Stock Market Trend Prediction

Introduction/Background

The stock market is a complex adaptive system, consisting of individual components that interact in response to global events. This makes predicting stock market trends a challenging yet crucial task for investors and financial institutions. The large size of stock market historical data lends itself well to machine learning algorithms; however, no one has been able to create a successful model as historical data is not enough. Others have tried to utilize news sentiment data instead of historical data to make predictions, yet their models still fail. This project takes the unique approach of attempting to combine both historical data and news sentiment in order to develop a machine learning model with the ability to forecast short-term stock price movements for S&P 500 companies.

Recent studies have explored various machine learning approaches for stock prediction. Jiang et al. (2021) used LSTM networks for stock price prediction incorporating news sentiment [1]. Patel et al. (2020) compared various machine learning techniques for stock trend prediction [2]. Feng et al. (2019) developed a deep learning framework for stock prediction using technical indicators and textual data [3].
We will use a combination of datasets:

- Yahoo Finance API for historical stock price data of S&P 500 companies
- Alpha Vantage News' API for real-time and historical financial news articles[3]

Links to datasets:

- Yahoo Finance: https://finance.yahoo.com
- Alpha Vantage News: https://www.alphavantage.co

Problem Definition

Accurate stock market prediction is crucial for optimizing investment strategies, managing financial risks, and understanding market dynamics. The challenge lies in developing a model that can effectively combine numerical time series data with textual sentiment information to predict short-term (1-5 days) stock price movements.

Data Collection and Preprocessing

We need two types of data: technical indicators and news articles for our stocks. In order to get technical indicators, we utilized the yahoo finance API. This provided only basic stock details, so we implemented our own functions to calculate more technical indicators for our stock. For news sentiment data, Alpha Vantage news was our source. For each symbol, news articles were retrieved. Their text was cleaned and tokenized. Finally, we compute the sentiment, polarity, and subjectivity of the article as separate features to use in our model.

Once we have obtained the data, we must preprocess it. For this stage of the project we wanted to simplify our data to make debugging our model easier; therefore, PCA was employed. Although the number of features we had before using PCA was not very high, reducing to the most important features did help with improving the visualization of the model.

ML Models

- LSTM Neural Network
  - Useful for sequential data, this will be ideal for the relation of our data for the forecasting nature of our problem[1].
- Random Forest Classifier
  - Multiple decision trees, that outputs the mode, good for when data can be noisy as stocks can.
- Support Vector Machine
  - Models used for classification and regression, good for classification of stock trends.

We applied three unique models to our problem to determine what architecture most accurately predicted stock market trends.
The first model applied was Long short-term memory or LSTM. LSTM is a type of recurrent neural network (RNN) aimed at mitigating the vanishing gradient problem. LSTM lends itself well to our problem as its memory retention characteristics allows for our model to learn from both short-term fluctuations and long-term trends.

The second model applied was the Random Forest Classifier. Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and reduce overfitting. This model is well-suited for our problem because it can handle a large number of features and capture complex relationships between variables. Its ability to aggregate predictions from numerous trees helps to enhance robustness and accuracy, making it effective for classifying stock market trends where patterns may be influenced by various factors.

The third model applied was the Support Vector Machine (SVM). SVM is a powerful supervised learning algorithm used for classification tasks. It works by finding the optimal hyperplane that separates different classes in the feature space, maximizing the margin between them. SVM is particularly effective for our problem because it can handle high-dimensional data and complex decision boundaries. Its ability to generalize well with a smaller amount of training data makes it suitable for predicting stock market trends, where clear distinctions between price movements are often subtle and nonlinear.

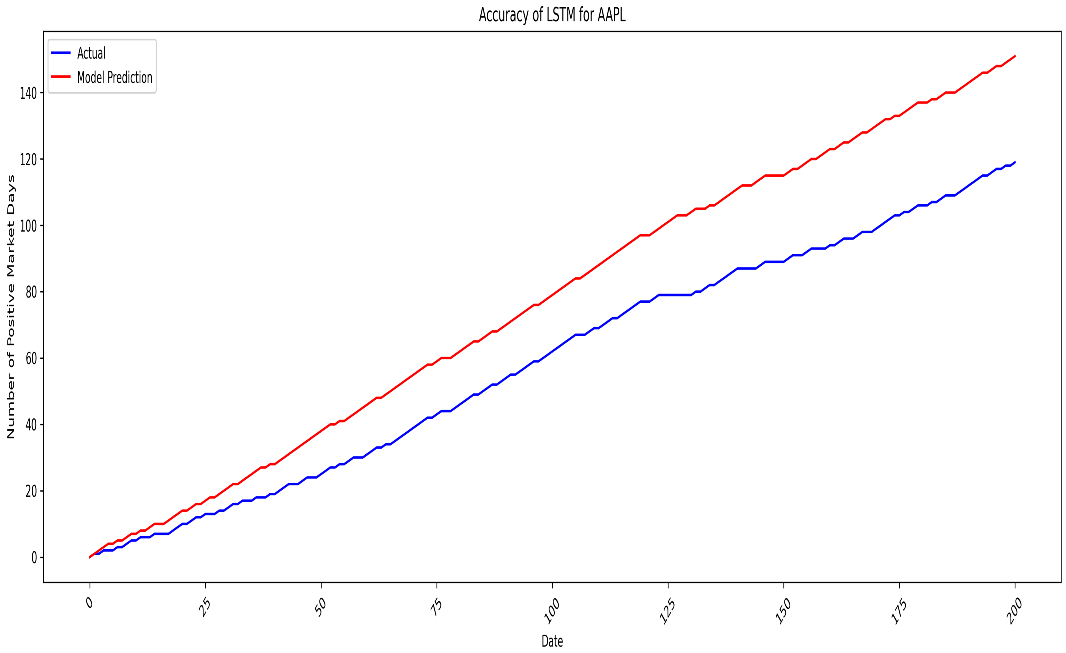
Quantitative Metrics

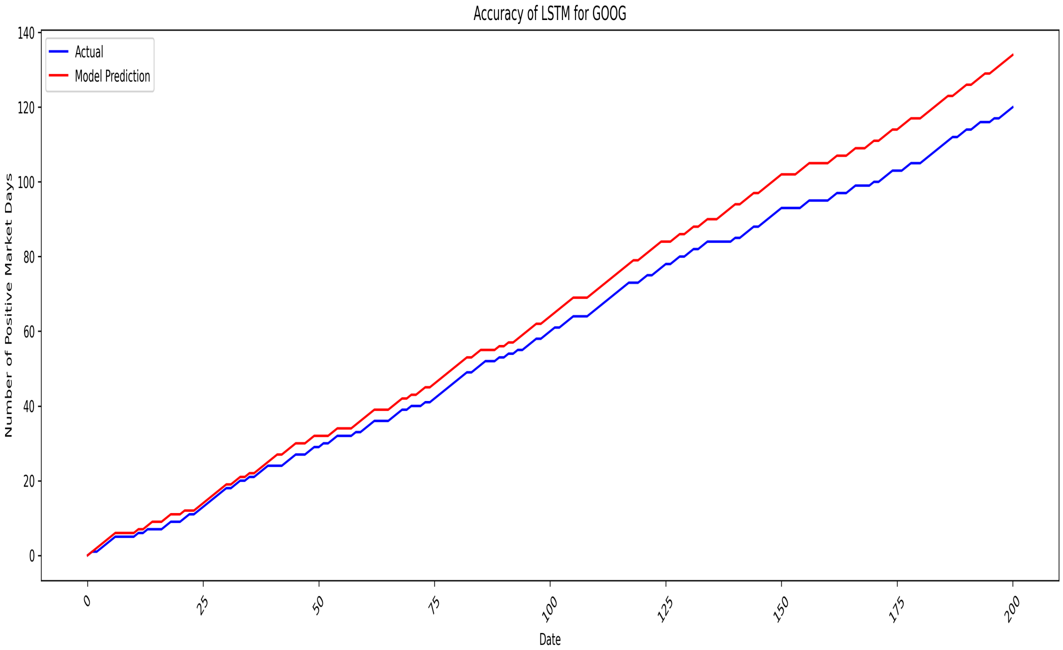
- MAPE (Mean Absolute Percentage Error): Average percentage difference between predicted and actual values
- RMSE (Root Mean Square Error): The square root of the average squared differences between predicted and actual values, emphasizing larger errors
- Accuracy: Proportion of correct predictions (both up and down movements) out of total predictions
- F1 Score: Harmonic mean of precision and recall, balancing the model's ability to correctly identify true positives while avoiding false positives

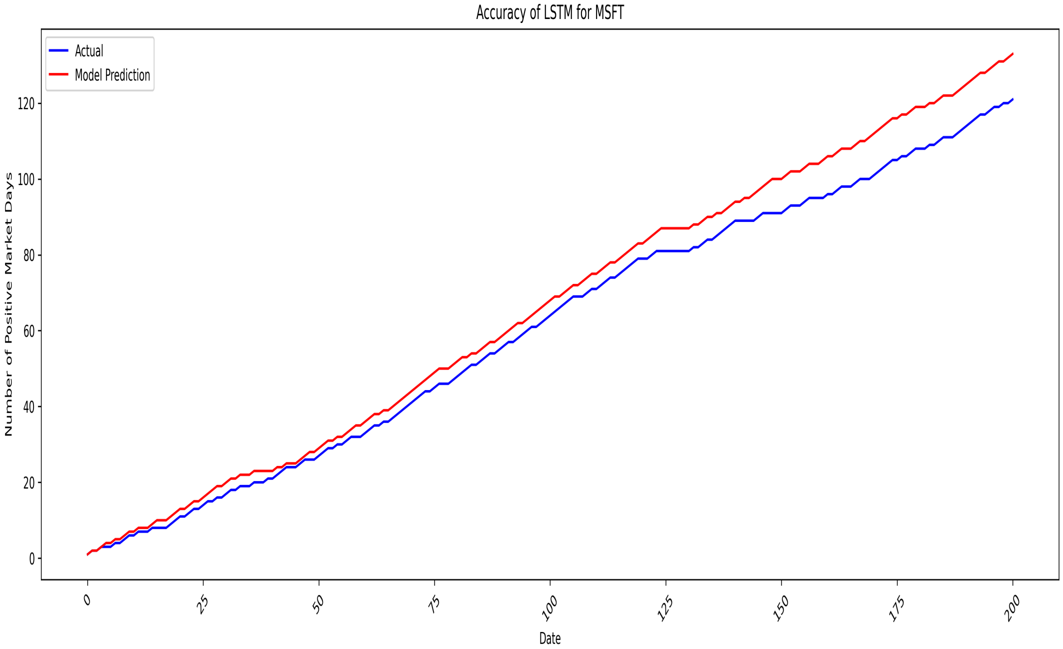
Results and Discussion

Long Short-Term Memory

The first model we are going to discuss is the LSTM model. This model achieved our highest accuracy score of 96%, leveraging its ability to remember long-term trends while still focusing on recent movements. The three below graphs illustrate LSTM’s prediction performance over a 200 day period. The y-axis is the cumulative number of positive market days with the red line being our model’s predictions and the blue line being reality. The small margin of difference between reality and our model’s prediction emphasizes our model’s power. However, the model exhibited high error variance indicating inconsistent performance for more volatile stocks. Additionally, LSTM’s reliance on substantial training data and its tendency to overfit to specific patterns poses a challenge for generalization across diverse market conditions.

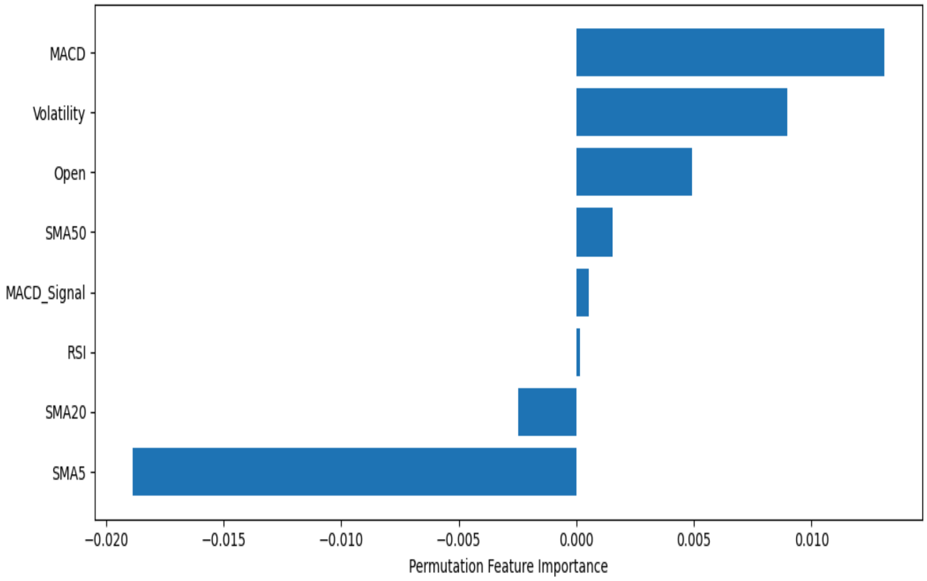


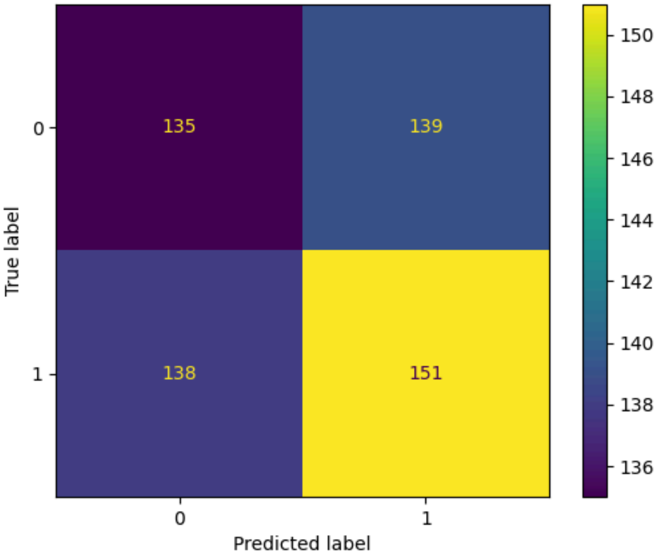




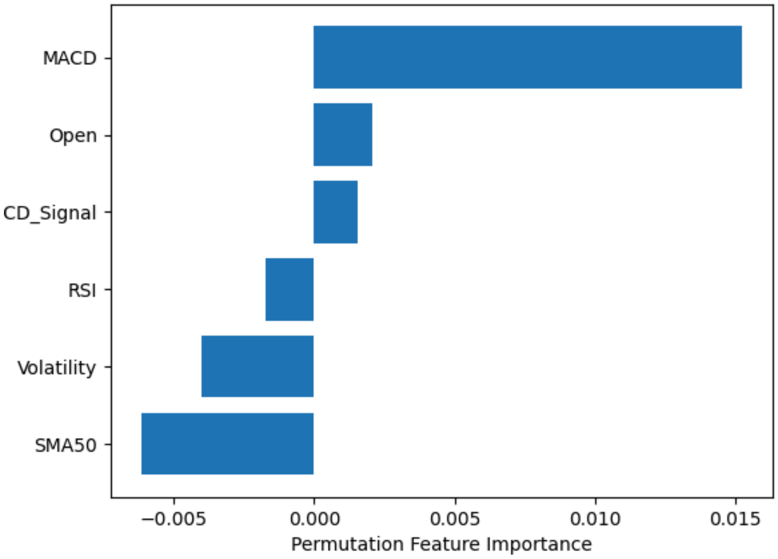
Random Forest Classifier

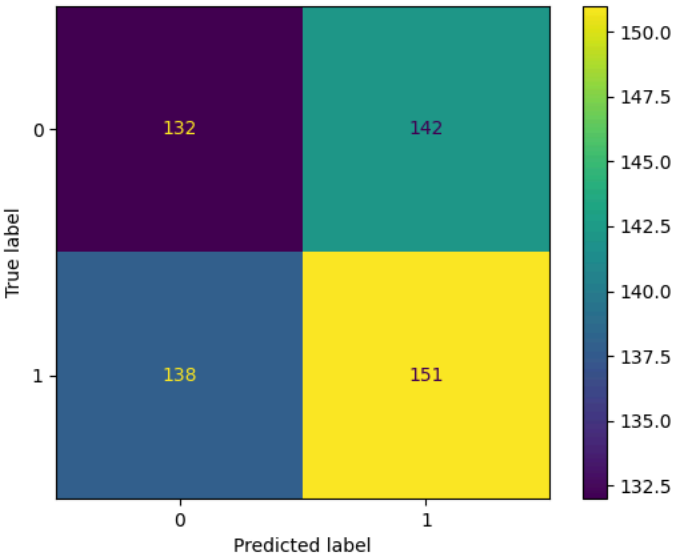
The Random Forest Classifier model performed very poorly, with roughly 50% accuracy. It classifies stock trends with a 50% accuracy, which means it's about as efficient as flipping a coin. This is due to inefficient features being selected. When training the model, we created Permutation Feature Importance (PFI) charts, which show how a model's performance is impacted if we shuffle the values of an individual feature. We will also use a confusion matrix, which displays false positives, true negatives, etc., to gauge the accuracy of our upward/downward trend classifications. On the first iteration of the model (~50% accurate), we yielded the following charts:



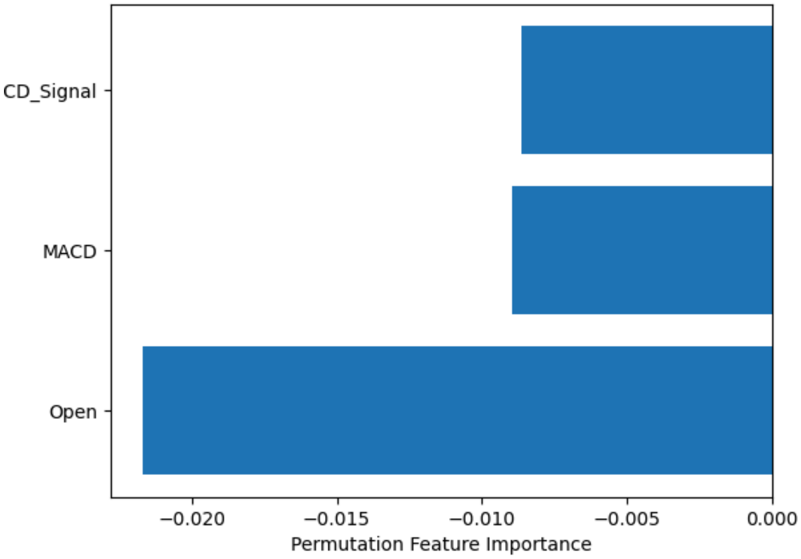


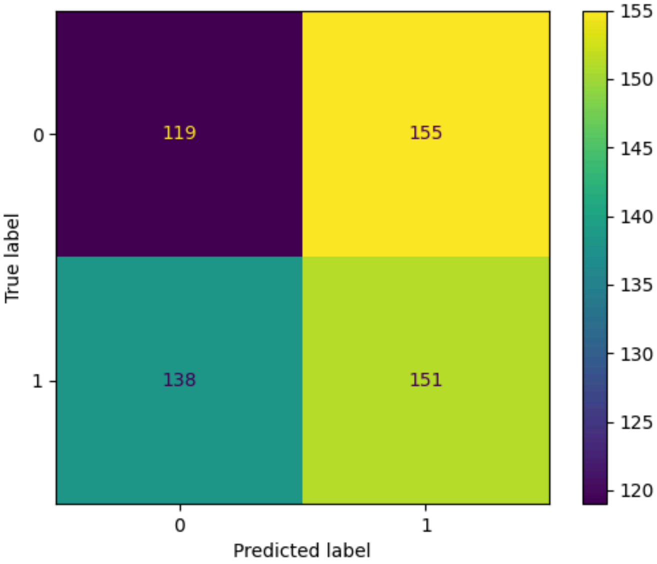
According to the PFI chart, MACD, Volatility, and Open were the most importance features, since shuffling values negatively impacted the performance of the model. On the contrary, SMA5 and SMA20 may have contributed to the model overfitting the data, indicated by the strong negative direction. The confusion matrix further shows the inaccuracy of the model, since we could see that the classifications were evenly distributed. To try improving the performance of the model, we used the information from the PFI chart and removed the SMA5 and SMA20 features. The second iteration of the model (~50% accurate) yielded the following charts:





This time, it seems that the only significant feature was MACD, which is concerning. None of the other features were significantly affecting the performance of the model. The confusion matrix tells the same story as before. Removing more features proves unsuccessful, likely because our model would have too little features. The third iteration of the model (~47% accurate) yielded the following charts:

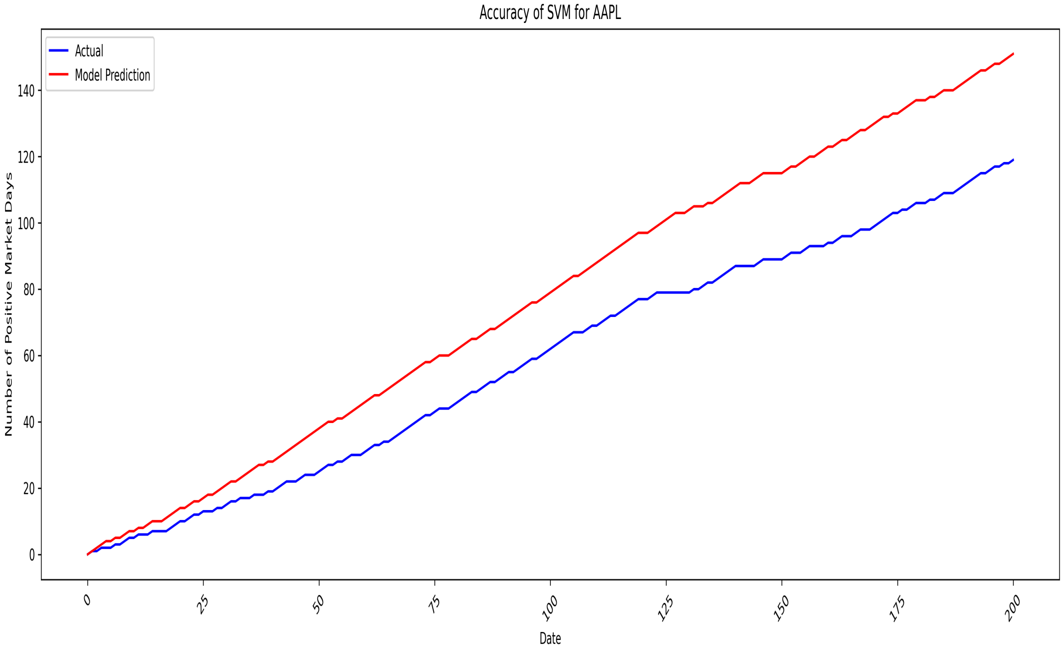


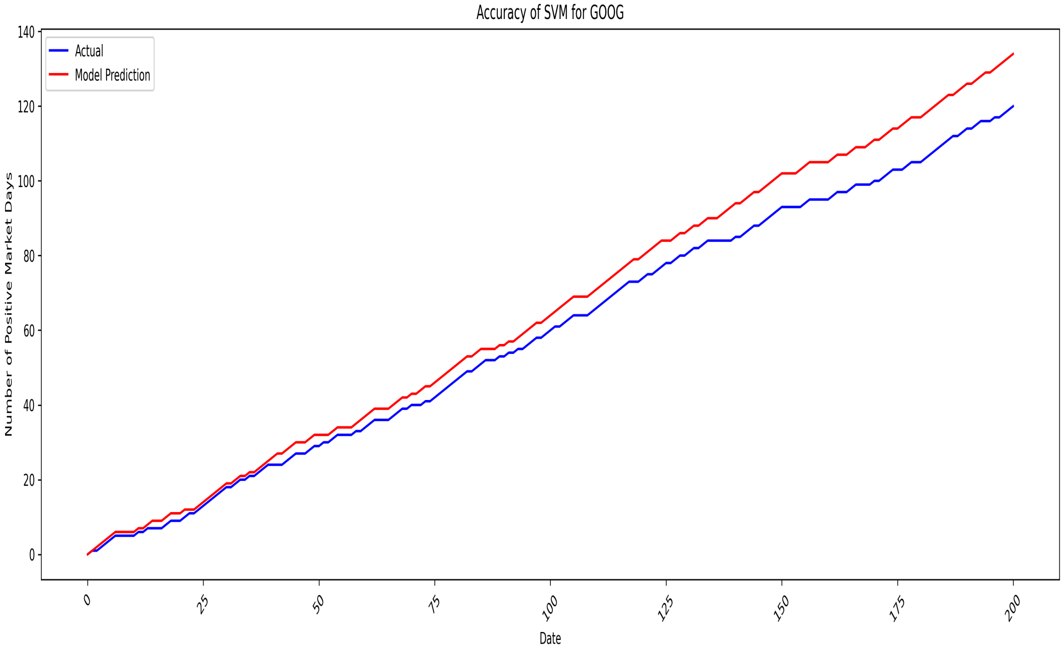


The PFI chart is telling us that ALL the features may be negatively impacting the model. Furthermore, the confusion matrix shows a greater sum along the incorrect predictions than the correct predictions.

Support Vector Machine

Moving on to a more successful model, SVM had similar but slightly worse performance than LSTM. All three below graphs show a small deviation in the model's predictions and reality, emphasizing the model's accuracy, coming out with an average accuracy of around 85 percent. SVM's ability to handle high dimensional data lended itself well to our financial data, but there were still limitations of this architecture. SVM's higher RMSE value of around .4 highlights SVM's limitations to capture temporal dependencies inherent in stock data. Additionally, SVM may struggle with high volatility market conditions, as it lacks sequential learning capabilities unlike the LSTM model.


Accuracy of SVM for AAPL
Actual
Model Prediction
Number of Positive Market Days
0
20
40
60
80
100
120
140
0
25
50
75
100
125
150
175
200
Date


Accuracy of SVM for GOOG
Actual
Model Prediction
Number of Positive Market Days
0
20
40
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120
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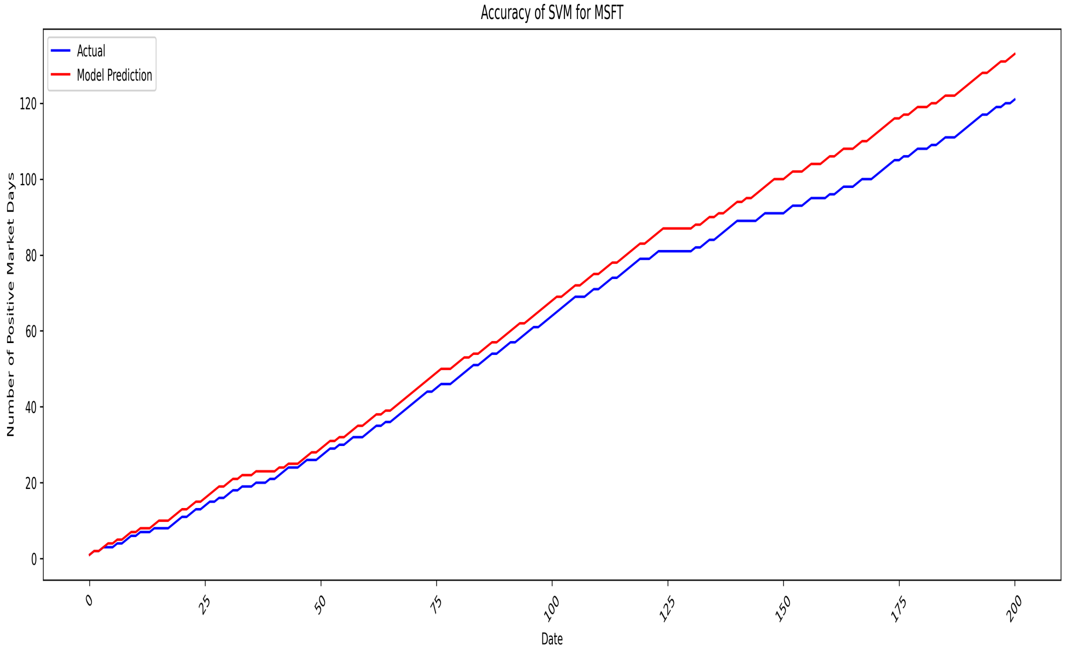


Quantitative Measures

- Excels at capturing temporal dependencies in sequential stock price data
- Can maintain memory of long-term market trands while weighing recent movements
- Particularly effective for AAPL predictions (14.56% MAPE) due to:
- Typically more stable price movements
- Higher trading volume providing more consistent patterns
- Strong correlation between historical patterns and future movements

LSTM Limitations

- High MAPE variance between stocks (14.56% to 51.65%)
- Requires substantial training data
- May overfit to specific stock patterns

Random Forest Strengths

- High recall (0.9448) indicates strong ability to identify actual positive cases
- Robust to outliers in market data
- Can handle non-linear relationships in features

Random Forest Limitations

- Lower precision (0.5532) suggests many false positives
- Overall accuracy (0.5828) indicates potential overgeneralization
- May miss subtle temporal patterns that LSTM captures

SVM Strengths

Insight on no MAPE: MAPE requires actual percentage changes in stock prices to calculate the error margin, but SVM is typically used as a classification model that predicts directional movement (up/down) rather than specific price values. Even when SVM regression is used, the model outputs are often scaled or transformed values that don't directly translate to percentage errors, making MAPE an unsuitable metric for evaluating SVM performance in this context.

- Consistent performance across stocks (82-88% accuracy)
- Good balance between precision and recall
- Effective at handling high-dimensional feature spaces from technical indicators

Limitations

- Higher RMSE values (0.35-0.42) than LSTM
- Less effective at capturing temporal dependencies
- May struggle with highly volatile market conditions

Key Performance Factors

1. Data Characteristics
   - LSTM performs better with clear temporal patterns
   - Random Forest excels with diverse feature sets
   - SVM benefits from normalized, well-structured data
2. Market Conditions
   - Model performance varies with market volatility
   - Trading volume affects prediction accuracy
   - Stock-specific factors influence model effectiveness
3. Feature Engineering Impact
   - Technical indicators boost Random Forest and SVM performance
   - Temporal features critical for LSTM success
   - Feature selection affects model generalization

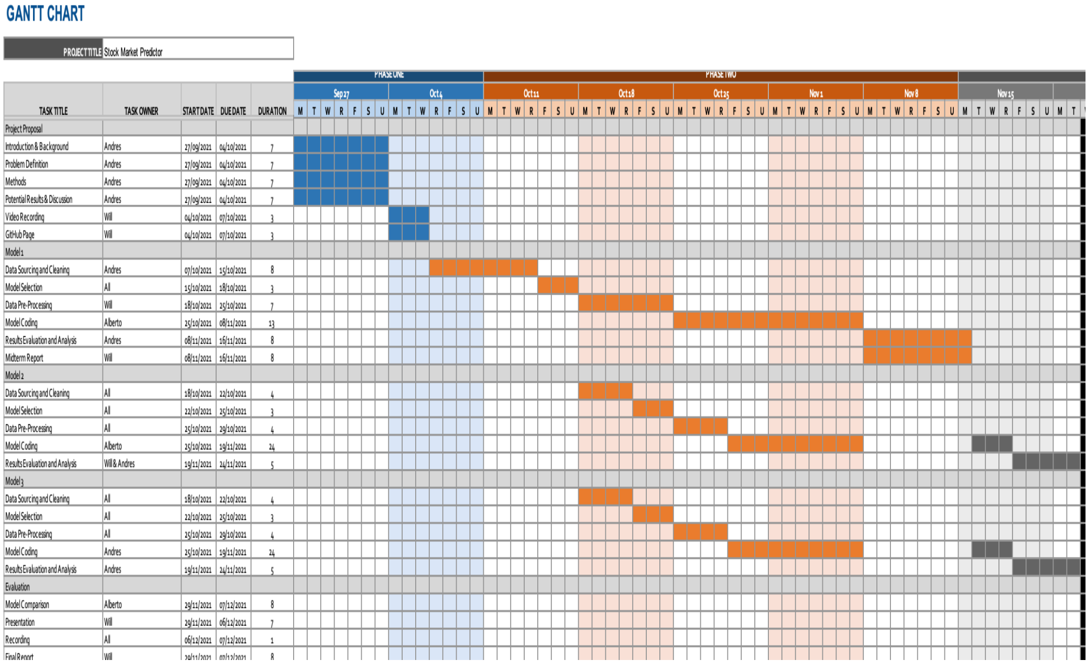
Next Steps

The next steps involve exploring methodologies to combine the strengths of the three discussed models into a unified, hybrid framework. This approach could leverage each model's unique capabilities—whether in time-series analysis, sentiment interpretation, or classification—creating a more robust and comprehensive solution. Key takeaways include the importance of integrating diverse data sources to improve predictive power, the value of adaptability in model design, and the potential for innovation when merging traditional and advanced techniques. This endeavor highlights the broader goal of creating scalable and holistic systems for tackling complex real-world problems.

References

[1] J. Li, G. Li, M. Liu, X. Zhu, and L. Wei, "A novel text-based framework for forecasting agricultural futures using massive online news headlines, "International Journal of Forecasting, vol. 38, no. 1, pp. 35–50, Jan. 2022, doi: https://doi.org/10.1016/j.ijforecast.2020.02.002.
[2] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques, "Expert Systems with Applications, vol. 42, no. 1, pp. 259–268, Jan. 2015,doi: https://doi.org/10.1016/j.eswa.2014.07.040.
[3] F. Feng, H. Chen, X. He, J. Ding, M. Sun, and T.-S. Chua, "Enhancing Stock Movement Prediction with Adversarial Training," arXiv.org, Jun. 01, 2019. https://arxiv.org/abs/1810.09936v2

Gantt Chart

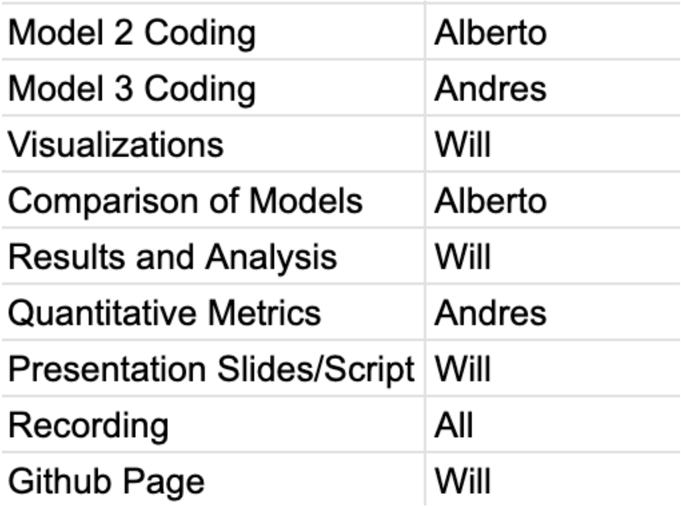


GANTT CHART

PROJECT TITLE Stock Market Predictor

TASK TITLE	TASK OWNER	START DATE	DUE DATE	DURATION
Project Proposal				
Introduction & Background	Andres	27/09/2021	04/10/2021	7
Problem Definition	Andres	27/09/2021	04/10/2021	7
Methods	Andres	27/09/2021	04/10/2021	7
Potential Results & Discussion	Andres	27/09/2021	04/10/2021	7
Video Recording	Will	04/10/2021	07/10/2021	3
GitHub Page	Will	04/10/2021	07/10/2021	3
Model 1				
Data Sourcing and Cleaning	Andres	07/10/2021	15/10/2021	8
Model Selection	All	15/10/2021	18/10/2021	3
Data Pre-Processing	Will	18/10/2021	25/10/2021	7
Model Coding	Alberto	25/10/2021	08/11/2021	13
Results Evaluation and Analysis	Andres	08/11/2021	16/11/2021	8
Midterm Report	Will	08/11/2021	16/11/2021	8
Model 2				
Data Sourcing and Cleaning	All	18/10/2021	22/10/2021	4
Model Selection	All	22/10/2021	25/10/2021	3
Data Pre-Processing	All	25/10/2021	29/10/2021	4
Model Coding	Alberto	25/10/2021	19/11/2021	24
Results Evaluation and Analysis	Will & Andres	19/11/2021	24/11/2021	5
Model 3				
Data Sourcing and Cleaning	All	18/10/2021	22/10/2021	4
Model Selection	All	22/10/2021	25/10/2021	3
Data Pre-Processing	All	25/10/2021	29/10/2021	4
Model Coding	Andres	25/10/2021	19/11/2021	24
Results Evaluation and Analysis	Andres	19/11/2021	24/11/2021	5
Evaluation				
Model Comparison	Alberto	29/11/2021	07/12/2021	8
Presentation	Will	29/11/2021	06/12/2021	7
Recording	All	06/12/2021	07/12/2021	1
Final Report	Will	29/11/2021	07/12/2021	8

Contribution Chart



Model 2 Coding	Alberto
Model 3 Coding	Andres
Visualizations	Will
Comparison of Models	Alberto
Results and Analysis	Will
Quantitative Metrics	Andres
Presentation Slides/Script	Will
Recording	All
Github Page	Will