to rapid price changes. In the graph, there are periods where the actual stock prices experience sudden increases or decreases, but the SMA line lags behind, failing to capture these short-term fluctuations promptly.

The results of the SMA model show an average MSE of 23.10 and an average MAE of 3.56. These metrics indicate that while the SMA model provides a basic understanding of the general trend in NVIDIA's stock prices, it has notable prediction errors. The relatively high MSE and MAE values suggest that the model struggles to capture precise price movements, especially short-term fluctuations. However, it is important to note that the SMA model is used as a baseline method to compare our other, more sophisticated models. By assessing the performance of the ARIMA and SVM models against this baseline, we can better evaluate their effectiveness and potential improvements in forecasting accuracy.

5.4 ARIMA historical data model

ARIMA historical.png

Figure 2: ARIMA historical data only

The graph for the ARIMA model with historical data in Figure 2 provides a visual comparison between the training data, actual prices, and forecasted prices. There is a close alignment between the forecasted prices and the actual prices, showing that the ARIMA model performed well in predicting future stock prices based on only historical data.

In this analysis, we employed the ARIMA model with exogenous variables to forecast NVIDIA's stock prices. Using historical stock data from 2023, we split the dataset into training and testing sets, with the variables 'Open,' 'High,' 'Low,' and 'Volume' providing additional context. We performed cross-validation using TimeSeriesSplit to ensure the model's robustness, a method well-suited for time series data as it respects temporal order by progressively expanding the training set and moving the test set forward. This approach offers a realistic evaluation of how the model performs on unseen data. Our cross-validation results showed an MAE of 0.552 and an MSE of 0.508, indicating the model's strong predictive accuracy. These metrics suggest that the model can reliably forecast stock prices by leveraging both historical and market sentiment data, providing valuable insights for decision-making.

5.5 ARIMA historical data and market sentiment data model

ARIMA mkt sent.png

Figure 3: ARIMA historical and market sentiment data

For Figure 3, the graph with the ARIMA model using historical data and market sentiment data, we can see that there is a similar close alignment between the red and blue lines. This suggests that incorporating the sentiment variables can enhance the model's predictive accuracy. In this analysis, we employed the ARIMA model with both historical and market sentiment data to forecast NVIDIA's stock prices. In addition to historical stock data, we added market sentiment data including 'OBV,' 'AD,' 'ADX,' 'MACD,' 'MACD_Signal,' 'MACD_Diff,' 'RSI,' 'Stoch_K,' 'Stoch_D,' and Google Search Trend. The dataset was split into training and testing sets, with 80% of the data used for training. We performed cross-validation using TimeSeriesSplit to ensure the model's robustness, as this method respects the temporal order of data by progressively expanding the training set and moving the test set forward. This realistic evaluation approach allowed us to assess how the model performs on unseen data. Our cross-validation results showed an MAE of 1.093 and an MSE of 2.513, indicating that the model has reasonable predictive accuracy. These metrics suggest that the model can reliably forecast stock prices, balancing errors between over- and under-predictions and thus providing valuable insights for decision-making based on historical and exogenous data.

5.6 SVM historical data model

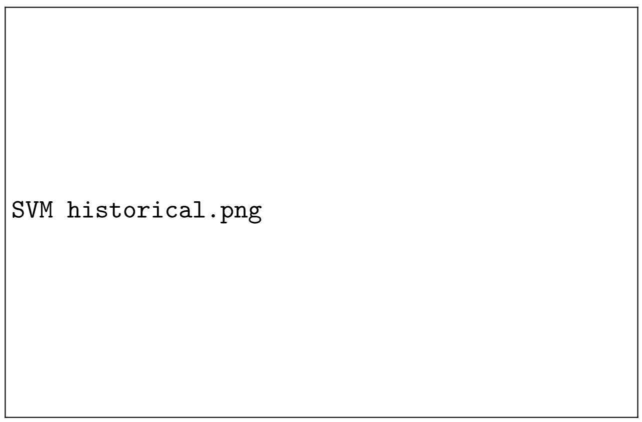

Figure 4: SVM historical data only

From the graph in Figure 4, we can deduce that the SVM model captures the overall trend of stock prices to some extent, as indicated by the general alignment between the forecasted prices and the actual prices. However, there are noticeable deviations, particularly during periods of high volatility, suggesting that the model might struggle to predict sudden market changes accurately.

The MAE and MSE metrics further support these observations. The SVM model achieved an MAE of 8.936 and an MSE of 109.905, indicating discrepancies between the predicted and actual prices. These results suggest that while the SVM model is partially capable of capturing broad trends, its predictive accuracy could be improved, potentially by incorporating additional variables or refining the model parameters.

5.7 SVM historical data and market sentiment data model

According to the graph in Figure 5, it is evident that incorporating market sentiment data enhances the SVM model's predictive accuracy. The alignment between the forecasted prices (red line) and actual prices (dark blue line) is particularly notable during periods of stability and moderate market fluctuations. This indicates that market sentiment data adds valuable context, enabling the SVM model to more accurately capture and predict stock price trends. Despite this improvement, discrepancies remain, especially during extreme market movements. This suggests that while the model benefits from the additional data, there is still a lot of potential for further enhancement. Overall, this visual comparison highlights the effectiveness of including market sentiment data in achieving more accurate and reliable stock price predictions, underscoring the advantages of a comprehensive approach to financial forecasting.

The MAE and MSE metrics reinforce our analysis of the model's performance. The SVM model attained an MAE of 5.342 and an MSE of 53.649. These values indicate a notable discrepancy

Figure 5: SVM historical data and market sentiment data

between the predicted and actual prices. While the SVM model demonstrates some capability in capturing overall trends, the current level of predictive accuracy suggests there is room for improvement. Enhancements could be achieved by incorporating additional features or adjusting the model parameters for better precision.

5.8 Best model and reasoning

Table 2: Comparison of cross-validation metrics for ARIMA, SVM, and SMA models

Type	Data Type	Metric	Value
ARIMA	Historical Data Only	MAE	0.55
		MSE	0.51
	Historical Data w/ Market Sentiment Data	MAE	1.09
		MSE	2.51
SVM	Historical Data Only	MAE	8.94
		MSE	109.90
	Historical Data w/ Market Sentiment Data	MAE	5.34
		MSE	53.65
SMA	Baseline Method	MAE	3.56
		MSE	23.10

Considering the cross-validation results, the ARIMA model with only historical data appears to perform better than the other models. It achieved the lowest MAE of 0.552 and MSE of 0.508, indicating the highest predictive accuracy. This model's performance suggests it is more effective at forecasting NVIDIA's stock prices, making it a more reliable choice for decision-making.

Using the result of the best model for 2023, we predicted December 2024 NVDA stock prices. The following is a result based on the historical data of January 2023 to November 2024 with the ARIMA model.

Table 3: NVIDIA in December 2024

Date	Price	Date	Price	Date	Price	Date	Price
2024-11-25	143.70	2024-12-02	143.59	2024-12-09	143.77	2024-12-16	143.75
2024-11-26	143.90	2024-12-03	143.74	2024-12-10	143.74	2024-12-17	143.75
2024-11-27	143.83	2024-12-04	143.77	2024-12-11	143.75	2024-12-18	143.75
2024-11-28	143.75	2024-12-05	143.77	2024-12-12	143.75	2024-12-19	143.75
2024-11-29	143.92	2024-12-06	143.74	2024-12-13	143.75	2024-12-20	143.75

`ARIMA hist for dec 2024.png`

Figure 6: Data prediction using ARIMA

6 Conclusion

Through this project, our goal was to predict future trends in NVIDIA's stock prices by using both market sentiment data and historical stock data. By examining historical data from January 1, 2023, to December 31, 2023, and using TimeSeriesSplit to maintain temporal order, we ensured realistic model evaluation.

The ARIMA model with historical data alone performed well, with an MAE of 0.552 and an MSE of 0.508. The model showed effectiveness in aligning forecasted and actual prices. While experimenting with data from 2023, the ARIMA model that included market sentiment data226 performed the best. However, for the 2023 dataset alone, the historical data model proved superior.

The SVM model captured broad stock price trends but struggled during high volatility, achieving an MAE of 8.936 and an MSE of 109.905. Incorporating market sentiment data improved its performance to an MAE of 5.342 and an MSE of 53.649, though discrepancies remained during extreme market movements. This indicates room for improvement, potentially through additional features or adjusted parameters. Enhancements could be achieved by incorporating additional features or adjusting the model parameters for better precision.

Our analysis highlighted the strengths of the ARIMA model with historical data and the benefits of adding market sentiment, especially for the SVM model. However, the SVM model with historical data alone had higher errors, indicating a need for better handling of non-linear relationships. The ARIMA model with sentiment data performed well for extended datasets but was sensitive to data range.

This project contributes to the field by demonstrating the utility of integrating market sentiment data with historical stock data. Leveraging real-time data sources like Google Trends adds predictive power, reflecting public feature engineering or alternative kernel functions could help with the volatility of SVM model and sentiment. Future work could enhance the predictive accuracy of these models by incorporating more diverse data sources, including economic indicators and news sentiment. Feature engineering or alternative kernel functions could help with the volatility of SVM model. Utilizing advanced machine learning techniques like deep learning models for better handling sequential data and continuously updating and validating models with real-time data will ensure adaptability to market changes. Additionally, combining the strengths of different models (e.g., ARIMA for trend capturing and SVM for non-linear relationships) could improve overall accuracy.

In conclusion, the ARIMA model with historical data demonstrated the best performance for the 2023 dataset. These findings highlight the importance of choosing the right dataset and model configuration for accurate stock price forecasting. Our project underscores the potential of combining historical and market sentiment data in improving financial predictions, providing valuable information to investors, and enhancing decision-making processes.

7 Contributions

Minwoo Kwak, Min Kim, and Erin Cho each met twice a week to work on this project, with additional meetings scheduled as needed. Every member was consistently present and on time for these meetings. Tasks were delegated with mutual agreement at the beginning of each session, fostering a collaborative environment throughout. For each meeting, Min took meeting notes to summarize our tasks.

In preparation for the proposal, each member identified five related works. After discussing the strengths and weaknesses of these works, the group collectively narrowed them down to four per person. The proposal was a collective effort, with each member contributing ideas, researching models, and identifying resources for the project.

The code for historical stock data was written together. Min was in charge of finding and organizing resources for algorithms to help us code the project. Minwoo took the lead on coding the market sentiment portion, while Erin focused on the dataset and features, as well as the methods sections of the report. Min worked on the introduction and the latex coding. Each member then began to work collaboratively on finishing the combination of the model for historical data and the market sentiment data. Erin worked on the SMA model using historical data and cross-validation. Minwoo completed the final code for the cross-validation in SVM models, while Erin worked on the cross-validation code for the ARIMA models and the December 2024 prediction using the best model.

After receiving feedback, Minwoo added the Google Search Trends to the market sentiment data, and Erin validated the usage of methods that were commented on. Min did the same for the market sentiment factors.

Afterward, the experiments and results were written, and Erin wrote paragraphs on different aspects of the results and the conclusion. Min wrote the report into Overleaf, following the guidelines for the project. The team ensured overall formatting and alignment with the guidelines, each proofreading it multiple times. Each member also contributed to the contributions section of the report in order to ensure accuracy and detail.

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