DAYANANDA SAGAR UNIVERSITY
SCHOOL OF ENGINEERING

VISUALIZATION AND FORECASTING OF STOCKS USING HISTORICAL DATA

Implementation On Model

Implementation

Code

```
from keras.models import Sequential
from keras.layers import Dense, LSTM

# Build the LSTM model
model = Sequential()
model.add(LSTM(128, return_sequences=True,
input_shape= (x_train.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))
# Compile the model
model.compile(optimizer='adam',
loss='mean_squared_error')
# Train the model
model.fit(x_train, y_train, batch_size=1, epochs=1)
```

```
# Create the testing data set
test_data = scaled_data[training_data_len - 60: , :]
# Create the data sets x_test and y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])
# Convert the data to a numpy array
x_test = np.array(x_test)
# Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0],
x_test.shape[1], 1 ))
# Get the models predicted price values
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
# Get the root mean squared error (RMSE)
rmse = np.sqrt(np.mean(((predictions - y_test) ** 2)))
```

Result Analysis

Online Stock Dataset - APPLE(AAPL)

Date	Open	High	Low	Close	Adj Close	Volume	company_name
2021-06-01	125.080002	125.349998	123.940002	124.279999	123.573990	67637100	APPLE
2021-06-02	124.279999	125.239998	124.050003	125.059998	124.349556	59278900	APPLE
2021-06-03	124.680000	124.849998	123.129997	123.540001	122.838203	76229200	APPLE
2021-06-04	124.070000	126.160004	123.849998	125.889999	125.174850	75169300	APPLE
2021-06-07	126.169998	126.320000	124.830002	125.900002	125.184792	71057600	APPLE
...	...	...	...	...	...	...	...
2022-05-23	137.789993	143.259995	137.649994	143.110001	143.110001	117726300	APPLE
2022-05-24	140.809998	141.970001	137.330002	140.360001	140.360001	104132700	APPLE
2022-05-25	138.429993	141.789993	138.339996	140.520004	140.520004	92482700	APPLE
2022-05-26	137.389999	144.339996	137.139999	143.779999	143.779999	90601500	APPLE
2022-05-27	145.389999	149.679993	145.259995	149.639999	149.639999	90796900	APPLE

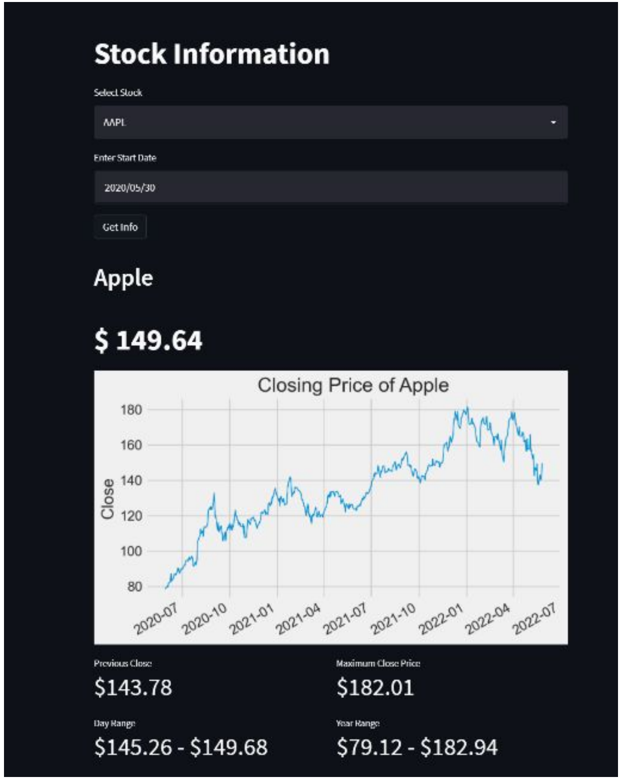
Summary statistics of attributes of Training Dataset

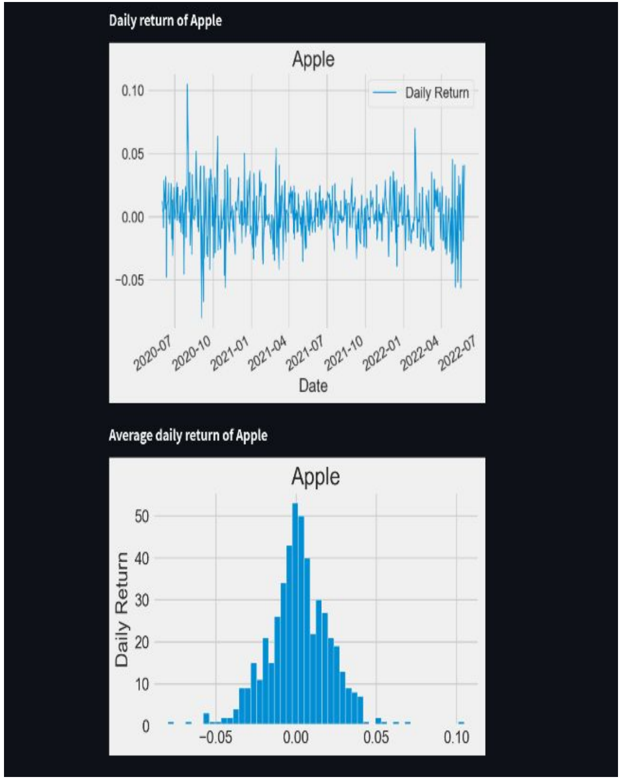
	Open	High	Low	Close	Adj Close	Volume
count	252.000000	252.000000	252.000000	252.000000	252.000000	2.520000e+02
mean	155.075357	156.930318	153.398968	155.263849	154.786610	8.883695e+07
std	14.100912	14.344764	13.723100	13.987362	14.096246	2.679411e+07
min	124.070000	124.849998	123.129997	123.540001	122.838203	4.100000e+07
25%	145.514999	147.052502	144.419998	145.857502	145.246201	6.955788e+07
50%	152.235001	154.675003	150.510002	152.284996	151.900703	8.489835e+07
75%	167.607498	169.727493	165.512501	166.727497	166.482895	1.035052e+08
max	182.630005	182.940002	179.119995	182.009995	181.511703	1.954327e+08

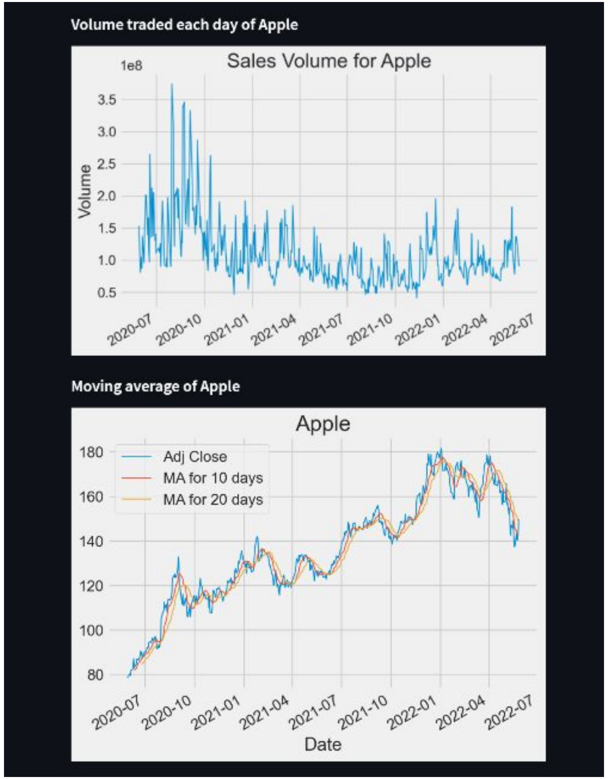
Summary statistics of LSTM Model

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 128)           66560

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 25)                1625

 dense_1 (Dense)             (None, 1)                 26

=================================================================
Total params: 117,619
Trainable params: 117,619
Non-trainable params: 0
```

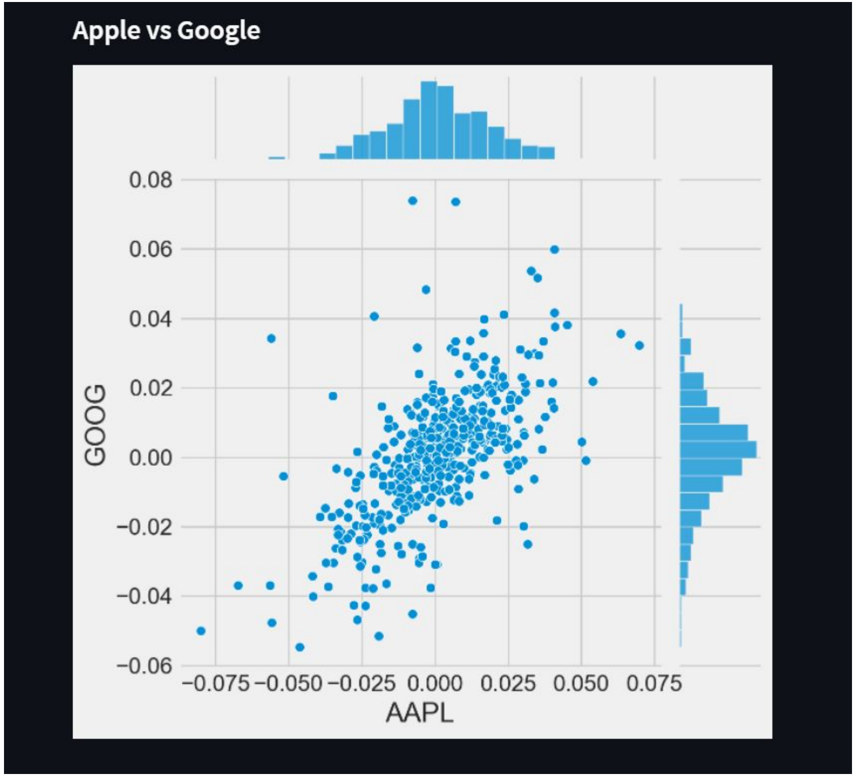
Stock Information Page







Stocks Comparing Page



Forecast Stock Page

Forecast stock price

Select Stock

AAPL

Enter Start Date

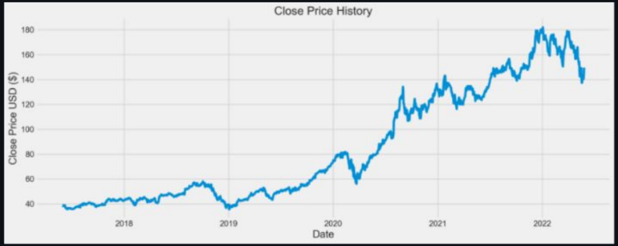
2017/05/31

Forecast

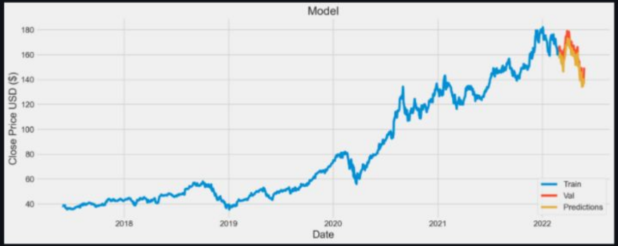
Apple Dataset

	High	Low	Open	Close	Volume
2017-05-30T00:00:00	38.6075	38.3325	38.3550	38.4175	80,507,600.0000
2017-05-31T00:00:00	38.5425	38.0950	38.4925	38.1900	97,804,800.0000
2017-06-01T00:00:00	38.3325	38.0550	38.2925	38.2950	65,616,400.0000
2017-06-02T00:00:00	38.8625	38.2225	38.3950	38.8625	111,082,800.0000
2017-06-05T00:00:00	38.6125	38.3650	38.5850	38.4825	101,326,800.0000
2017-06-06T00:00:00	38.9525	38.4450	38.4750	38.6125	106,499,600.0000
2017-06-07T00:00:00	38.9950	38.6200	38.7550	38.8425	84,278,400.0000
2017-06-08T00:00:00	38.8850	38.6000	38.8125	38.7475	85,003,200.0000
2017-06-09T00:00:00	38.7975	36.5050	38.7975	37.2450	259,530,800.0000
2017-06-12T00:00:00	36.5225	35.6275	36.4350	36.3550	289,229,200.0000

Close Price History



Predicted Close Price



	Close	Predictions
2022-03-01T00:00:00	163.2000	159.73947143554688
2022-03-02T00:00:00	166.5600	157.68978881835938
2022-03-03T00:00:00	166.2300	161.47586059570312
2022-03-04T00:00:00	163.1700	160.48129272460938
2022-03-07T00:00:00	159.3000	157.46168518066406
2022-03-08T00:00:00	157.4400	154.13502502441406
2022-03-09T00:00:00	162.9500	152.90823364257812
2022-03-10T00:00:00	158.5200	158.7203826904297
2022-03-11T00:00:00	154.7300	153.14845275878906
2022-03-14T00:00:00	150.6200	150.04893493652344

Testing

Stock Information Testing

	Input	Expected Output ($)			Actual Output ($)			Status
Sl NO.:	Stocks Name	Closed Price	Max. Close	Day Range	Closed Price	Max. Close	Day Range	
1	AAPL	149.64	182.01	145.26-149.68	149.64	182.01	145.26-149.68	Pass
2	GOOG	2255.98	3014.18	2191.0-2257.36	2255.98	3014.18	2191.0-2257.36	Pass
3	MSFT	273.24	343.11	267.56-273.34	273.24	343.11	267.56-273.34	Pass
4	AMZN	2302.93	3731.41	2252.56-2303.74	2302.93	3731.41	2252.56-2303.74	Pass
5	TSLA	759.63	1229.91	720.53-759.8	759.63	1229.91	720.53-759.8	Pass
6	FB	195.13	382.18	189.8-195.33	195.13	382.18	189.8-195.33	Pass

Conclusion

Conclusion

We've discovered that machine learning can be used to anticipate and compare stock market prices. The result demonstrates how historical data may be used to anticipate stock movement with fair accuracy, but the technique chosen is dependent on the factors required, such as time, variance, and mean accuracy. The LSTM is a superior choice if high accuracy and low variation are required, but it is also slower. Backpropagation is preferable if high speed and accuracy are required. We've included seven criteria (Date, Open, Close, High, Low, Adj Close, Volume) that influence stock performance in this implementation. A better degree of accuracy can be attained if a larger number of factors are employed, and the data is preprocessed and filtered properly before being used to train the network model.

THANK YOU