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Time Series Forecasting for Stock Market Prices

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INTRODUCTION

The stock market has attracted customers over the years with its built-in high risk and high reward system. With an endless increase in market capitalization, stock trading has become the center of investment for many investors. The savings and investments that the system can potentially generate have vitalized the continuously growing national economy. However, this system has proven to be dynamic and complex, which supplies to the risk factor involved. In order to reduce risk, experienced investors have found it advantageous to use technology that predicts future stock prices.

A classic approach to Stock Market Prediction (SMP) includes fundamental and technical analysis, but a more modern approach includes machine learning and sentiment analysis. In this paper, time series forecasting for SMP will be explored. The Auto-Regressive Integrated Moving Average (ARIMA), which is a classical statistical method, will be the primary method and described in detail. The Long-Short Term Memory (LSTM) method, which is under deep machine learning, will be the secondary method and described briefly. The stock market price time series data that expands over six years for a group of high tech companies will be used and prediction of each stock price will be presented by both ARIMA and LSTM models.

ARIMA is a statistical analysis model that uses time series data to either better understand the data set or to determine future trends, predicting future values based on past values. For example, an ARIMA model might seek to predict a stock's future prices based on its past performance or forecast the earnings of a company based on past periods. The LSTM model is a powerful recurrent neural network (RNN) approach that has been used to achieve the best-known results for many problems on sequential data. LSTM cells are used in recurrent neural networks to predict future values from sequences of variable lengths. Recurrent neural networks work with any kind of sequential data and, unlike ARIMA and Prophet, are not restricted to time series data. The main idea behind LSTM is to learn the important parts of the sequence seen so far and disregard the parts that are not as significant. This is achieved by the so-called functions that have different learning objectives such as representing the time series in a compact manner, combining the past representation of the series with new inputs, forgetting the insignificant parts of the series while generating a prediction for the next time step.

DATA

Our data was sourced from Yahoo Finance, a public domain that provides financial news, data, and commentary updated in real time. Originating from the United States Securities and Exchange Commision (SEC), the data supports over 40,000 stock quotes across multiple exchange markets and is provided in statement categories such as income, balance, and cashflow. For this paper, we will target the historical price data pertaining to certain stocks we have hand-picked in order to predict the future values of those stocks.

Our data contains the daily historical price data over the past 28 years, from 1994 to 2022. Data for each individual stock quote is downloaded as a dataframe, which provides 1) the daily opening price of the stock (Open), 2) the daily maximum price of the stock (High), 3) the daily minimum price of the stock (Low), 4) the daily closing price of the stock (Close), 5) the daily adjusted closing price (Adj Close), and 6) the daily total number of shares traded (Volume).

Figure 1: IBM Closing Price Data from 1994-2022

	Date	Open	High	Low	Close	Adj Close	Volume
0	1994-01-18	13.712954	13.712954	13.473948	13.653203	7.524245	9438686
1	1994-01-19	13.563576	13.623327	13.324570	13.384321	7.376061	8198548
2	1994-01-20	13.354446	13.354446	13.175191	13.205067	7.277275	9533244
3	1994-01-21	13.175191	13.294694	13.085564	13.205067	7.277275	13290894
4	1994-01-24	13.324570	14.041587	13.324570	14.011711	7.721817	17653551
...	...	...	...	...	...	...	...
7213	2022-09-12	130.330002	130.990005	129.889999	130.660004	130.660004	3741100
7214	2022-09-13	129.139999	129.910004	126.769997	127.250000	127.250000	4565600
7215	2022-09-14	127.500000	129.000000	126.849998	127.690002	127.690002	3819100
7216	2022-09-15	127.389999	127.470001	124.900002	125.489998	125.489998	5141700
7217	2022-09-16	124.360001	127.529999	123.830002	127.269997	127.269997	9838600

Figure 2: Head of IBM Historical Price Data

ANALYTICAL METHODS - ARIMA MODEL AND RESULTS

We want to construct a model that can investigate patterns in the stock market by reviewing the trends constructed from the data we collected and concatenated. The ARIMA model uses time series data to predict future points in the series (also known as time-series forecasting).

There are three integers that are typically used to parametrize nonseasonal ARIMA models. They are *p*, the number of autoregressive terms (AR order), *d*, the number of nonseasonal differences (differencing order), and *q*, the number of moving-average terms (MA order). One method to select these values for the ARIMA model is by using the *auto_arima* function from the *pmdarima* package. This machine learning approach chooses values in such a way that the Akaike Information Criterion (AIC) score is minimized. We can store this model as a variable for future reference. Another method that is more complex and subjective involves differencing the data to determine the *d* parameter and then generating autocorrelation (ACF) and partial autocorrelation (PACF) plots to determine the *q* and *p* parameters, respectively. We will explore this method shortly.

The ARIMA model, among other models such as linear regression, assumes that the data is stationary, meaning that the data and its variance should not be a function of time. In other words, the dependent values of an observation should not depend on when it is observed. By removing any obvious correlation and collinearity within past data, we can ensure that the data will have the same behavior at some later point in time and is therefore predictable. We can determine whether or not our data is stationary by running an Augmented Dicky-Fuller (ADF) Test from the *statsmodels* package. For instance, we ran the test on the daily closing price for our selected stocks. Since the p-value in each output was far greater than the threshold of 0.05, we cannot reject the null hypothesis of the test, which concludes the data is nonstationary. We would expect this data to be nonstationary as stock prices have naturally changed over time, and there would be no trend to predict if this was not the case. If we were to continue using this data without transformation, we would most likely run into bias within our results. A simple method to make the data stationary involves taking the log of one of the dependent variables (we performed this operation on the daily adjusted closing price of the stock). This lowers the rate at which the dependent variable changes, removing any signs of correlations within the data. Another method which is more necessary for determining the ARIMA parameters is differencing the data. This involves taking the difference between the dependent values of the two data points adjacent to each point. This value then becomes the new value of the dependent variable. We can graph these new values as “first-order differencing.” Differencing can be iterated on the same data multiple times if necessary, which would allow plots for “second-order differencing,” “third-order differencing,” and so on.

When the ADF test was run again after first-order differencing, the p-value was slightly below 0.05, indicating the time series had become more stationary than with the original data. The stationary nature could be further enhanced by applying second-order differencing. We could further confirm that our data is stationary by plotting the rolling mean and standard deviation. This meant taking the mean of the dependent values of a certain number of data points before each point and recording this mean as the new dependent value (shown in Figure 3). After second-order differencing was applied, the ADF test generated p-values well below 0.05 for each of the stocks. Therefore, we were safe to assume that this data was now stationary and that a value of 2 for the *d* parameter was acceptable for each stock. There were other methods that could be implemented to make the data stationary, and although they made the data more stationary than the original, they performed worse than taking the log of the dependent variable and then differencing.

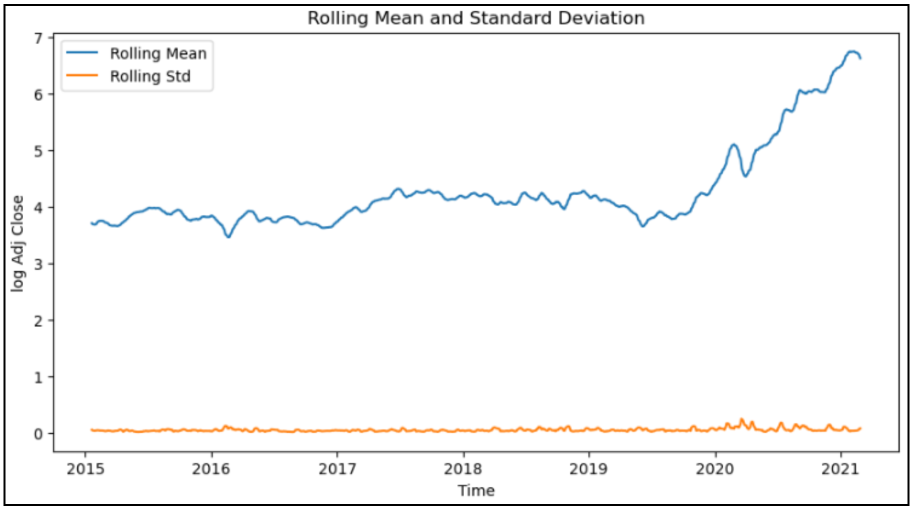


Figure 3: Rolling Mean and Standard Dev. of the Transformed Data for TSLA

Once a time series has been made stationary by differencing, we will need to split the data into training and testing datasets. The training dataset will be used to prepare the ARIMA model and generate a prediction. The testing dataset, which is much smaller than the training dataset, will be the part of the data that we will try to predict. The size of our testing dataset, with dates ranging from October 2020 to February 2021, is about 7 percent of the size of our training dataset, which ranges back to the beginning of 2015 (shown below).

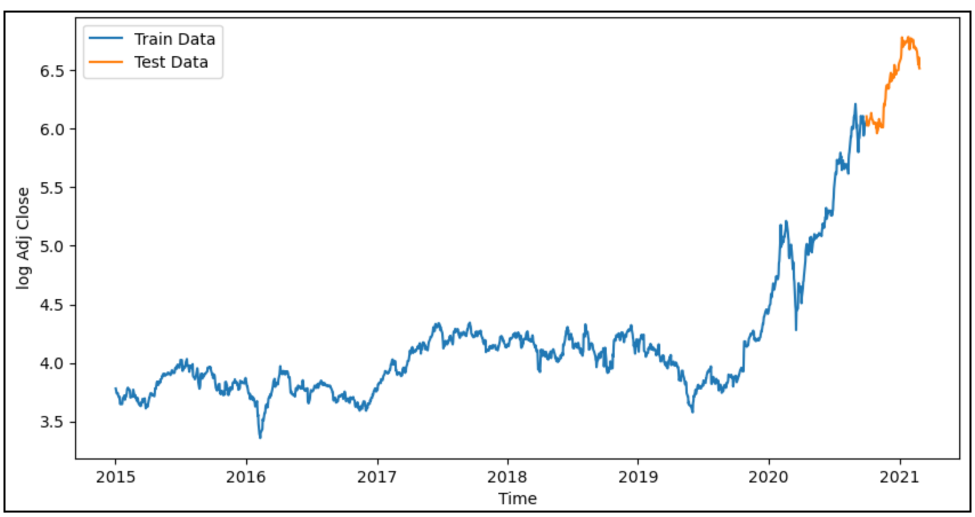
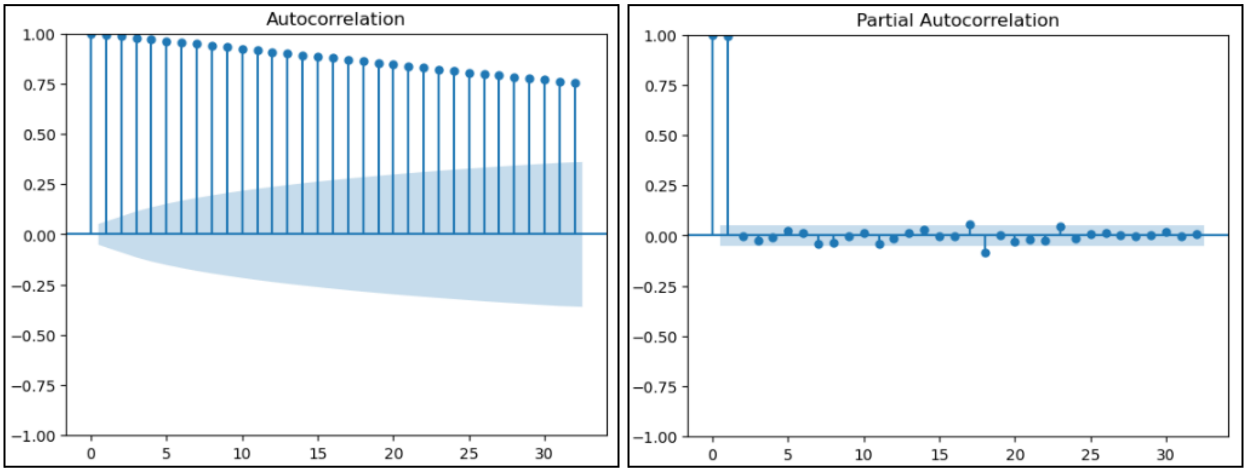


Figure 4: The Train and Test Data for TSLA

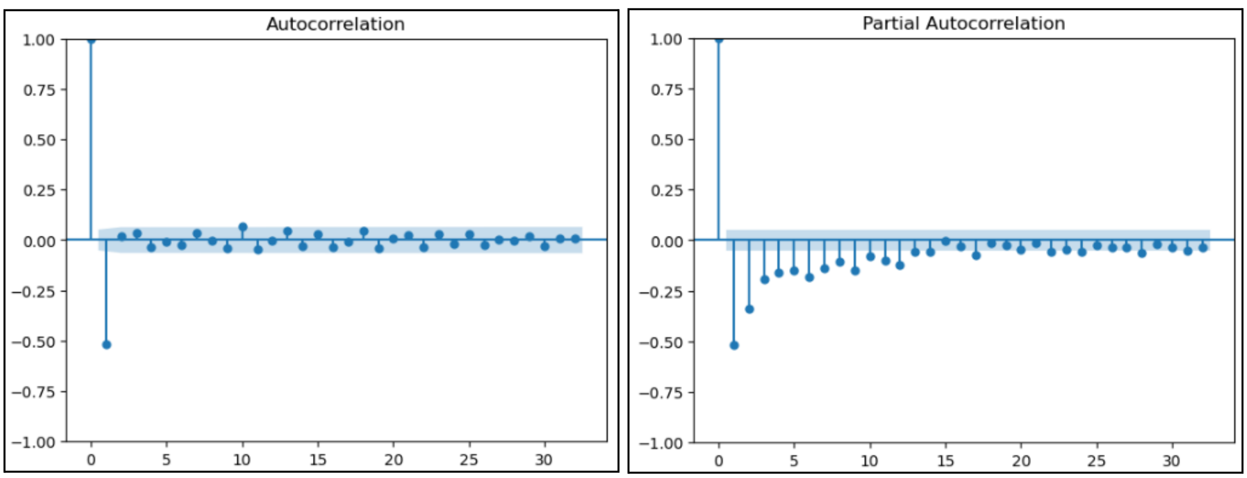
The next step in fitting the ARIMA model is to determine the *p* and *q* parameters. Of course, we could use the *auto_arima* function that was discussed earlier to determine these values, or we could also test various combinations of *p* and *q* values and see what works best. However, observing the autocorrelation function (ACF) and partial autocorrelation (PACF) plots is probably the most systematic (if not accurate) method. With these plots generated from the *statsmodels* package, we can tentatively identify the values of AR and/or MA terms that are needed. They calculate the mean correlation between points that are a certain number of lags apart, with the number of lags being the independent variable. A lag refers to the time period between each point in the original data, with two adjacent points being one lag apart, for example.

Shown in Figures 5-6, Both the ACF and PACF plots start at a lag value of 0, which always has a correlation value (the dependent variable) of 1. This is because we are essentially calculating the correlation between identical points at this stage. With a lag value of 1, we can determine the relation between adjacent observations and whether or not this relation is significant. The ACF and PACF plots can differ starting at the lag value of 2. This is because the ACF takes into account indirect correlations from previous lags in the calculation. The PACF, meanwhile, does not consider the common correlation involving data points that are between the points being evaluated (lower-order lags). Therefore, the PACF is expected to decay much faster. A region that depicts the 95% confidence interval for correlation is displayed within each plot. Correlation values are deemed statistically close to zero if they fall inside this region. Whether or not certain points fall within the confidence interval will determine our prediction for the *p* and *q* parameters.

The PACF plot is used to estimate the *p* parameter. We can take the order of the AR term to be equal to the number of a lag that is outside the 95% confidence interval. By selecting a lag in this manner, we are implying that the selected lag explains the autocorrelations of all lags of a higher order (number), most of which we are assuming are within the confidence interval. We can do the same for the ACF plot to estimate the *q* parameter and take the order of the MA term.



Figures 5A-B: ACF and PACF plots of Transformed Data for TSLA Before Differencing



Figures 6A-B: ACF and PACF plots of Transformed Data for TSLA After 2nd Order Differencing

The ARIMA model can be constructed with the *p*, *d*, and *q* parameters that were determined by the *auto_arima* function or with the ACF and PACF plots. Going back to *auto_arima*, the function outputs the ARIMA model with the parameters that minimize the Akaike Information Criterion (AIC) score. We can feed these parameters along with our data into the *ARIMA* function from the *statsmodels* package, which will return a trained model used for evaluation and inference. This process can be repeated with the parameters determined by the

ACF and PACF plots, or for the sake of experimentation and adjusting the AIC score, parameters of our own choosing as long as they are positive integers. The model summary accepts and displays the parameters in the form (p, d, q) and will provide several measures that can evaluate the performance of the model. A number of coefficient values equal to the value of the p and q parameters are also provided for each. For instance, if the value of the p parameter was 2, there would be two coefficient values provided in the model for that parameter, as shown in Fig. 7.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:          log Adj Close   No. Observations:                 1447
Model:                 ARIMA(5, 2, 2)   Log Likelihood                2810.889
Date:                Sat, 26 Nov 2022   AIC                          -5605.778
Time:                        02:26:42   BIC                          -5563.571
Sample:                             0   HQIC                         -5590.025
                               - 1447
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.8604      0.453     -1.900      0.057      -1.748       0.027
ar.L2          0.0428      0.022      1.924      0.054      -0.001       0.086
ar.L3          0.0678      0.028      2.452      0.014       0.014       0.122
ar.L4         -0.0097      0.032     -0.303      0.762      -0.073       0.053
ar.L5         -0.0379      0.022     -1.690      0.091      -0.082       0.006
ma.L1         -0.1355      0.451     -0.301      0.764      -1.019       0.748
ma.L2         -0.8563      0.449     -1.907      0.057      -1.737       0.024
sigma2         0.0012   2.38e-05     50.244      0.000       0.001       0.001
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):              2690.67
Prob(Q):                              0.92   Prob(JB):                         0.00
Heteroskedasticity (H):               3.41   Skew:                            -0.29
Prob(H) (two-sided):                  0.00   Kurtosis:                         9.66
===================================================================================
```

Figure 7: Example of ARIMA Model Output for TSLA

These coefficients are taken into account when the *forecast()* function from the *statsmodels* package is run. This function generates predictions for the dependent variable for the timespan of the test data. The output is stored as a series of values which we can convert into a two-column *pandas* dataframe. We can plot our predictions along with the train and test data to compare them visually, reverting any transformations done on the data if necessary by applying the inverse of those transformations. Once the train, test, and predictions data have been plotted together on the correct scale, we can calculate the root mean squared error (RMSE) of the prediction data and repeat this process for other combinations of the *p*, *d*, and *q* parameters. A smaller RMSE indicates that the prediction data aligns better with the test data, therefore we will want to compare RMSE values associated with various parameter combinations, including the ones calculated by the *auto_arima* function as well as the ACF and PACF plots.

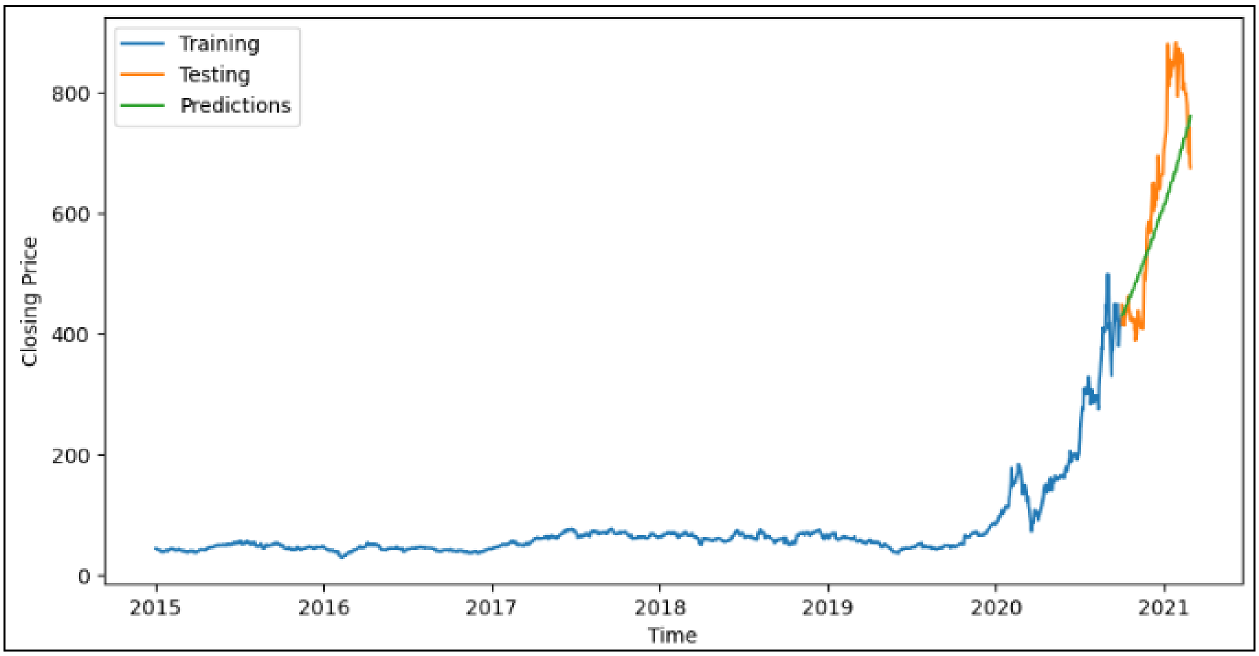


Figure 8A: TSLA Model Prediction with Parameters (5, 2, 2)

We can objectively compare the results taken from our prediction dataframe with the original test data. From the example in Figure 8A (in which the prediction data used the parameters suggested by the *auto_arima* function), we can observe that the prediction data follows the overall trend of the test data. The root mean square error (RMSE) provided by this prediction data was determined to be 102.60. When using the parameters suggested by the ACF and PACF plots instead, the prediction data also followed a positive trend. However, some of the predicted values strayed beyond the range of the dependent values of the test data. Furthermore, the RMSE of this data was calculated to be greater than the previously mentioned RMSE.

Therefore, we can conclude that the *auto_arima* function offers a better model prediction for the Tesla (TSLA) stock. In this case, the prediction was accurate enough to the point that further experimentation with combinations of parameters was not necessary. This would be done with data involving other stocks where the model predictions offered by both of the two previously discussed methods were inadequate.

The similar practices are performed to the stock price data of APPLE, Google, Microsoft, Amazon, Gamestop, Costco, GE and the corresponding best results are shown in Figs. 8B-8H.

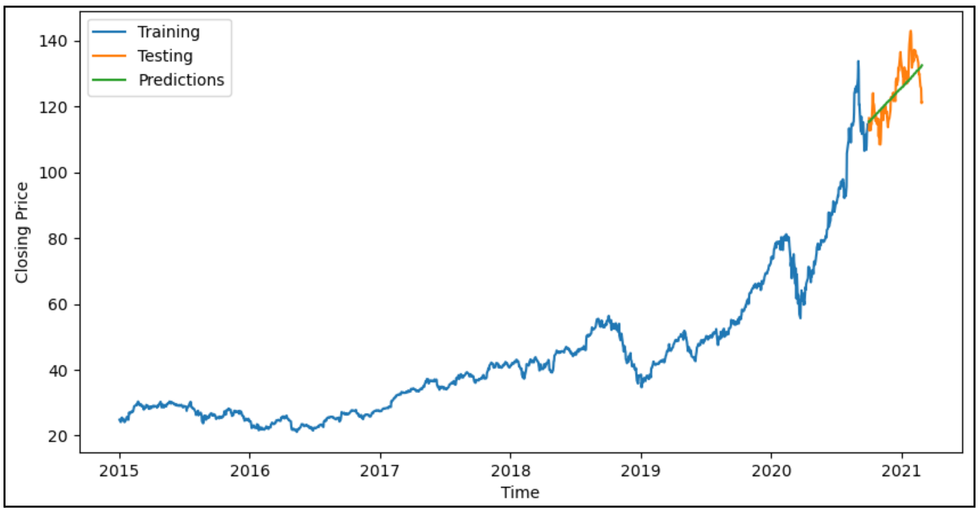


Figure 8B: APPL Model Prediction with Parameters (2, 2, 2)

Figure 8C: GOOG Model Prediction with Parameters (2, 2, 0)

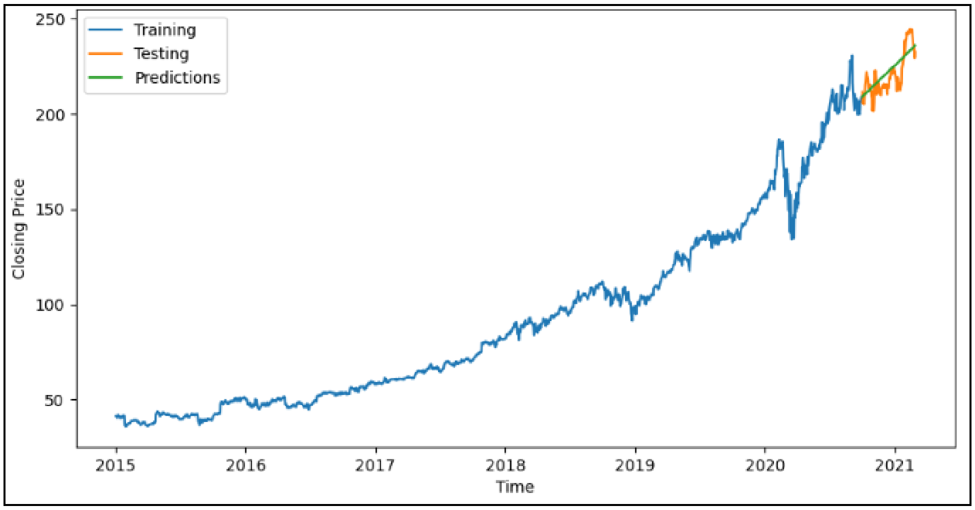


Figure 8D: MSFT Model Prediction with Parameters (2, 2, 2)

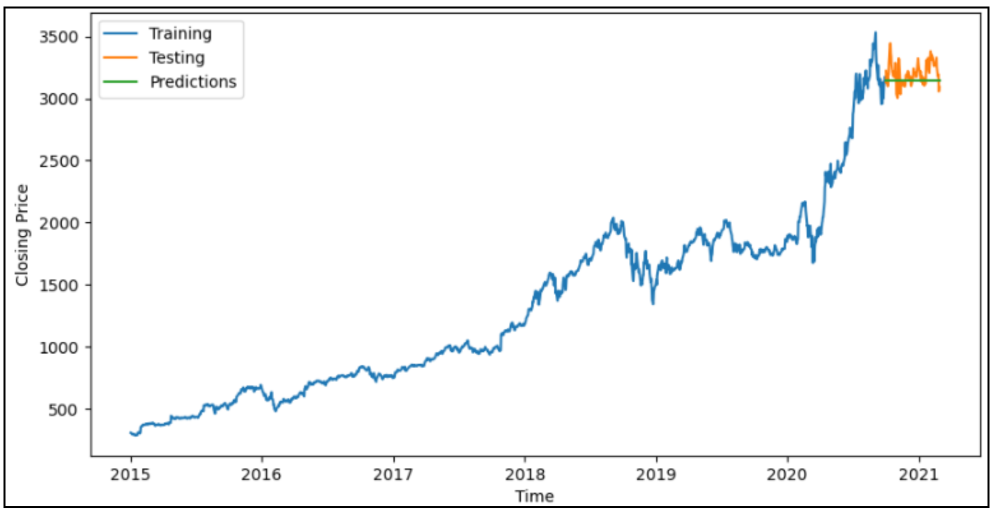


Figure 8E: AMZN Model Prediction with Parameters (0, 1, 0)

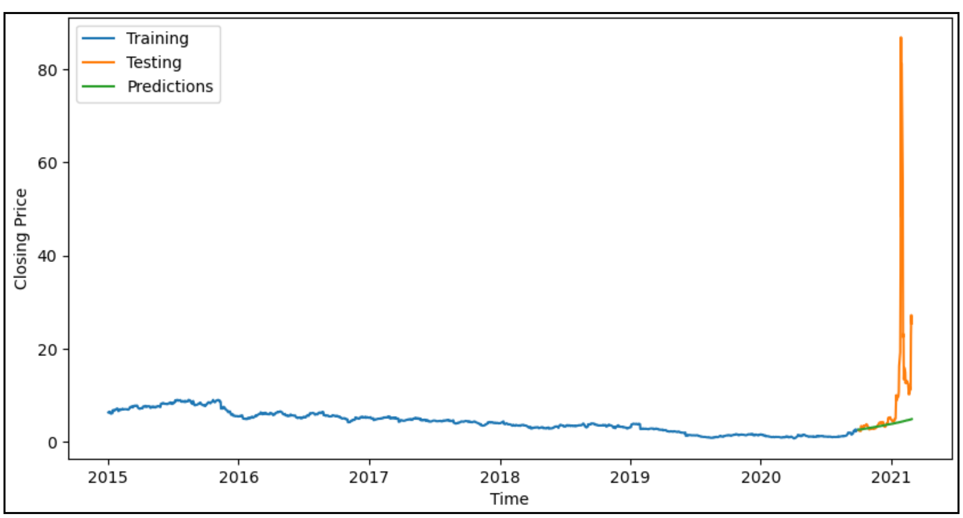


Figure 8F: GME Model Prediction with Parameters (5, 2, 2)

Figure 8G: COST Model Prediction with Parameters (2, 2, 2)

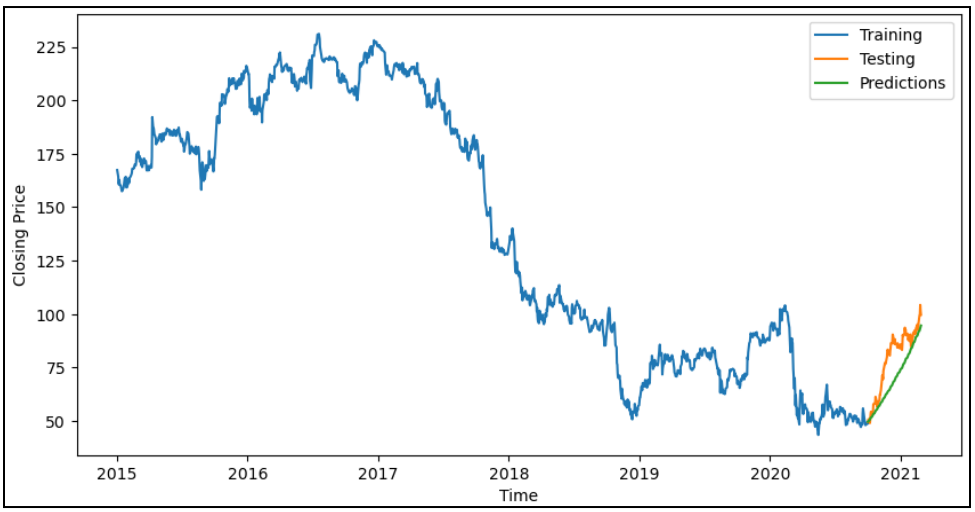


Figure 8H: GE Model Prediction with Parameters (2, 2, 0)

ANALYTICAL METHODS - LSTM MODEL AND RESULTS

The LSTM model is an artificial Recurrent Neural Network (RNN) used in deep learning that can process entire sequences of data. The model has become a trending approach to time series forecasting. RNNs typically have short term memory, persistently using previous information in the current neural network. They can frequently experience a loss of information due to the repeated use of the Recurrent Weight Matrix (RWM). This is sometimes referred to as the “Vanishing Gradient Problem.”

Other time series forecasting models can predict future values based on previous, sequential data using the LSTM model. This provides greater accuracy for demand forecasters which can result in better decision making for the business. The model provides nonlinear forecasts but requires more computation than other RNNs. This is mainly due to the additional parameters used for demand forecasts. Advanced theory on the LSTM model will not be provided in this study. We have instead described the major steps of the modeling process and visually presented the model results (shown below). The model generates a prediction over the test data in a similar manner to the ARIMA model. The corresponding results are shown in Figs. 9A-9H, which provided much more details of the trend of the stock price.

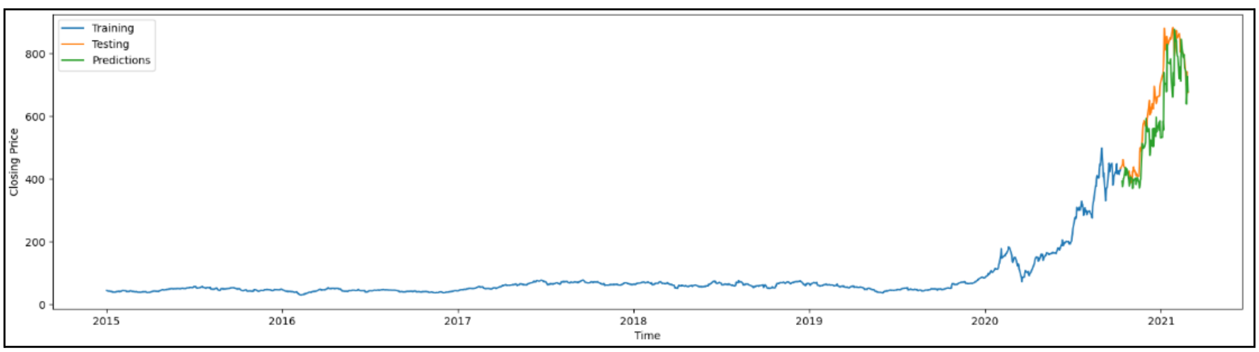


Figure 9A: TSLA LSTM Model Prediction

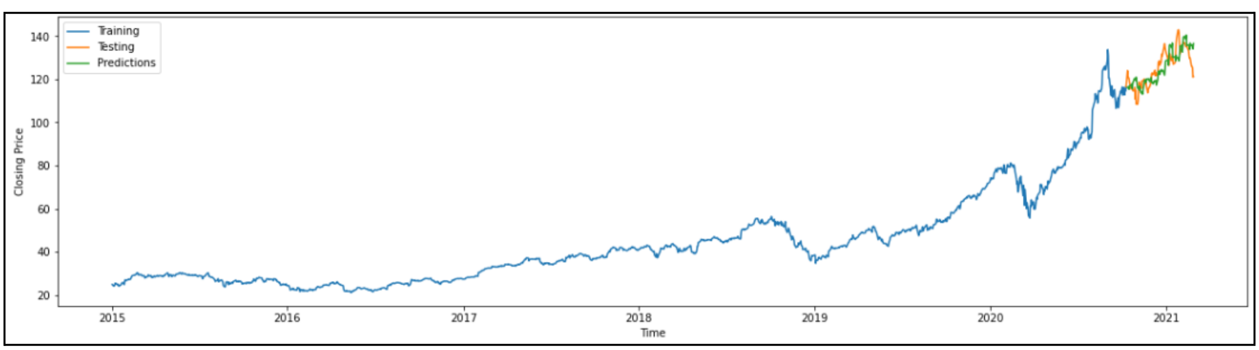


Figure 9B: AAPL LSTM Model Prediction

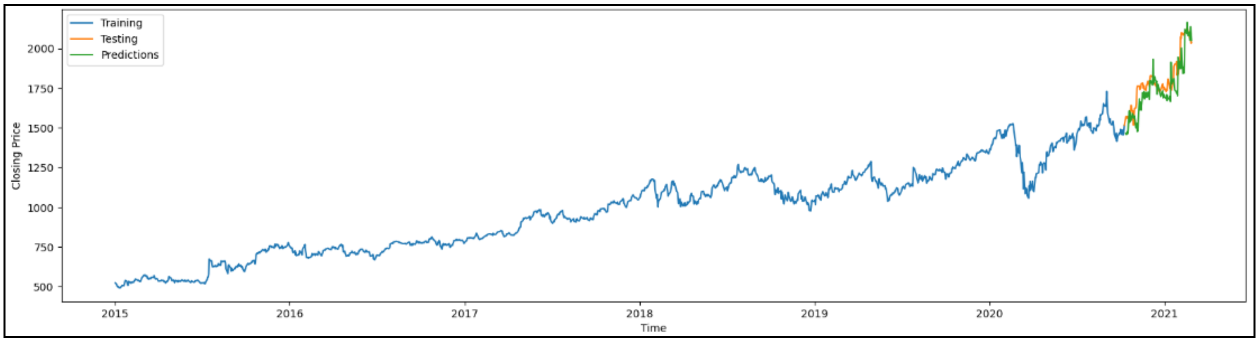


Figure 9C: GOOG LSTM Model Prediction

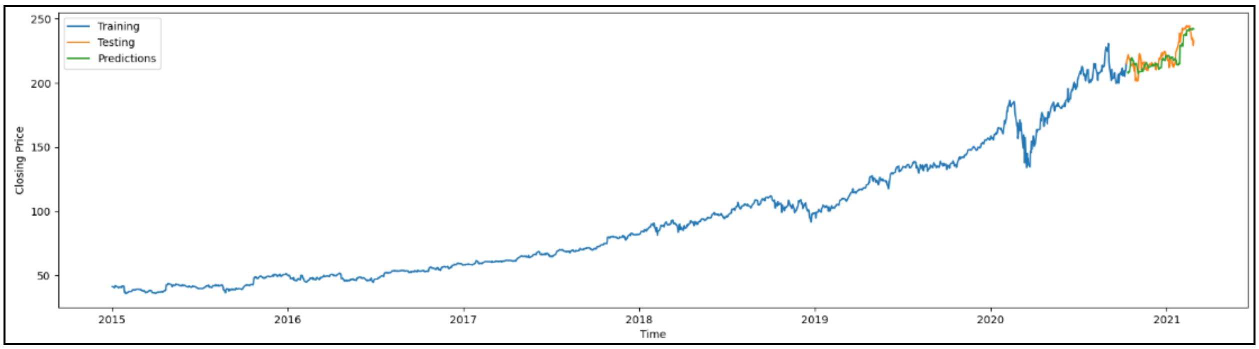


Figure 9D: MSFT LSTM Model Prediction

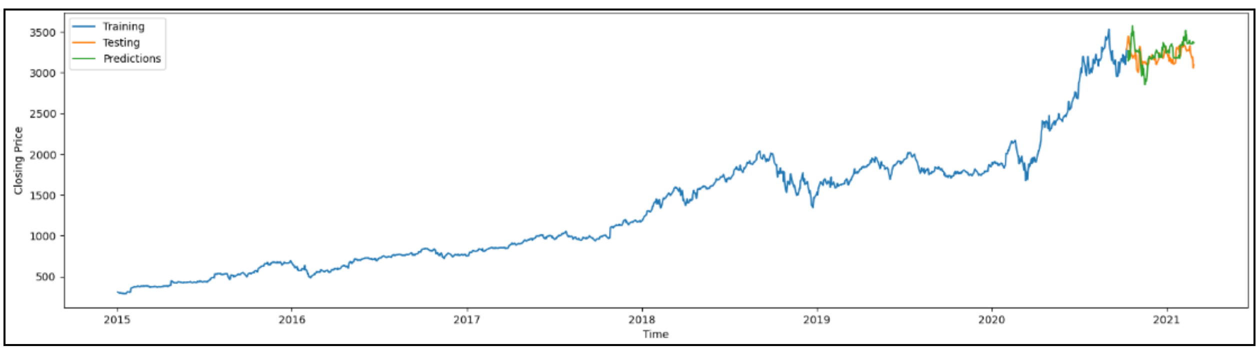


Figure 9E: AMZN LSTM Model Prediction

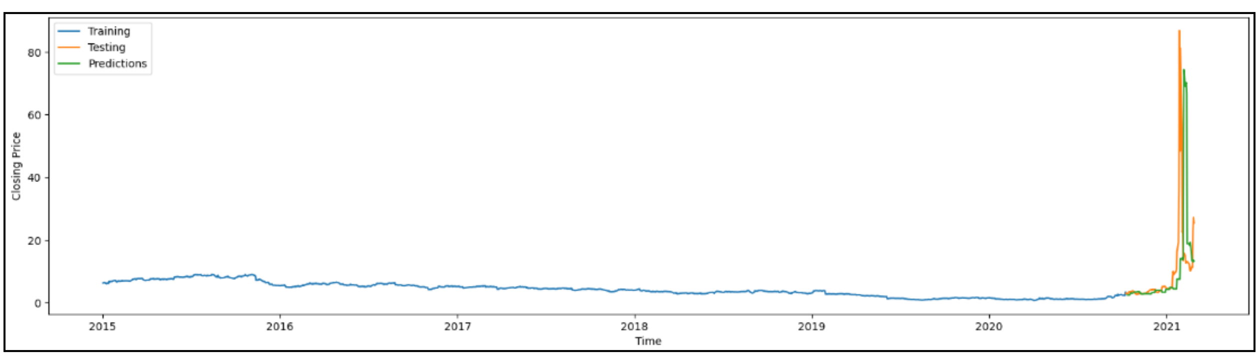


Figure 9F: GME LSTM Model Prediction

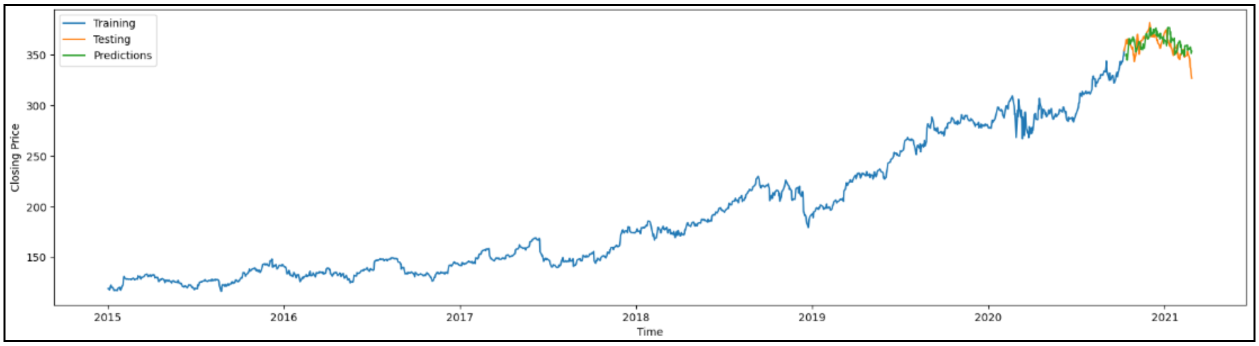


Figure 9G: COST LSTM Model Prediction

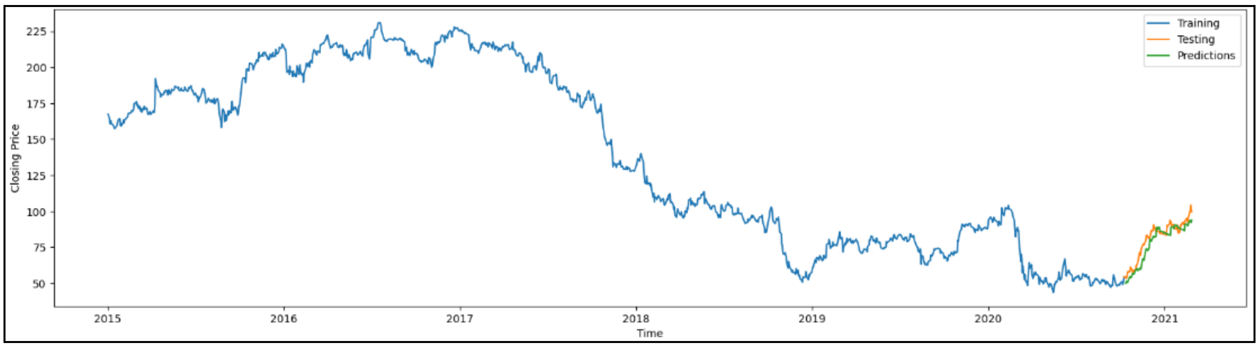


Figure 9H: GE LSTM Model Prediction

DISCUSSION

In summary, the ARIMA model is a statistical technique that can be used to forecast time series data. It is a linear model. The LSTM could predict the nonlinear relationship for forecasting. It can predict the trend more accurately. The RMSE results for eight stocks are summarized in Table 1 from both ARIMA and LSTM models. However the LSTM approach requires more computation than other recurrent neural networks. The main reason is that it has more parameters, which are used for demand forecasts. Both techniques can be effective and valuable to investigate trends in stock market prices over large periods of time and provide some important information for investors to make decisions when investing in the stock market.

Table I: The Root Mean Square Errors (RMSEs) for Model Predictions

Stock	RMSE (ARIMA)	RMSE (LSTM)
TSLA	102.60	65.14
APPL	5.40	4.69
GOOG	80.69	70.76
MSFT	7.32	5.87
AMZN	105.70	154.76
GME	14.59	14.05
COST	16.44	8.44
GE	11.17	5.21

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