Macroeconomic Indicators Predict Stock Price

Executive Summary

1)Problem

2)Goal

3)Technical Challenges

4)Solution Approach

5)Benefits

Stock prices are complex and challenging to predict

Develop model using macroeconomic data to forecast S&P 500 performance

Integrating diverse data sets, and optimizing machine learning models

Utilizing LSTM neural networks with economic indicators to forecast SPY prices

Enhanced understanding of market dynamics and improved predictive accuracy for investment strategies

Motivation

Related Work

- U.S. stock markets: 42% of global equities, 24% of global GDP
- NYU's proximity to major financial institutions
- LSTM model for NYSE stock prices[1]

Methodology

1)Data Set

GDP, Federal Funds Rate, Unemployment Rate, CPI, PPI, and SPY ETF prices
(7/1/18~12/15/23)

2)Data Preparation

Integration, cleaning, and normalization

3)Feature Engineering

Including 20, 50, 200 days moving averages and 20 days exponential moving averages

4)Modeling Technique

LSTM neural network with hyperparameter tuning

Implementation

1) Hyperparameter Configuration

Optimization using Keras Tuner

2) Additional LSTM Layers

Enhanced model complexity to better capture temporal dependencies in data

3) Regularization Techniques

Implementation of L1 and L2 regularization to prevent overfitting

4) Early Stopping

Integrated to halt training when no improvement is observed

5) Data Scaling

Utilization of MinMaxScaler for feature normalization

6) Training and Testing

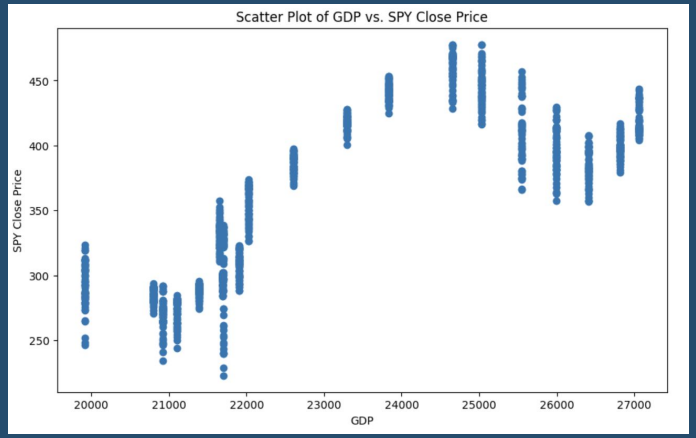
Splitting data into training (80%) and testing (20%) sets

7) Model Evaluation Metrics

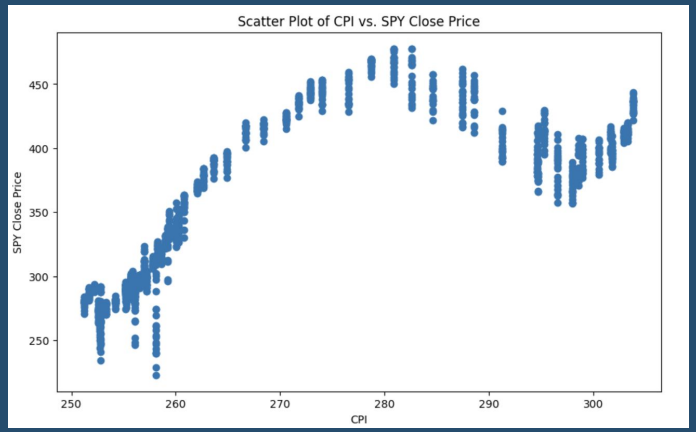
Metrics: MSE, MAE, and R2 Score

Result

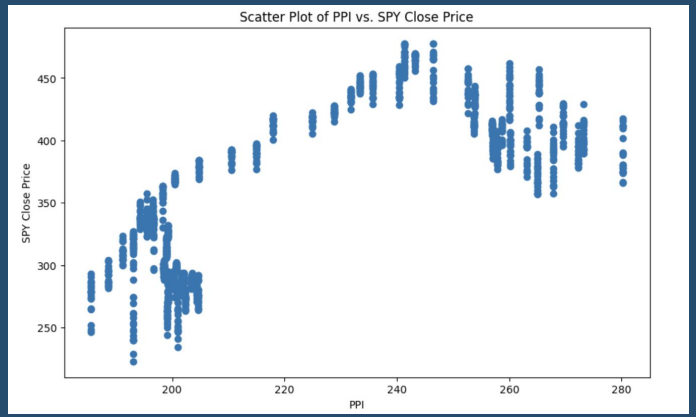
GDP



CPI



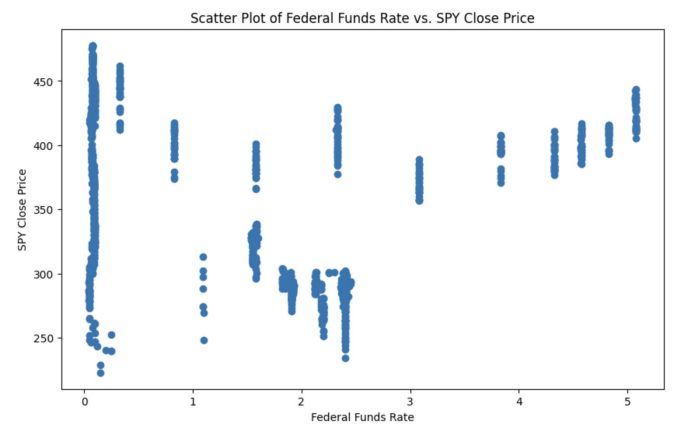
PPI



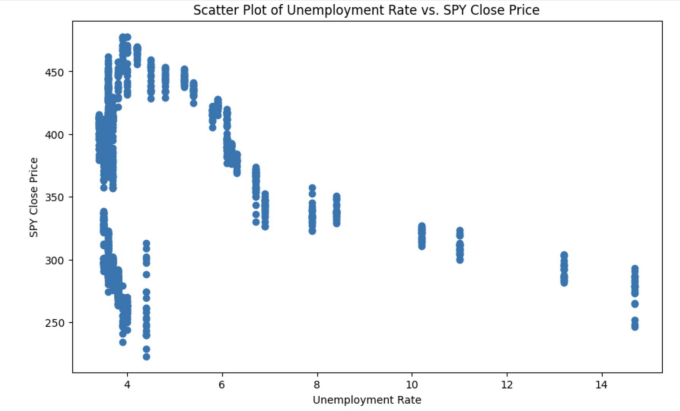
Strong Positive Relationship

Result

Federal Fund Rate

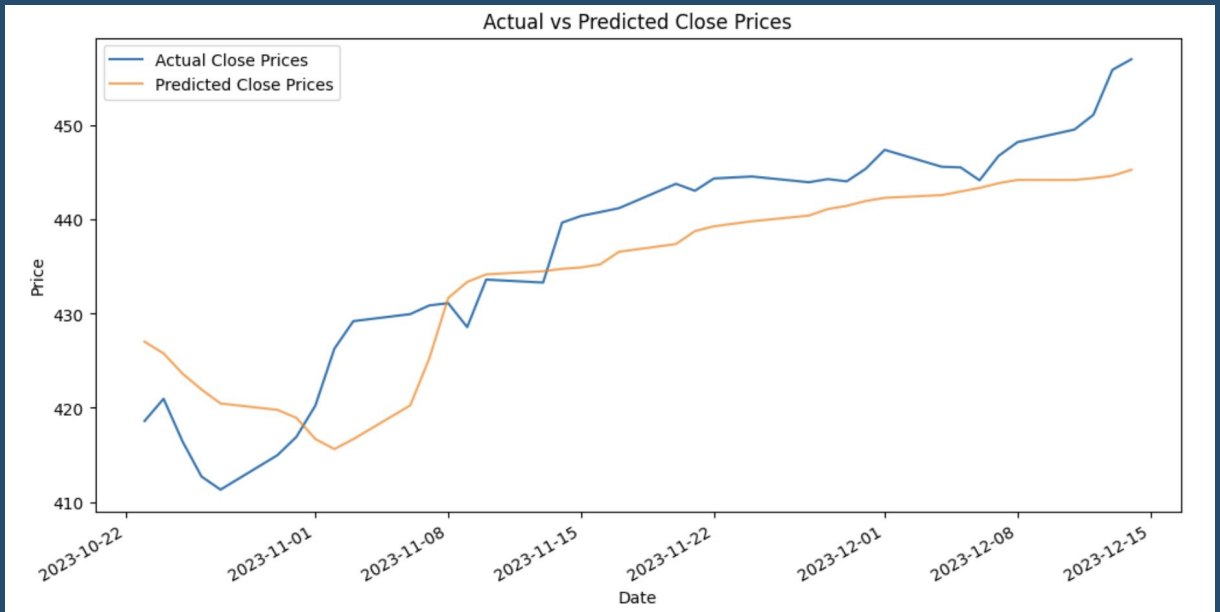


Unemployment Rate



Weak Negative Relationship

Result

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Mean Squared Error: 37.81908878482734
Mean Absolute Error: 5.320306869999788
R2 Score: 0.757542536642084
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	Date	Actual Price	Predicted Price
0	2023-10-23	418.593020	427.019462
1	2023-10-24	420.956031	425.772380
2	2023-10-25	416.423827	423.625651
3	2023-10-26	412.696696	421.938223
4	2023-10-27	411.302752	420.458942
5	2023-10-30	414.962798	419.777433
6	2023-10-31	416.908372	418.927319
7	2023-11-01	420.232967	416.678860
8	2023-11-02	426.270924	415.613476
9	2023-11-03	429.200444	416.666577
10	2023-11-06	429.945870	420.256569
11	2023-11-07	430.870191	425.224395
12	2023-11-08	431.108733	431.664708
13	2023-11-09	428.566827	433.361618
14	2023-11-10	433.613354	434.167500
15	2023-11-13	433.300288	434.502392
16	2023-11-14	439.666234	434.754792
17	2023-11-15	440.374376	434.906675
18	2023-11-16	440.784374	435.223191
19	2023-11-17	441.201811	436.568588
20	2023-11-20	443.788441	437.390030
21	2023-11-21	443.050453	438.761653
22	2023-11-22	444.354949	439.279028
23	2023-11-24	444.563667	439.808044
24	2023-11-27	443.952435	440.414479
25	2023-11-28	444.287863	441.105020
26	2023-11-29	444.049321	441.444988
27	2023-11-30	445.383641	441.963175
28	2023-12-01	447.396301	442.301338
29	2023-12-04	445.599821	442.587493

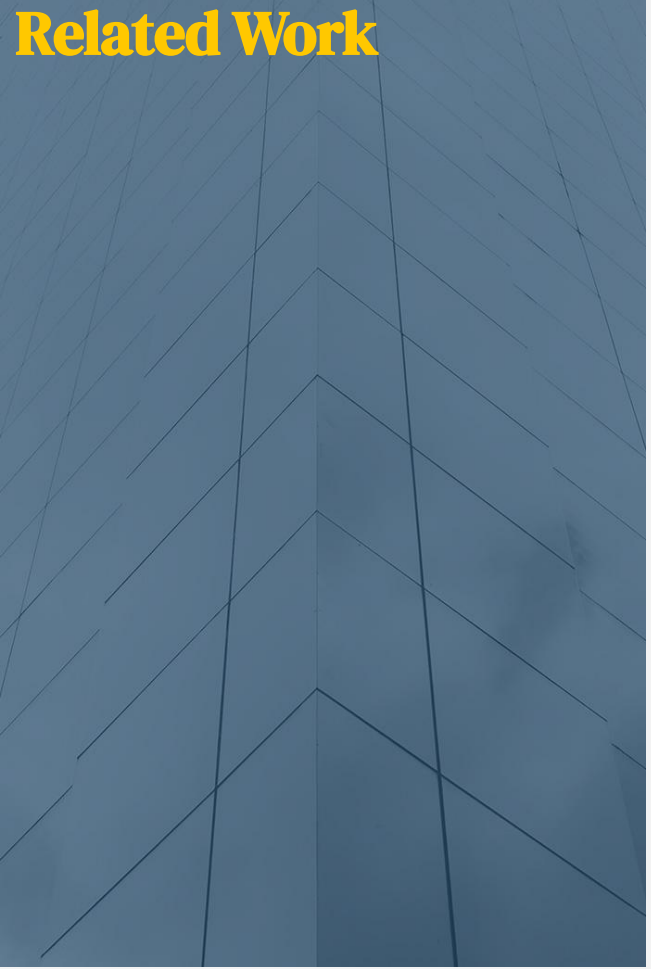
Predictive Model Performance

Conclusion

- Impact of External Factors
  Influence on stock prices
- Model Performance
  Improved predictive accuracy with LSTM model
- Future Work
  Exploring additional indicators and refining model
- Limitations
  Heavy reliance on historical patterns in a dynamic market


Thank You

Related Work



1. Discolll,N. (2023,May10). StockpricepredictionLSTMhyperparametertuning. Medium. https://medium.com/@redeaddiscolll/stock-price-prediction-lstmhyperparameter-tuning-ad69d409ae29