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MSc Data Science Project

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Department of Physics, Astronomy and Mathematics

**Data Science FINAL PROJECT REPORT**

**Project Title:**

Predicting Daily Stock Close Price using Deep Learning Models

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DECLARATION STATEMENT

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in Data Science at the University of Hertfordshire.

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# Abstract

The stock price of a company is a volatile number and changes moment to moment depending on number of factors. People buy stocks and sell them at higher prices or when there is a loss predicted with holding the stock, to make profits. People trade stocks in different ways and for swing trading and position trading, the daily close price of a stock is a crucial feature determining the decision to hold the stock for next day. People use different methods to predict stock prices. The aim is to create prediction models that can predict stock close prices accurately. It is seen in the literature that machine learning is widely used to predict stock price. It is observed that neural networks perform better than the traditional machine learning methods for stock price prediction. After a detailed literature review and analysis, it is concluded that neural networks like LSTM, GRU and Bidirectional models are performing better with optimal training and computing. Six different deep learning models namely LSTM, LSTM with dropout layer, GRU, GRU with dropout layer, Bidirectional LSTM and Bidirectional GRU are created for predicting the next day stock close price. All these models are trained for different epochs between 20 to 150, different lookback periods of 10, 25 and 50, and the training data scaled using StandardScaler and MinMaxScaler.

British Petroleum (BP) stock data is used for training in different combinations for all models. BP, Shell plc (SHEL), Exxon Mobil Corporation (XOM) and Chevron Corporation (CVX) are used for testing all models’ predictions. 10 years data of all four stocks from 2nd February 2014 to 2nd February 2024 is used. The training and testing data is split with a ratio of 80:20 respectively. The models are used to predict next day close price of all four different stocks using test data and a further 30 days stock prices are forecasted. The predicted and forecasted stock prices are compared and evaluated with actual stock prices using MAPE and R2 score metrics. It is seen that the average MAPE for predictions from test data of all stocks is 2.06% and the MAPE ranged from 1.13% to 5.97%. The R2 score of test predictions ranged from -0.02 to 0.97. Bidirectional LSTM and Bidirectional GRU models performed better than the other models over all combinations and the MAPE values of these models ranged from 1.13% to 2.27%. The forecast made to predict the next day stock close prices is satisfactory, beyond a couple of days the predictions are capturing a huge error. The MAPE variation in all combinations of models for 15 days and 30 days forecasted stock price is 0.41% to 21.07% and 0.77% to 42.26% respectively. It is also observed that the MAPE values from models trained with MinMaxScaler scaled data ranged lower than the models trained with StandardScaler scaled data.

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# Introduction

The stock price is the price that it costs to own a share of a company. Stock Prices are listed on financial exchanges and enables the public to buy, sell or trade stocks. As per (Egan, 2024), the stock price is determined by the supply and demand of the stock. If the public is willing to buy the stock over the supply, the stock price normally rises. If the public is not willing to buy the stock or willing to sell the stock, the stock price typically fails. There are other factors that affects the stock price of listed stock in the exchanges such as company activity, state of the economy, inflation, interest rates, consumer spending, world events, major investors activity etc. With all these factors affecting the stock price, the price is very volatile and changes from moment to moment. These changes in stock price can be either a rise or a fall, which involves a risk to the investor.

The public buys stocks and sell them when the stock price rises which makes them a profit. With all the risk involved with the factors affecting the stock price, investors use stock market prediction methods to forecast the stock price to reduce their exposure to risk. Stock market prediction is broadly categorised into three main methods.

* fundamental analysis – which is a method concerned in finding the company stock price by evaluating the companies past performance and its credibility.
* technical analysis – analysing and forecasting stock prices using past market data, a form of time series analysis.
* machine learning – with advancements in technology, machine learning techniques like Artificial Neural Networks (ANN), Random Forests, Regression are used to predict the stock price.

Fundamental analysis requires more information about the company, while with technical analysis and machine learning we can utilize past market data to analyse and predict future stock price. It is said by (Thompson, 2023) that fundamental analysis uses tools such as financial statements, economic indicators, interest rates, news and events, and qualitative information etc. Technical analysis uses tools such as technical indicators, volume analysis, relative strength, chart pattern analysis, candlestick pattern analysis, support and resistance, trend analysis etc. It is said that fundamental analysis is used for long-term investments and is not adaptable for short-term stock movements. Technical analysis provides a visual way to assess the stock.

Machine learning is a vast field and has numerous methods and techniques to predict the unknown by training with the known data. Machine learning techniques like neural networks, SVM, regression, LSTM, RNN, KNN, random forests etc are used for stock market prediction. A recent study by (Latrisha, et al., 2023) concluded that, machine learning techniques like neural networks and LSTM networks are used more than other techniques for stock market prediction. However, all these methods and techniques use past market data. Yahoo! Finance provides the public with past market data which is good enough to implement stock market prediction methods.

Yahoo! Finance (Yahoo Inc., 1997), launched on 19th January 1997 provides us with the data needed for performing stock market prediction with financial analysis, technical analysis, and machine learning. Yahoo! Finance provides data such as finance news, stock quotes, livestock price changes, past stock price analytics and features such as portfolio tracking and watch lists. Yahoo! Finance provides us with all the necessary information regarding selected stock symbol and gives the first insight into trading the stock. Yahoo! Finance provides past stock market data with the features: Date, Open Price, High Price, Low Price, Close Price, Adjusted Close Price, and Volume of the selected stock. The stock can also be identified using symbols or tickers to access the past stock market data. For Shell plc, ‘SHEL’ is used as symbol or ticker for accessing the past stock market data in Yahoo! Finance. The Shell plc stock summary from Yahoo! Finance is presented in Figure 1.

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Figure 1: Shell plc. Stock summary (Yahoo Inc., 1997)

There are different ways of how people trade the stocks. For example,

* scalping – trading in very short intervals of time ranging from few seconds to minutes.
* day trading – trading within the same day.
* swing trading – trading between days, weeks, or few months.
* position trading – trading in the long-term, ranging from several months to years, a form of investment.

For swing trading and position trading, the closing price of the day is a decision-making feature for whether to hold the stock for the next trading day. In the view of swing trading and position trading, we decided to predict the closing price of the chosen stock accurately. Machine learning is preferred over other methods for predicting the stock market, so we chose to build machine learning models for predicting the close price of the given stock. It is seen that neural networks are most used for stock prediction and a thorough literature review is made.

# Literature Review

Neural networks like RNN, LSTM, GRU, and Bidirectional LSTM are the most used methods for stock price prediction. For understanding and gaining confidence about the methods and approaches to building the model and evaluate its performance, the following literature review was reviewed.

The review from (Chawalit, et al., 2018) speaks about Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM) and how they were applied to forecast the next day stock price. The results achieved were compared with those obtained by a hybrid model with a Deep Belief Network (DBN). The results were compared using metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). (Chawalit, et al., 2018) used different input features such as four inputs, five inputs and six inputs from Open Price, High Price, Low Price, Close Price, Volume, 3-day Simple Moving Average. The LSTM blocks used default sigmoid activation function while DBN used default ‘relu’ activation function. Both the networks are trained for 200 epochs with one look back and two look backs. The network is trained with data from the past 1 year, 3 years and 5 years. The average MAPE for the test data is less than 2% for all the stocks with different lengths of training data. The MAPE variation with test data is visualized and presented in Figure 2. It is said that LSTM provides reliable performance for low volatile stocks and the DBN gives better result for high volatile stocks.

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Figure 2: Box Plot Comparisons of MAPE (Chawalit, et al., 2018)

While (Chawalit, et al., 2018) built models using LSTM blocks and DBN blocks to compare their performance in predicting the stock price, we can see (Mohammad, et al., 2018) proposed a hybrid model with a combination of LSTM and Gated Recurrent Unit (GRU). (Mohammad, et al., 2018) used around 66 years of data, out of which 80% of the data is used for training and 20% is used for evaluating the model. The data have been scaled using ‘MinMaxScaler’ and for training (Mohammad, et al., 2018) used the Adam Optimizer with the learning rate set to 0.001 and trained for 20 epochs. The model performs better with a dropout layer and achieved a 0.00098 MSE. The MAPE of (Mohammad, et al., 2018) proposed model is 4.13% which is reasonably good but is not preferred when compared with (Chawalit, et al., 2018). Tabulated metrics are presented in Figure 3.

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Figure 3: Tabulated Metrics of different models (Mohammad, et al., 2018)

Looking at (Almusawi, et al., 2023), a set of optimizing algorithms were used to optimize the LSTM model to increase the accuracy of stock price prediction. The MAPE of the models that were optimized using the algorithms are less than 1%. These values are too good to be true and it is thought that the proposed model with Improved Artificial Optimization Algorithm (IARO) overcame limitations such as distortion in price prediction and was able to predict non-volatile stock entities. (Almusawi, et al., 2023) performed Principal Component Analysis (PCA) to extract the features of the data. For evaluating the performance of the models MSE, MAPE, Mean Absolute Error (MAE) and Coefficient of Determination (R2 score) have been used.

Like (Chawalit, et al., 2018), (Bathla, 2020) did similar work comparing LSTM with Support Vector Regression (SVR) and it is seen that the MAPE for all the selected stocks is less than 2% for LSTM. MAPE values achieved by SVR model is close to the LSTM model MAPE values, but relatively higher which makes LSTM model more accurate and efficient. The MAPE variation is tabulated and can be seen in Figure 4. Stock data of about 4 years is used for the LSTM blocks, default sigmoid activation and a dropout of 0.2 has been used with a window size of 30 days. Furthermore, Adam optimizer is used while training. The LSTM model is built with 7 hidden layers and the model is trained for 100 epochs.

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Figure 4: MAPE variation between LSTM and SVR models (Bathla, 2020)

(Pushpendra, et al., 2022) proposed an LSTM model using a dropout layer after each LSTM block, which gave an accuracy of 83%. The model is trained on the Nifty50 index and evaluated on 10 stocks from the Nifty50 index. The ratio of train and test data is 75:25, respectively. Data from 10th December 2011 to 10th December 2021 is used for this study, which is a span of 10 years. (Pushpendra, et al., 2022) used the data normalization technique to scale the values to between 0 to 1. Adam optimizer is used for compiling the model and the model is trained on 25 epochs. The metrics used to evaluate the model are MSE, RMSE, MAE, MAPE and Accuracy. A total of 4 hidden LSTM layers are used and total number of parameters of the model are about 71,051.

(Yonten, et al., 2023) performed comparative analysis on four models built using LSTM, Bi-LSTM, Conv LSTM and GRU layers. Data from 23rd April 2020 to 15th July 2022 is used for this study. Train and test data is split into 65:35 ratio, respectively. All 4 models built used data with 10 look backs and trained for 200 epochs. Different activations such as elu, relu and selu are used for the deep learning layers with a combination of optimizers such as adam, adamax and nadam. Metrics used in this study to evaluate the performance of the models are RMSE, MAE and R2. It is concluded that Bi-LSTM model with relu activation and Nadam optimizer is the best combination and best performed model with lowest MAE of 9.53 when compared with other models and combinations. The models are evaluated on the forecast of the stock price for the next 15 days.

(Karim & Ahmed, 2021) proposed a Bidirectional GRU model and compared with a traditional Bidirectional LSTM model. Three different stocks from Nifty50 are used to implement this comparative analysis. Five different metrics namely MSE, RMSE, MAE, MSLE and R2 are used to evaluate both the models. The models are built with 1, 2 and 3 hidden layers and evaluated, respectively. A window size of 60 and a learning rate of 0.001 is used and the models are trained for 100 iterations. The train and test data are split into 80:20 ratio, respectively. The Closing Price is the feature used to evaluate the models. MinMaxScaler function is used to normalize the stock price data between 0 and 1. It can be seen by the results that the Bidirectional GRU model is performing better than Bidirectional LSTM model in forecasting the stock prices. It is said that the Bidirectional GRU model can accurately predict the stock price for the next 1000 days with near zero deviation. The Bidirectional GRU model forecasts the sudden drop or rise in the stock price accurately.

(Jia, et al., 2019) built a Bidirectional LSTM model and compared with the LSTM model with same set of parameters. Dropout layers are used to prevent the model from over fitting. Both the models are evaluated using RMSE, MAE. Different Dropout frequencies are used while building the models. GREE stock price data from 1st January 2017 to 14th May 2019, is used in this study. Preprocessing techniques like normalization and standardization are conducted. Looking at the metrics, the two-way LSTM or Bidirectional LSTM model is better than LSTM model. Looking at the results against the Dropout frequencies, the RMSE, MAE and Loss are increasing with increasing Dropout frequency.

(Ali, et al., 2014) performed a comparative study between Auto Regressive Integral Moving Average (ARIMA) and Artificial Neural Networks (ANN) for predicting stock price of Dell Inc. from the New York Stock Exchange. Feature chosen for prediction is Closing Price of the selected stock data. Data from 17th August 1988 to 25th February 2011 is used for this study, roughly 33 years. The ANN model consisting of 10 input neurons, 17 hidden neurons and 1 output neuron is the most accurate model for stock price prediction. Both ARIMA and ANN models have relatively close accuracy. But ANN gives less error for the forecasted price when compared with ARIMA. It is observed that the ARIMA model forecast pattern is directional.

(Istiake Sunny, et al., 2020) performed a simulation study between LSTM and Bidirectional LSTM model with a different combination of epochs, hidden layers, dense layers, and varying units. Google stock data from 19th August 2004 to 4th October 2019 is used for this study, nearly 15 years of data. The data is collected from yahoo finance. Train and test data are split into 88:12 ratio respectively. RMSE metric is used to evaluate the models in this study. ‘Relu’ is used as the activation function for the hidden layers. The models are trained from 10 to 250 epochs. Models are built with 2 and 4 hidden layers and hidden layer units as 64 or 128 and dense layer units as 16 and 1. It is seen that Bidirectional LSTM is performing well at 250 epochs while LSTM RMSE increased at 250 epochs. LSTM model with 2 hidden layers and 1 dense layer trained for 100 epochs gave good results among LSTM models. Bidirectional LSTM model formed with 2 hidden layers and 2 dense layers gave the lowest RMSE. It is seen that the increase in number of units in the hidden layers results in an increase in consuming the computing resources and time to train the model. The time consumed for training the model along with RMSE of LSTM and Bi-LSTM model is noted and can be seen in Figure 5.

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Figure 5: RMSE of LSTM and Bi-LSTM over epochs (Istiake Sunny, et al., 2020)

(Amini & Kalantari, 2024) proposed a hybrid model based on LSTM and Convolutional Neural Networks (CNN) layers to predict gold price and evaluated using metrics such as RMSE, RMAE and R2. The Gold price from 1978 to 2021, nearly 44 years is used for this study. The Closing Price feature from the selected data is used for this study. The model used Adam optimizer with learning rates chosen between 0.05, 0.005, 0.0005 and 0.00005. The lookback values are ranged from 1 to 40 with one step. The Dropout frequency is ranged between 0.1 to 0.9 with 0.1 step. 70% of the data is used for training the model and 20% of the data for validation and 10% of the data for testing. It is seen the proposed CNN-Bi-LSTM resulted in a high R2 score when compared with Stacked LSTM, CNN, CNN-LSTM and Convolutional LSTM. It is said that the lookback of 24 is the optimal for the proposed model. 0.0005 learning rate provided highest R2 score for the proposed model. The box plot of R2 variations can be seen in Figure 6.

A diagram of a graph

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Figure 6: Box plot of R2 Score variation of different models (Amini & Kalantari, 2024)

(Varadharajan, et al., 2024) built an LSTM-RNN model to predict the Amazon stock closing price with high accuracy. The data is split into training and testing data with 80:20 ratio respectively. The data is scaled using MinMaxScaler. A total of 27 combinations of models with parameters of epochs, neurons and batch size are made. The proposed LSTM-RNN model achieved MAPE of 1.84% and RMSE of 2.51 on the training set.

(Divy & Warish, 2023) proposed a method using Bi-LSTM model to predict Open High Low Close Volume (OHLCV) values of APPLE stock. The APPLE stock data listen on the NASDAQ stock market is collected from yahoo finance. The data is selected between 2013 and 2018. The train and test data are split into 75:25 ratio respectively. The data is scaled using MinMaxScaler from sklearn. The model used RMSProp optimizer and a learning rate of 0.001 and the loss function used is Mean Squared Error. Metrics used for evaluating the models are MAE, MSE and RMSE. The RMSE values of Bidirectional LSTM sequential and multitasking are less when compared with other models.

(Behura, et al., 2023) proposed a multi-layer LSTM model to predict stock price. TATA Consumer stock data from National Stock Exchange is used for this work. The data is selected from 1st January 2018 to 31st December 2022. The last 5 records of the selected data are used to test the model. The model is built to predict the closing price of the stock. The data is normalized for training the model. Lookback of 10 is used and the Adam optimizer is used, and the model is trained for 10 epochs. Relu activation is used and return\_sequences is enabled. 2, 3 and 4 hidden layers models were built and compared. It is said that the forecast gave high accuracy for only near future values and fails to predict the stock price for the next 30 or 60 days.

(Shah, et al., 2021) proposed a Bidirectional LSTM model to predict the stock closing price. Previous 6 years data of Tesla and Citi Bank are used for this study and the data is collected using yahoo finance. The models are trained for 80% of the data and tested on 20% data. The data is scaled using MinMaxScaler from scikit-learn. The model is trained for 200 epochs. The model training MAPE values are 1.669% and 0.445% for the Tesla and Citi Bank training data respectively. The model test MAPE values are 3.379% and 1.412% for Tesla and Citi Bank respectively. It is stated that the model with MAPE less than 10% is considered as a good model. The model test accuracy for Tesla is 0.96 and for Citi Bank is 0.98.

The above literature review is thoroughly done to understand and know the different machine learning and deep learning algorithms or methods implemented to predict stock price. It is seen there are different traditional ways apart from neural networks to predict the stock price. (Ali, et al., 2014) stated that the traditional ways are sensitive to the sudden drops and rise in the stock price and are directional in predicting the stock price. Different neural networks namely RNN, DBN, LSTM, GRU, Bi-Directional LSTM, CNN etc are used to predict stock prices.

Comparing the neural networks with the accuracy obtained at different studies, it is seen that the models with LSTM, GRU and Bi-Directional models are trusted to give high accuracy. It is not always the same for these models to perform better than other models. It can be said that these models with a smaller number of units, epochs and number of layers are able to produce good accuracy when compared with other models. Hybrid models with a combination of these layers performs better than the stacked layers.

All the above discussed studies utilize historical stock price data to predict the next day or future stock prices. It is seen in the study by (Puh & Marina, 2023) that NLP can be used to analyse the news headlines about a particular stock and feed the neural networks the trend of the stock price and this helps in predicting the stock price. It is said that the resources required to perform the text processing is high and acceptable results can be achieved by using neural networks without extensive computing. It is said that Fin BERT model outperformed all other models with least RMSE for stock price prediction using news polarity.

Looking at the work done for predicting the stock price, it is common in all the reports that the common metrics used to assess the performance of predicting the stock price are MSE, RMSE, MAE, MAPE and R2. Out of these, we prefer to evaluate the performance of the models using MAPE which says the average error rate of the predicted and actual stock prices and R2 score which figures out the accuracy score between the predicted and actual values. They speak about the exact model performance which can be evaluated for comparison. The MSE, RMSE and MAE are not preferred since the data used for this analysis is varied.

To overcome this, we can perform data processing to scale the data, yet the errors can never be known if they are minimal. It is recommended to scale the data due to the differences between the minimum and maximum prices of the stock, which makes it difficult while training. (Chawalit, et al., 2018) used MinMaxScaler for scaling the data and we prefer to experiment with the performance of the model using StandardScaler. We would not recommend using MaxAbsScaler, as it is not efficient in handling outliers within the data.

Referring to the studies, there is no explanation given for why a certain number of look backs are selected while training the model, and the data used for training is varied from being the past 4 years data to 66 years data. Thinking of the computing resources used to train the models for the vast data, we prefer to use data varying from 5 to 10 years for training and testing. The ratios for splitting training and testing data are used as 80:20 and 75:25 and 65:35 in the related works. The epochs are ranged between 10 and 200. The parameters are not similar in any of the works, and it is recommended to experiment with them for the efficiency of the model.

# Methodology

Considering the literature review, different models with the combination of LSTM, GRU, Bi-Directional and Dropout layers are built and evaluated with the chosen metrics. We chose four different stocks from Oil and Gas Integrated sector for this project namely British Petroleum (BP), Shell plc (SHEL), Exxon Mobil Corporation (XOM) and Chevron Corporation (CVX). Past 10 years data of these 4 stocks from 2nd February 2014 to 2nd February 2024 is used for this project. The BP stock is listed in London Stock Exchange (LSE) and other stocks are listed in New York Stock Exchange (NYSE). These four stocks exhibit similar performance over years and the price variations of these stocks over years can be seen below in Figure 7.

A graph of stock performance

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Figure 7: Stocks performance over years.

The data is gathered from Yahoo! Finance using yfinance library in python, which uses an API to pull the data from Yahoo! Finance and ticker helps gathering the desired stock data. The data collected does not include any personal information or any information that leads to ethical considerations.

A function named ‘data\_download’ is created which takes in ticker and gives out desired stock close price for the 10 years and further days beyond 2nd February 2024. Another function named ‘train\_test\_gen’ takes the stock close price data, scaler and look back period and scales the data using either MinMaxScaler or StandardScaler. This scaled data is transformed into timeseries data using TimeSeriesGenerator with the given lookback period. This function returns the total stock data and both the test and train data in timeseries format. The data is split into training and testing data with a ratio of 80:20 respectively. LSTM model with and without dropout layers, GRU model with and without dropout layers and Bi-LSTM, Bi-GRU models are created, trained, tested with the test data and evaluated with selected metrics. All the models created are trained for 20, 50, 100 and 150 epochs. The timeseries data is generated for 10, 25 and 50 lookback periods and these data is used for training and testing the models for different epochs.

BP stock data is used for training the models for different epochs and lookback periods. The trained models are tested using the BP, SHEL, XOM and CVX test data for predicting the next day close price. These test predictions are evaluated with MAPE and R2 Score for all the stocks for different epochs, lookback periods and different scaled data. The models are used to forecast these four stocks for further days for up to 30 days and metrics for 1 day forecast, 15 days forecast, and 30 days forecast are calculated and evaluated. Only MAPE is calculated for 1 day forecast data, since R2 cannot be calculated for 1 record of data. A brief about the layers, parameters and metrics are detailed below:

## Long-Short Term Memory (LSTM)

Long-Short Term Memory (LSTM) network is a Recurrent Neural Network (RNN) built to solve the vanishing gradient issue with the RNN network. LSTM block is composed of one or more cells with an input gate, forget gate and output gate. It is described by (Danker, 2022) that, cells flow information from forget gate through input gate to output gate. The information passed through the cells are controlled by the three gates and they act as filters and determine if the information to be kept or deleted. Forget gate decides the amount of information to be kept, input gate decides which information to be passed to the cell and output gate decides which part of the cell builds the output. These gates are combined with sigmoid function for making the decision about the information. Sigmoid function output ranges between 0 and 1, and these outputs states how much information can be kept or forget. A schematic structure of an unfolded LSTM cell can be seen below in Figure 8.

A diagram of a machine

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Figure 8 : Unfolded LSTM Cell (Danker, 2022)

## Gated Recurrent Unit (GRU)

Like LSTM, GRU solves the vanishing gradient issue from simple RNNs. Unlike LSTM, GRU have fewer gates and do not have separate memory and uses hidden state as the memory. GRU consists of reset gate and update gate. The reset gate decides the amount of past information to be kept or deleted, responsible for short-term memory. The update gate works as LSTM’s forget gate and is responsible for long-term memory. A schematic structure of an unfolded GRU cell can be seen below in Figure 9.

A diagram of a diagram

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Figure 9 : Unfolded GRU Cell (Danker, 2022)

## Bi-Directional

Bidirectional networks are special type of neural networks with two hidden layers of opposite directions connected to the output. The output layer gets both the past and future information from the hidden layers. These hidden layers can be RNN, LSTM or GRU. With two layers in one hidden layer, bidirectional can enhance the model learning and improve the model performance. Unfolded Bidirectional LSTM with 3 cells can be seen in Figure 10.

A diagram of a block diagram

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Figure 10 : Unfolded Bi-LSTM with 3 cells (Li, et al., 2020)

## Dropout

Dropout layer is used to drop the number of nodes or neurons with given frequency or probability over each iteration or batch while training the deep learning model. Deep learning models are very effective in learning from the training data and the model easily gets overfitted, learning the statistical noise. It reduces the training loss but fails greatly while testing with new data. As a solution to avoid overfitting dropout is added to the model. During training the model, the neurons trained over the data gains a weight and with dropout in place the neurons are dropped with the drop probability leading the weights of the remaining neurons change and this happening over iterations leads to regular change in the weights of the neurons which makes the model not to fix its weights, which avoids overfitting. Difference between a standard neural network and the same network after applying dropout can be seen in Figure 11.

A diagram of a neural network

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Figure 11 : Standard Neural Network with and without Dropout (Nitish, et al., 2014)

We used Adam optimizer and mean squared error as loss function for compiling the models.

## Adam Optimizer

Adaptive Moment Estimation (Adam) optimizer reduces the loss function while training the neural network model. Adam optimizer incorporates the combination of momentum method and RMSprop method along with bias correction. Gradient descent is used to find the minimum value of the loss function over iterative optimization, momentum method uses gradient descent method and accelerates it using exponentially weighted averages of the gradients towards the minimum of the loss function in a faster way. RMSprop method is a process of applying exponential weighted averages to the second momentum gradients. Adam optimizer uses bias correction which results in faster convergence and stable training process. Adam optimizer uses adaptive learning rates and optimizes efficiently, and its robustness makes it a popular choice for deep learning models as optimizer, during training.

## Mean Square Error – Loss Function

Loss function is used for evaluating model, during training. If the model predictions are close to ground truth values, the loss function will be low, else high. Looking at the variation in loss function values, we can see where the model is going with the training. We used mean squared error as loss function for all the models built during this project. Detailed formula for mean squared error is given below in equation 1.

**MSE = *----(1)***

Where is actual value, is predicted value.

Unlike loss function, the model needs to be evaluated on new data and we cannot rely on MSE, as it depends on the data. We used preprocessing methods like MinMaxScaler and StandardScaler which scales the data to different ranges and the MSE values differ while training. MinMaxScaler scales data by changing its minimum value to zero and maximum value to 1. MinMaxScaler scaled data ranges from 0 to 1 and it can scale data to specific data ranges. StandardScaler scales data to get zero mean and standard deviation of 1. StandardScaler scaled data is distributed with mean as zero and it results in data distributed with both positive and negative values. The variation of BP stock close price data scaled with both MinMaxScaler and StandardScaler can be seen in Figure 12.

A graph showing a price

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Figure 12 : BP Stock Close Price with MinMaxScaler and StandardScaler

We used MAPE and R2 metrics for evaluating the model while testing with new data.

## Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error (MAPE) is a measure used to determine prediction accuracy of a forecast model. It resembles the accuracy with the ratio defined in the formula. In general, MAPE value of 5% says that the model predicts values with a range of average 5% variation to the actual value. MAPE formula is given below in equation 2.

**MAPE *= ----(2)***

Where is actual value, is predicted value.

## R2 Score – Coefficient of Determination

Coefficient of Determination (R2 Score) is determined by calculating the proportion of sum of squares of error between actual and predicted values called residuals, by sum of squares of error between actual values and mean actual value, subtracted from 1. R2 Score ranges from 0 to 1. R2 Score close to 1 tells the model is accurate and is achieved when the sum of squares of residual values is minimum. Sometimes the R2 score can go less than 0 when the sum of squares of residual values is greater than the variance. R2 score formula is detailed below in equation 3.

***----(3)***

Where is actual value, is predicted value, is mean value.

With the above networks, parameters and metrics, stock prediction models are built and evaluated. A thorough analysis is done and documented below in results and discussion.

# Results and Discussion

Considering the literature survey, following deep learning models are created for predicting the next day close price of the stock. The model plots and parameters are detailed below:

## Model – 1: LSTM Model without Dropout Layer

It is seen that (Bathla, 2020) and (Pushpendra, et al., 2022) used 7 and 4 LSTM hidden layers and achieved good performance. So, model – 1 is built with four LSTM layers with varying number of units. The number of units for all the models built are chosen based on the varying lookback periods. As per (Istiake Sunny, et al., 2020), it is suggested to have the number of neurons optimal as it consumes more computational resources. Model - 1 plot and summary is given below in Figure 13 and 14.

A screenshot of a computer

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Figure 13: Model - 1 Summary

A diagram of a diagram

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Figure 14: Model - 1 Plot

## Model – 2: LSTM Model with Dropout Layer

Model – 2 is built on top of model – 1 by adding dropout layers after each of the first 3 LSTM hidden layers. The dropout frequencies are 0.2, 0.1 and 0.05 respectively. Model – 2 summary and plot can be seen below in Figure 15 and 16.

A screenshot of a computer

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Figure 15: Model - 2 Summary

A diagram of a computer program

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Figure 16: Model - 2 Plot

## Model – 3: GRU Model without Dropout Layer

Model – 3 is build using GRU layers. Unlike model – 1, model – 3 is made using only 2 hidden layers with 50 and 25 number of units. Model – 3 is initially built with same number of parameters and layers, from Model – 1. The results achieved were not as expected. The number of units and layers were experimented to achieve the final model. Model – 3 summary and plot can be seen in Figure 17 and 18.

A screenshot of a computer program

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Figure 17: Model - 3 Summary

A diagram of a block diagram

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Figure 18: Model - 3 Plot

## Model – 4: GRU Model with Dropout Layer

Like model – 2, model – 4 is built on top of model – 3 by adding a dropout layer after GRU layer. Dropout frequency of 0.2 is used in both dropout layers. Model – 4 summary and plot can be seen below in Figure 19 and 20.

A screenshot of a computer

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Figure 19: Model - 4 Summary

A diagram of a dropout

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Figure 20: Model - 4 Plot

## Model – 5: Bidirectional LSTM Model

Model – 5 is built using Bidirectional LSTM, with 50 number of units. Model – 5 summary and plot can be seen in Figure 21 and 22.

A screenshot of a computer program

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Figure 21: Model - 5 Summary

A diagram of a computer

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Figure 22: Model - 5 Plot

## Model – 6: Bidirectional GRU Model

Like model – 5, model – 6 is built using Bidirectional GRU, with 50 number of units. It is thought, a thorough comparison between LSTM and GRU with same number of units can be compared to evaluate their performance. Model – 6 summary and plot can be seen in Figure 23 and 24.

A screenshot of a computer program

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Figure 23: Model - 6 Summary

A diagram of a computer

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Figure 24: Model - 6 Plot

The total number of parameters of model – 1 and model – 2 is 39,651, model – 3 and model – 4 is 13,751, model – 5 is 20,901 and model – 6 is 16,001. The LSTM layer has higher number of parameters when compared with GRU layer.

Batch size is observed as one other key factor with model training. It is seen in (Varadharajan, et al., 2024) that a total of 27 combinations of models are built with different combinations and batch size is one of the parameters which is optimized for a new combination of the model. A simple analysis is done with different batch sizes of 10, 32, 64 and 128 while training model – 1 for 20 epochs with StandardScaler scaled BP training data with 10 look back values. It is seen that the convergence of the loss function delays over epochs, with increase in batch size. Batch size also affects the computing time and increase in batch size results in less time to train the model. With these two inputs, it is considered to use batch size of 32 for the whole project. Change in loss convergence over batch size can be seen below in Figure 25.

A graph of loss convergence

Description automatically generated with medium confidence

Figure 25: Loss Convergence Vs Batch Size

For different combinations of models, BP training data i.e. first 80% of the data is used for training and last 20% data of all four stocks is used for evaluating test metrics. For forecasting, total BP data of all 10 years is used for training the model. The correlation coefficient of the four stocks actual close price, of all 10 years is visualised below in Figure 26.

A chart with different colored squares

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Figure 26 : Correlation Coefficient of Stocks Close Price

We can see a positive correlation of 0.81 between BP and SHEL stock price. Correlation between BP and XOM, CVX is 0.64, 0.52 respectively. There is no strong correlation for BP with XOM, CVX.

All models are trained over BP stock data, metrics of MAPE and R2 score is calculated and noted for both test predictions and forecast predictions. For different number of epochs, lookback periods and scalers used, the test predictions and forecast predictions are visualised and analysed. Test predictions of SHEL stock close price from model – 1 trained for 150 epochs with StandardScaler scaled BP training data is visualised below in Figure 27. The actual and predicted stock prices are moving very close to each other. MAPE for this test prediction is 1.35% and 0.96 R2 score.

A graph showing the price of a stock price

Description automatically generated

Figure 27: SHEL Stock Price Prediction by Model – 1

The forecasted data of SHEL stock price over actual data is visualised below in Figure 28. The forecasted data is very linear and is not able to adapt to the uncertainty. Yet, the MAPE for 30 days forecasted stock price is 1.37%.

A graph with a line

Description automatically generated

Figure 28: SHEL Stock Price Forecast by Model - 1

Similarly, the forecasted stock price of SHEL from model – 3 can be seen below in Figure 29. The forecast is still linear and the MAPE for 30 days forecast data is 2.11%. Even though model – 3 forecasted the SHEL stock price with the same direction of actual price, the MAPE is more when compared with model – 3 forecasted data metrics, as seen above.

A graph with a line and a green line

Description automatically generated

Figure 29: SHEL Stock Price Forecast by Model - 3

(Ali, et al., 2014) said the forecast pattern is directional of ARIMA model. Most of the forecasted data is directional with the trained models and it is only seen in few models that the forecasted data in not directional. It can be seen in Figure 30, variation of forecasted CVX stock price from model – 6 with 50 lookbacks, StandardScaler scaled data trained for 150 epochs.

A graph with lines and numbers

Description automatically generated

Figure 30: CVX Stock Price Forecast by Model – 6

The forecasted stock price movement is very unpredictable, when compared with different combinations and the forecast pattern would drift away from the actual prices as shown in Figure 31.The lowest MAPE with 30 days forecast stock price data is 0.77% and is achieved for SHEL stock with Model – 4 trained for 100 epochs using 25 lookbacks and MinMaxScaler scaled data. The highest MAPE with 30 days forecast stock price data is 42.46% and is achieved for SHEL stock with model – 3 trained for 150 epochs using 10 lookbacks and MinMaxScaler scaled data, and the R2 score is -1920.97. The highest R2 score achieved with 30 days forecasted data is 0.61. Similarly, the highest MAPE achieved for 15 days forecasted stock prices is 21.07% and the lowest is 0.41%. The R2 score for 15 days forecasted stock prices ranged between -1854.30 to 0.82.

A graph of a price

Description automatically generated with medium confidence

Figure 31: CVX Stock Price Forecast with Model - 6

The wide range of MAPE and R2 scores with 15 days and 30 days forecasted stock prices makes it tough to rely on forecasted stock prices of more than a couple of days. The test metrics and one day forecast metrics are further analysed.

The MAPE of all models trained for different epochs with 10 lookbacks and StandardScaler scaled data can be seen in below Figures 32 to 37.

A graph of different colored bars

Description automatically generated

Figure 32: Model - 1 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 33: Model - 2 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 34: Model - 3 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 35: Model - 4 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

A chart of different colored bars

Description automatically generated with medium confidence

Figure 36: Model - 5 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 37: Model - 6 MAPE Vs Epochs for 10 lookbacks and StandardScaler scaled data.

When looked at model - 1, model - 2, model - 3 and model - 4 MAPE performance over epochs in Figures 32 to 35, we can see the MAPE is decreasing with increase in epochs and the MAPE ranges from 1% to 6% over different epochs. When looked at Figure 36 and 37, we can see that the MAPE of model - 5 and model - 6 is less than 2% for all stocks and there isn’t a big change in MAPE over different epochs. Further, the MAPE variation of all models with 25 lookbacks is visualised.

A graph of different colored bars

Description automatically generated with medium confidence

Figure 38: Model - 1 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 39: Model - 2 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 40: Model - 3 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 41: Model - 4 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

A chart of different colored bars

Description automatically generated with medium confidence

Figure 42: Model - 5 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

A chart of different colored bars

Description automatically generated with medium confidence

Figure 43: Model - 6 MAPE Vs Epochs for 25 lookbacks and StandardScaler scaled data.

Figures 38 to 43, shows MAPE values of all models trained on 25 lookbacks and standardscaler scaled data. We can see that all the models perform similarly with 10 lookbacks and we can observe for except CVX stock and XOM stock at 20 epochs, the MAPE values are less than 3%. For model – 3, all stocks MAPE value increased for 150 epochs from 100 epochs of training, which can be seen in Figure 40.

A graph of different colored bars

Description automatically generated with medium confidence

Figure 44: Model - 1 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 45: Model - 2 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

A screenshot of a graph

Description automatically generated

Figure 46: Model - 3 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 47: Model - 4 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 48: Model - 5 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

A graph of different colored lines

Description automatically generated

Figure 49: Model - 6 MAPE Vs Epochs for 50 lookbacks and StandardScaler scaled data.

Figures 44 to 49, shows MAPE values of all models trained on 50 lookbacks and standardscaler scaled data. We can see that the MAPE of all models trained with 50 lookbacks and StandardScaler scaled data are quite similar and close to the models trained with 25 lookbacks and StandardScaler scaled data.

A graph of different colored bars

Description automatically generated with medium confidence

Figure 50: Model - 1 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

A graph of different colored bars

Description automatically generated with medium confidence

Figure 51: Model - 2 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

A chart of different colored bars

Description automatically generated

Figure 52: Model - 3 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 53: Model - 4 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

A graph of different colored bars

Description automatically generated

Figure 54: Model - 5 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

A graph of different colored bars

Description automatically generated with medium confidence

Figure 55: Model - 6 MAPE Vs Epochs for 10 lookbacks and MinMaxScaler scaled data.

Figures 50 to 55,shows MAPE values of all models trained on 10 lookbacks and minmaxscaler scaled data. Unlike models trained with standardscaler scaled data, minmaxscaler scaled data trained models at 10 lookbacks have lower MAPE values in a range between 1.25% to 3% except with model - 2 trained for 20 and 50 epochs. CVX stock MAPE values are in close proximity to other stocks MAPE values for all models.

A chart with different colored lines

Description automatically generated with medium confidence

Figure 56: Model - 1 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

A screenshot of a graph

Description automatically generated

Figure 57: Model - 2 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

A chart of different colored bars

Description automatically generated with medium confidence

Figure 58: Model - 3 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

A chart of different colored bars

Description automatically generated with medium confidence

Figure 59: Model - 4 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

A chart with different colored lines

Description automatically generated with medium confidence

Figure 60: Model - 5 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

A chart of different colored lines

Description automatically generated with medium confidence

Figure 61: Model - 6 MAPE Vs Epochs for 25 lookbacks and MinMaxScaler scaled data.

Figures 56 to 61, shows MAPE values of all models trained on 25 lookbacks and MinMaxScaler scaled data. We can see that the MAPE variation for model - 5 and model - 6 in Figure 60 and 61 are very minimal and ranges between 0.3%. It is observed the same with these models trained with 10 lookbacks. All the models are exhibiting similar behaviour with both 10 and 25 lookbacks.

A chart of different colored lines

Description automatically generated with medium confidence

Figure 62: Model - 1 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

A graph of different colored lines

Description automatically generated with medium confidence

Figure 63: Model - 2 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

A chart of different colored lines

Description automatically generated

Figure 64: Model - 3 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

A screenshot of a graph

Description automatically generated

Figure 65: Model - 4 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

A chart of different colored lines

Description automatically generated

Figure 66: Model - 5 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

A chart of different colored lines

Description automatically generated

Figure 67: Model - 6 MAPE Vs Epochs for 50 lookbacks and MinMaxScaler scaled data.

Figures 62 to 67, shows MAPE values of different models trained on 50 lookbacks and MinMaxScaler scaled data. All the models exhibit similar performance in stock price prediction on the test data, when evaluated with MAPE values of different lookback periods of data and trained on different epochs. The MAPE values of model – 2 and model – 4 ranged more than 4%, while other models MAPE values are less than 2%.

Looking at the MAPE variations over all combinations of different models, model - 5 and model – 6, which are Bidirectional LSTM and Bidirectional GRU achieved less MAPE values over different lookback periods, epochs and on both StandardScaler scaled and MinMaxScaler scaled data. The MAPE of model – 5 and model – 6 at all combinations is seen less than 2% and the variation of MAPE with increase in epochs is not great. Model – 2 and model – 4, which are built on top of model – 1 and model – 3 respectively, by adding dropout layers, tend to give high MAPE values. As observed in (Jia, et al., 2019), the MAPE is increased by adding dropout layers. The dropout layers are used to avoid overfitting and it resulted in increase with MAPE.

The R2 scores of all models at different combinations are observed and the highest R2 score obtained over all different combnations of parameters with test predictions for model – 1, model – 3, model – 5 and model – 6 is 0.97. While for model – 2 is 0.94 and for model – 4 is 0.96. Similarly, the lowest R2 score is resulted by model – 2 with -0.02 at 20 epochs with 10 lookbacks using StandardScaler for CVX stock. It is further analysed that about 20 combinations of models test predictions have given R2 score less than 0.5 for CVX stock. For once, SHEL test predictions R2 score is noted less than 0.5 with model – 2 trained for 50 epochs with 10 lookbacks and MinMaxScaler scaled data. Out of 576 predictions made on test data with different combinations of models including epochs as an parameter, 416 combinations achieved R2 score greater than 0.90. Around 245 combinations of models achieved R2 score greater than or equal to 0.95.

Similarly, 1 day forecasted stock price MAPE values ranged from 0.00%(not exactly 0%, it may be because of values rounded to 2 digits after decimals) and 4.98%. These MAPE values are absolute percentage errors (APE) as the predicted stock price is only one record. These forecasted values are nothing but similar to one prediction made on test data. It can be said each prediction made to predict next day stock price can range between 0 to 5% error. It is seen that the highest MAPE value over test data is 5.97% and it is not explored or analysed the variations of errors with each day prediction and depending on the the deviation of the APE values there will be even higher errors with 1 day predicted prices on the test data.

We can see in Figure 68, CVX stock price variation with stock price predicted using model – 4 with 50 lookbacks and StandardScaler scaled data trained for 150 epochs. The MAPE obtained for this combination is 2.99% and R2 score of 0.69 is achieved. We can see the variation between the actual and predicted stock prices and a rough error of 10% is definitely captured with this combination at index 200.

A graph showing a graph of a stock price

Description automatically generated with medium confidence

Figure 68: CVX Stock Price Prediction with Model - 4 (epochs = 150, lookback = 50, StandardScaler)

When looked at these metrics over different stocks for all combination of models, MAPE variation for BP stock is ranged between 1.13% and 5.18%. R2 score for BP stock is ranged between 0.67 and 0.97. Similarly for SHEL stock, MAPE is ranged between 1.32% to 5.30%, R2 score is ranged between 0.48 to 0.96. It can be seen that SHEL stock never achieved R2 score of 0.97 over any combination, and the correlation between BP and SHEL is 0.81 which is higher than other pair of stocks with BP. The XOM stock MAPE is ranged between 1.45% to 5.60%, R2 score is ranged between 0.66 to 0.97. The CVX stock MAPE is ranged between 1.34% to 5.97%, R2 score is ranged between -0.02 to 0.94. The price variation of CVX stock test data is different when compared with other stocks. As seen in Figure 68, the CVX stock price faced sudden rise and falls frequently when compared with other stocks.

All the combination of models are trained only on BP stock data and the MAPE variation is quite close to each other, but the R2 score for CVX model is less when compared with other models. The correlation coefficient of test data used for predictions of different stocks is visualized below in Figure 69. We can see strong relation between BP and XOM stock which can be the reason for good R2 scores for XOM stock and correlation between BP and CVX is 0.35 and it explains why the R2 scores are less for CVX stock predictions.

A chart with different colored squares

Description automatically generated

Figure 69: Correlation Coefficient of Test Stock Price Data

MAPE variations with lookbacks for different models is tabulated below in Table 1.

Table 1: MAPE variations over different Lookback periods with different Models for Test Data

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Lookback = 10, MAPE | | | Lookback = 25, MAPE | | | Lookback = 50, MAPE | | |
|  | Min | Mean | Max | Min | Mean | Max | Min | Mean | Max |
| Model – 1 | 1.35 | 1.90 | 4.20 | 1.37 | 1.99 | 5.04 | 1.37 | 1.90 | 4.33 |
| Model – 2 | 1.71 | 3.20 | 5.97 | 1.76 | 2.91 | 5.34 | 1.81 | 2.81 | 5.48 |
| Model – 3 | 1.33 | 1.89 | 4.92 | 1.32 | 1.76 | 4.61 | 1.34 | 1.84 | 4.79 |
| Model – 4 | 1.62 | 2.74 | 5.51 | 1.70 | 2.50 | 5.48 | 1.51 | 2.73 | 5.13 |
| Model – 5 | 1.37 | 1.58 | 2.10 | 1.34 | 1.55 | 2.21 | 1.33 | 1.51 | 2.27 |
| Model - 6 | 1.33 | 1.47 | 1.77 | 1.34 | 1.44 | 1.70 | 1.13 | 1.42 | 1.68 |

Like Table 1, MAPE variations over different lookback periods for different models for 15 days forecasted data is tabulated below in Table 2.

Table 2: MAPE variations over different Lookback periods with different Models for 15 days Forecasted Data

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Lookback = 10, MAPE | | | Lookback = 25, MAPE | | | Lookback = 50, MAPE | | |
|  | Min | Mean | Max | Min | Mean | Max | Min | Mean | Max |
| Model – 1 | 0.52 | 4.07 | 10.76 | 0.96 | 4.73 | 18.24 | 0.81 | 6.21 | 21.04 |
| Model – 2 | 0.69 | 3.78 | 8.56 | 0.78 | 3.89 | 9.24 | 0.43 | 2.15 | 7.12 |
| Model – 3 | 0.62 | 6.32 | 21.07 | 0.60 | 6.47 | 13.53 | 0.81 | 2.66 | 7.43 |
| Model – 4 | 0.42 | 3.02 | 7.62 | 0.41 | 3.75 | 9.69 | 0.55 | 2.93 | 8.30 |
| Model – 5 | 0.52 | 1.91 | 4.20 | 0.53 | 3.30 | 10.28 | 0.98 | 2.92 | 9.40 |
| Model - 6 | 0.98 | 3.65 | 8.82 | 0.54 | 3.20 | 8.67 | 0.52 | 2.41 | 6.05 |

MAPE variations over different lookback periods for different models for 30 days forecasted data is tabulated below in Table 3.

Table 3: MAPE variations over different Lookback periods with different Models for 30 days Forecasted Data

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Lookback = 10, MAPE | | | Lookback = 25, MAPE | | | Lookback = 50, MAPE | | |
|  | Min | Mean | Max | Min | Mean | Max | Min | Mean | Max |
| Model – 1 | 0.92 | 6.47 | 19.76 | 1.48 | 7.28 | 26.40 | 1.11 | 9.64 | 29.00 |
| Model – 2 | 0.99 | 5.89 | 14.04 | 1.02 | 6.43 | 15.93 | 0.79 | 2.78 | 8.94 |
| Model – 3 | 0.84 | 11.06 | 42.46 | 1.26 | 11.41 | 21.00 | 1.95 | 4.11 | 12.20 |
| Model – 4 | 0.80 | 4.41 | 11.92 | 0.77 | 5.59 | 14.07 | 0.81 | 4.14 | 10.69 |
| Model – 5 | 0.79 | 2.80 | 5.75 | 0.94 | 5.55 | 18.81 | 1.46 | 4.68 | 12.64 |
| Model - 6 | 1.13 | 6.04 | 13.69 | 0.82 | 4.96 | 13.18 | 0.89 | 3.38 | 8.04 |

Looking at Table 1, we can see that Model – 6 which is Bidirectional GRU performed better than all other models over all combinations. When different lookbacks are considered, the variations of metrics are quite like each other with test data. It is seen that with increase in lookback period, the time consumed for training the model is increased. Since the change in metrics are not remarkable, less lookback period can be used which can reduce the computing resource consumption.

Like MAPE variations, R2 score variations over different lookback periods for different models with test data is tabulated below in Table 4.

Table 4: R2 Score variations over different Lookback periods with different Models for Test Data

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Lookback = 10  R2 Score | | | Lookback = 25  R2 Score | | | Lookback = 50  R2 Score | | |
|  | Min | Mean | Max | Min | Mean | Max | Min | Mean | Max |
| Model – 1 | 0.44 | 0.90 | 0.97 | 0.24 | 0.89 | 0.97 | 0.41 | 0.90 | 0.97 |
| Model – 2 | -0.02 | 0.76 | 0.94 | 0.26 | 0.80 | 0.94 | 0.11 | 0.80 | 0.94 |
| Model – 3 | 0.29 | 0.90 | 0.97 | 0.37 | 0.92 | 0.97 | 0.29 | 0.91 | 0.97 |
| Model – 4 | 0.16 | 0.82 | 0.95 | 0.16 | 0.84 | 0.95 | 0.12 | 0.81 | 0.96 |
| Model – 5 | 0.87 | 0.94 | 0.97 | 0.85 | 0.95 | 0.97 | 0.84 | 0.95 | 0.97 |
| Model - 6 | 0.92 | 0.95 | 0.97 | 0.91 | 0.95 | 0.97 | 0.92 | 0.95 | 0.97 |

We can see the R2 score achieved by model – 6 is greater than 0.90 for different lookbacks. The minimum R2 score obtained by model – 2 is -0.02. A negative R2 score means the predicted values are worse than the average value of the data. For 15 days and 30 days forecasted data R2 score, negative R2 scores are seen quite commonly with every model.

We can see the metrics of all combinations of models in appendix from Table 5 to 52. The python programme built during the project is attached in appendix.

# Conclusion

Several combinations of deep learning models are built, trained, and tested with different lookback periods, scalers, and models trained for different epochs, for predicting the next day stock close price. The MAPE values of all the different combinations of models for different stocks is less than 6%, which means that with any of the built combination, we can predict the next day stock price of the four stocks with less than 6% error. As per (Shah, et al., 2021), MAPE value less than 10% is considered as a good measure. So, all the combinations built and evaluated can be considered as good prediction models when used to predict next day stock prices. It is seen that 345 combinations of models built can forecast stock prices with less than 5% MAPE values for both 15 days and 30 days forecast periods for all stocks. While MAPE values of all combinations of models for test data is good, the R2 scores for few combinations are seen less than 0.5 for CVX stock. The models can predict CVX stock test data with satisfactory MAPE values, even though the stock price has a sudden rise and fall. MinMaxScaler is recommended over StandardScaler for scaling the data used for training the models.

We noticed that the predicted and actual prices were closely moving along in the plotted visuals, and we can trust these predicted values for building the decision about trading the stock. Bidirectional LSTM and Bidirectional GRU models performed better, when compared with other models and takes less time to train than other models.

# Future Scope

(Karim & Ahmed, 2021), (Mohammad, et al., 2018), and (Varadharajan, et al., 2024) stated that they used MinMaxScaler to scale the data for training the models. It is not stated in all other works that the data is either scaled or trained with actual data. It is stated that scaling data is recommended for better training with the models. We can do a study with our models, if they can do better when trained with actual close prices.

Only stacked layers of LSTM, GRU and Bidirectional are used in this project. It is seen in the literature review that hybrid models are performing better than stacked layers. So, hybrid models with combinations of LSTM, GRU and Bidirectional can be built and evaluate their performance. It is common in portfolios that people invest in stocks from different sectors. We used stocks from Oil and Gas Integrated sector only and the models are trained on one individual stock data. We can use index stock data to train models and test them with top stocks from the selected index.

For this project, only stock close price is used to train the models. Features such as open price, high price, low price, and volume are available. We can use these features to train models, for predicting close price. Rather than only using these features, trends analysed from news headlines using NLP, like work done by (Puh & Marina, 2023), can be feed into our models for predicting the stock close price. Only MAPE values were evaluated for the test data, APE variation between actual and predicted values can be further analysed.

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# Appendix

## Results

All the results obtained during this project are tabulated and presented below in Tables 5 – 52.

Table 5: Model-1 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 2.58 | 0.89 | 0.2 | 2.82 | -2.72 | 3.31 | -5.24 |
| 50 | 1.9 | 0.94 | 1.76 | 10.76 | -58.92 | 19.76 | -234.23 |
| 100 | 1.55 | 0.96 | 0.82 | 2.44 | -1.88 | 2.26 | -2.11 |
| 150 | 1.43 | 0.97 | 0.73 | 1.89 | -0.86 | 1.44 | -0.5 |
| 25 | 20 | 2.97 | 0.87 | 0.32 | 5.32 | -13.05 | 9.49 | -54.98 |
| 50 | 1.97 | 0.94 | 0.65 | 1.55 | -0.29 | 1.99 | -1.29 |
| 100 | 1.45 | 0.97 | 0.44 | 1.51 | -0.13 | 3.01 | -4.56 |
| 150 | 1.46 | 0.97 | 0.78 | 1.82 | -0.78 | 1.48 | -0.55 |
| 50 | 20 | 2.78 | 0.87 | 1.27 | 3.85 | -7.4 | 7.7 | -35.28 |
| 50 | 1.91 | 0.94 | 0.37 | 1.71 | -0.7 | 4.12 | -10.16 |
| 100 | 1.52 | 0.97 | 0.94 | 3.13 | -3.56 | 4.13 | -8.69 |
| 150 | 1.62 | 0.96 | 1.07 | 4.99 | -11.38 | 14.39 | -181.17 |

Table 6: Model-1 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | Stock | Look Back | Epochs | MAPE | R2 |
| SHEL | 10 | 20 | 2.39 | 0.87 | SHEL | 10 | 20 | 2.39 | 0.87 |
| 50 | 1.75 | 0.93 | 0.65 | 1.06 | 50 | 1.75 | 0.93 |
| 100 | 1.45 | 0.95 | 0.25 | 5.77 | 100 | 1.45 | 0.95 |
| 150 | 1.35 | 0.96 | 0.8 | 2.15 | 150 | 1.35 | 0.96 |
| 25 | 20 | 2.79 | 0.84 | 0.01 | 25 | 20 | 2.79 | 0.84 |
| 50 | 1.96 | 0.91 | 1.42 | 4.18 | 50 | 1.96 | 0.91 |
| 100 | 1.37 | 0.96 | 1.08 | 3.11 | 100 | 1.37 | 0.96 |
| 150 | 1.4 | 0.95 | 0.21 | 2.86 | 150 | 1.4 | 0.95 |
| 50 | 20 | 2.63 | 0.84 | 1.78 | 50 | 20 | 2.63 | 0.84 |
| 50 | 1.79 | 0.93 | 0.98 | 1.98 | 50 | 1.79 | 0.93 |
| 100 | 1.39 | 0.96 | 0.72 | 1.04 | 100 | 1.39 | 0.96 |
| 150 | 1.57 | 0.95 | 1.38 | 6.57 | 150 | 1.57 | 0.95 |

Table 7: Model-1 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 3.01 | 0.88 | 0.24 | 1.58 | -2.6 | 4.36 | -4.27 |
| 50 | 2.35 | 0.93 | 0.65 | 1.06 | -0.09 | 2.42 | -0.72 |
| 100 | 1.67 | 0.96 | 0.25 | 5.77 | -32.48 | 10.18 | -20.77 |
| 150 | 1.53 | 0.97 | 0.8 | 2.15 | -3.28 | 2.12 | 0.09 |
| 25 | 20 | 3.59 | 0.83 | 0.01 | 2.9 | -9.35 | 6.99 | -11.28 |
| 50 | 2.29 | 0.93 | 1.42 | 4.18 | -13.15 | 4.17 | -2.12 |
| 100 | 1.65 | 0.96 | 1.08 | 3.11 | -7.36 | 3.02 | -0.71 |
| 150 | 1.56 | 0.97 | 0.21 | 2.86 | -8.93 | 6.56 | -9.53 |
| 50 | 20 | 3.18 | 0.87 | 1.78 | 2.3 | -3.63 | 2.01 | 0.19 |
| 50 | 2.49 | 0.92 | 0.98 | 1.98 | -2.63 | 1.84 | 0.3 |
| 100 | 1.87 | 0.95 | 0.72 | 1.04 | -0.04 | 2.14 | -0.32 |
| 150 | 1.69 | 0.96 | 1.38 | 6.57 | -37.4 | 7.13 | -8.06 |

Table 8: Model-1 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 4.2 | 0.44 | 0.0 | 4.33 | -12.12 | 5.18 | -14.72 |
| 50 | 3.46 | 0.59 | 0.1 | 3.42 | -7.02 | 3.27 | -5.56 |
| 100 | 2.05 | 0.86 | 1.03 | 8.54 | -48.54 | 10.8 | -65.0 |
| 150 | 1.96 | 0.87 | 0.05 | 1.64 | -1.16 | 2.03 | -1.93 |
| 25 | 20 | 5.04 | 0.24 | 0.22 | 5.66 | -21.53 | 7.71 | -34.24 |
| 50 | 3.1 | 0.68 | 0.64 | 1.18 | -0.06 | 2.98 | -5.92 |
| 100 | 2.21 | 0.83 | 0.27 | 0.96 | 0.14 | 2.19 | -3.02 |
| 150 | 2.06 | 0.85 | 0.54 | 5.91 | -22.97 | 7.52 | -31.59 |
| 50 | 20 | 4.33 | 0.41 | 1.38 | 1.35 | -0.33 | 1.34 | -0.27 |
| 50 | 3.33 | 0.65 | 0.23 | 1.55 | -0.9 | 1.42 | -0.49 |
| 100 | 2.57 | 0.79 | 0.1 | 3.34 | -6.61 | 2.93 | -4.52 |
| 150 | 2.18 | 0.84 | 0.43 | 2.97 | -6.36 | 5.57 | -19.8 |

Table 9: Model-1 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.86 | 0.95 | 1.02 | 7.12 | -26.41 | 13.37 | -105.64 |
| 50 | 1.62 | 0.96 | 0.32 | 6.03 | -20.23 | 12.55 | -97.24 |
| 100 | 1.69 | 0.96 | 0.81 | 2.93 | -3.06 | 3.3 | -5.14 |
| 150 | 1.44 | 0.97 | 0.63 | 1.74 | -0.64 | 1.29 | -0.22 |
| 25 | 20 | 2.06 | 0.94 | 0.64 | 3.78 | -5.75 | 6.17 | -22.58 |
| 50 | 1.48 | 0.97 | 1.1 | 6.01 | -17.37 | 10.53 | -66.51 |
| 100 | 1.56 | 0.96 | 0.72 | 2.37 | -1.67 | 2.35 | -2.33 |
| 150 | 1.65 | 0.96 | 1.53 | 15.45 | -121.91 | 23.19 | -294.07 |
| 50 | 20 | 1.53 | 0.96 | 2.69 | 17.85 | -152.4 | 25.43 | -342.75 |
| 50 | 1.45 | 0.97 | 1.64 | 9.1 | -40.7 | 14.88 | -127.18 |
| 100 | 1.55 | 0.96 | 0.66 | 1.75 | -0.58 | 1.52 | -0.6 |
| 150 | 1.48 | 0.97 | 0.35 | 7.99 | -36.67 | 15.89 | -153.8 |

Table 10: Model-1 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 2.13 | 0.9 | 0.11 | 8.95 | -329.27 | 15.56 | -235.11 |
| 50 | 1.69 | 0.94 | 0.72 | 7.86 | -261.22 | 14.75 | -218.15 |
| 100 | 1.75 | 0.93 | 1.96 | 1.97 | -13.38 | 2.73 | -6.85 |
| 150 | 1.38 | 0.96 | 1.74 | 0.52 | -0.53 | 0.92 | -0.09 |
| 25 | 20 | 2.41 | 0.88 | 1.67 | 2.26 | -20.41 | 4.49 | -23.14 |
| 50 | 1.42 | 0.95 | 2.27 | 5.61 | -128.17 | 10.84 | -124.88 |
| 100 | 1.51 | 0.95 | 1.87 | 1.27 | -5.36 | 1.64 | -2.37 |
| 150 | 1.53 | 0.95 | 0.61 | 18.24 | -1355.61 | 26.4 | -636.38 |
| 50 | 20 | 1.52 | 0.95 | 1.94 | 21.04 | -1698.0 | 29.0 | -746.77 |
| 50 | 1.37 | 0.96 | 2.84 | 9.07 | -327.78 | 15.73 | -246.11 |
| 100 | 1.52 | 0.95 | 1.87 | 0.81 | -2.04 | 1.11 | -0.75 |
| 150 | 1.43 | 0.95 | 0.67 | 10.09 | -445.22 | 18.43 | -338.56 |

Table 11: Model-1 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 1.81 | 0.96 | 2.19 | 7.15 | -42.09 | 8.78 | -12.36 |
| 50 | 1.56 | 0.97 | 1.45 | 6.83 | -39.82 | 8.76 | -12.6 |
| 100 | 1.67 | 0.96 | 0.28 | 1.33 | -1.45 | 3.59 | -2.62 |
| 150 | 1.46 | 0.97 | 0.7 | 1.62 | -1.62 | 1.55 | 0.49 |
| 25 | 20 | 1.91 | 0.95 | 1.13 | 3.35 | -8.68 | 4.78 | -3.18 |
| 50 | 1.51 | 0.97 | 0.06 | 3.45 | -13.94 | 8.7 | -18.13 |
| 100 | 1.61 | 0.96 | 0.48 | 0.97 | 0.05 | 1.69 | 0.09 |
| 150 | 1.82 | 0.96 | 2.75 | 13.88 | -164.08 | 15.67 | -41.06 |
| 50 | 20 | 1.72 | 0.96 | 3.45 | 15.02 | -188.21 | 17.64 | -52.07 |
| 50 | 1.49 | 0.97 | 0.72 | 8.12 | -66.6 | 15.9 | -54.54 |
| 100 | 1.58 | 0.97 | 0.73 | 5.48 | -28.47 | 9.35 | -17.01 |
| 150 | 1.53 | 0.97 | 1.81 | 9.21 | -73.12 | 11.3 | -21.38 |

Table 12: Model-1 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 1.75 | 0.91 | 1.63 | 5.64 | -24.8 | 11.66 | -91.93 |
| 50 | 1.48 | 0.93 | 0.74 | 4.82 | -19.03 | 11.13 | -87.7 |
| 100 | 1.59 | 0.93 | 0.45 | 4.06 | -10.14 | 4.3 | -9.72 |
| 150 | 1.37 | 0.94 | 0.19 | 2.44 | -3.12 | 1.93 | -1.5 |
| 25 | 20 | 1.9 | 0.9 | 0.02 | 3.32 | -6.73 | 3.36 | -5.91 |
| 50 | 1.41 | 0.94 | 0.7 | 7.27 | -37.0 | 11.51 | -81.54 |
| 100 | 1.53 | 0.93 | 0.33 | 3.38 | -6.78 | 3.23 | -5.41 |
| 150 | 1.72 | 0.91 | 2.05 | 13.76 | -143.8 | 20.93 | -264.67 |
| 50 | 20 | 1.57 | 0.93 | 3.2 | 15.82 | -177.9 | 23.12 | -314.94 |
| 50 | 1.39 | 0.94 | 1.31 | 10.78 | -81.99 | 16.64 | -167.79 |
| 100 | 1.48 | 0.93 | 0.54 | 4.12 | -10.5 | 4.33 | -9.86 |
| 150 | 1.39 | 0.94 | 0.88 | 7.07 | -42.27 | 14.44 | -141.12 |

Table 13: Model-2 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 3.06 | 0.86 | 1.55 | 3.32 | -4.24 | 3.88 | -7.34 |
| 50 | 2.66 | 0.89 | 1.41 | 5.13 | -13.68 | 11.29 | -79.97 |
| 100 | 1.96 | 0.94 | 0.59 | 2.9 | -3.0 | 3.1 | -4.39 |
| 150 | 1.88 | 0.94 | 0.65 | 3.38 | -4.38 | 4.39 | -9.85 |
| 25 | 20 | 3.04 | 0.86 | 1.8 | 4.71 | -9.69 | 6.63 | -23.57 |
| 50 | 2.37 | 0.9 | 2.67 | 9.24 | -40.19 | 15.93 | -148.71 |
| 100 | 2.04 | 0.94 | 0.76 | 3.59 | -5.11 | 4.97 | -13.15 |
| 150 | 1.91 | 0.94 | 0.71 | 2.94 | -3.09 | 3.53 | -6.12 |
| 50 | 20 | 2.8 | 0.87 | 2.11 | 4.51 | -8.67 | 6.09 | -19.53 |
| 50 | 2.52 | 0.9 | 0.08 | 1.46 | -0.21 | 1.2 | -0.04 |
| 100 | 1.97 | 0.93 | 0.53 | 3.24 | -3.93 | 4.47 | -10.6 |
| 150 | 1.96 | 0.94 | 0.27 | 1.57 | -0.35 | 1.22 | -0.11 |

Table 14: Model-2 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 2.95 | 0.82 | 2.72 | 2.92 | -29.98 | 4.24 | -16.67 |
| 50 | 2.46 | 0.86 | 0.68 | 7.21 | -207.82 | 12.03 | -137.23 |
| 100 | 1.76 | 0.93 | 2.26 | 4.08 | -60.54 | 5.68 | -28.93 |
| 150 | 1.71 | 0.93 | 1.4 | 1.22 | -5.11 | 1.87 | -3.59 |
| 25 | 20 | 2.65 | 0.84 | 2.84 | 3.8 | -52.71 | 6.14 | -36.87 |
| 50 | 2.16 | 0.89 | 3.67 | 8.85 | -300.13 | 15.5 | -243.29 |
| 100 | 1.85 | 0.92 | 1.37 | 0.78 | -1.69 | 1.02 | -0.36 |
| 150 | 1.78 | 0.93 | 1.52 | 1.46 | -7.45 | 2.06 | -4.0 |
| 50 | 20 | 2.44 | 0.86 | 3.44 | 4.22 | -62.96 | 6.35 | -37.83 |
| 50 | 2.4 | 0.87 | 1.45 | 1.14 | -4.32 | 1.55 | -2.14 |
| 100 | 1.86 | 0.92 | 1.33 | 1.11 | -4.18 | 1.7 | -2.96 |
| 150 | 1.81 | 0.93 | 1.36 | 0.84 | -2.03 | 1.12 | -0.7 |

Table 15: Model-2 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 4.06 | 0.78 | 1.52 | 2.44 | -5.63 | 5.51 | -6.49 |
| 50 | 2.86 | 0.89 | 3.06 | 6.47 | -32.21 | 6.04 | -5.27 |
| 100 | 2.4 | 0.92 | 0.76 | 5.94 | -35.29 | 11.06 | -25.26 |
| 150 | 2.21 | 0.93 | 1.88 | 4.23 | -13.75 | 3.95 | -1.85 |
| 25 | 20 | 3.33 | 0.85 | 1.18 | 1.49 | -1.77 | 3.56 | -2.4 |
| 50 | 2.86 | 0.89 | 0.81 | 4.0 | -17.55 | 10.75 | -28.97 |
| 100 | 2.42 | 0.92 | 2.0 | 4.38 | -14.68 | 4.18 | -2.13 |
| 150 | 2.25 | 0.93 | 0.71 | 1.54 | -2.43 | 4.45 | -4.52 |
| 50 | 20 | 3.66 | 0.81 | 3.13 | 4.84 | -19.89 | 8.65 | -14.92 |
| 50 | 2.85 | 0.89 | 0.1 | 1.15 | -0.72 | 3.14 | -1.85 |
| 100 | 2.55 | 0.91 | 1.36 | 1.86 | -2.24 | 1.76 | 0.34 |
| 150 | 2.31 | 0.93 | 0.75 | 1.54 | -2.34 | 4.4 | -4.38 |

Table 16: Model-2 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 5.95 | -0.02 | 1.27 | 5.06 | -16.13 | 6.13 | -20.45 |
| 50 | 3.67 | 0.58 | -2.78 | 2.95 | -5.13 | 4.59 | -12.14 |
| 100 | 3.7 | 0.53 | 1.12 | 8.56 | -49.92 | 11.55 | -76.21 |
| 150 | 3.38 | 0.59 | -1.16 | 1.16 | 0.03 | 2.69 | -4.56 |
| 25 | 20 | 4.87 | 0.26 | 0.8 | 3.96 | -9.44 | 4.05 | -8.53 |
| 50 | 3.89 | 0.51 | 0.91 | 6.74 | -31.38 | 11.43 | -82.97 |
| 100 | 3.53 | 0.58 | -1.38 | 1.24 | -0.17 | 2.91 | -5.49 |
| 150 | 3.21 | 0.65 | 0.1 | 4.37 | -12.5 | 5.39 | -16.06 |
| 50 | 20 | 5.48 | 0.11 | 2.64 | 7.12 | -31.85 | 8.94 | -43.93 |
| 50 | 4.0 | 0.49 | 0.06 | 3.6 | -8.01 | 3.81 | -7.64 |
| 100 | 4.05 | 0.45 | 0.85 | 1.56 | -0.85 | 1.42 | -0.46 |
| 150 | 3.66 | 0.53 | 0.11 | 4.38 | -12.52 | 5.36 | -15.81 |

Table 17: Model-2 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 4.15 | 0.78 | 1.52 | 5.56 | -15.8 | 11.5 | -80.98 |
| 50 | 5.18 | 0.67 | 0.03 | 1.52 | -0.34 | 3.12 | -5.12 |
| 100 | 2.13 | 0.93 | 1.14 | 4.49 | -8.72 | 6.96 | -27.44 |
| 150 | 2.13 | 0.93 | 0.36 | 1.94 | -0.9 | 1.66 | -0.82 |
| 25 | 20 | 2.77 | 0.88 | 1.23 | 3.48 | -5.91 | 7.31 | -32.38 |
| 50 | 4.39 | 0.77 | 2.31 | 5.36 | -12.84 | 8.03 | -35.68 |
| 100 | 2.26 | 0.92 | 0.82 | 2.55 | -2.05 | 2.69 | -3.22 |
| 150 | 1.96 | 0.94 | 1.13 | 3.19 | -4.87 | 7.09 | -31.22 |
| 50 | 20 | 3.36 | 0.84 | 0.96 | 1.55 | -0.32 | 1.49 | -0.38 |
| 50 | 3.42 | 0.85 | 1.03 | 2.29 | -1.49 | 2.2 | -1.97 |
| 100 | 2.12 | 0.93 | 0.2 | 1.33 | 0.08 | 1.82 | -0.99 |
| 150 | 2.02 | 0.93 | 0.03 | 1.48 | -0.23 | 1.19 | -0.04 |

Table 18: Model-2 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 4.64 | 0.59 | 1.22 | 7.73 | -234.23 | 14.04 | -193.53 |
| 50 | 5.3 | 0.48 | 0.77 | 2.12 | -16.52 | 3.96 | -14.74 |
| 100 | 1.94 | 0.92 | 2.17 | 3.73 | -54.22 | 6.73 | -47.31 |
| 150 | 2.01 | 0.91 | 1.31 | 0.69 | -1.28 | 0.99 | -0.4 |
| 25 | 20 | 2.4 | 0.86 | 1.09 | 5.5 | -113.01 | 9.45 | -84.62 |
| 50 | 4.71 | 0.62 | 3.44 | 5.0 | -92.21 | 8.25 | -66.58 |
| 100 | 1.99 | 0.91 | 1.86 | 1.54 | -8.35 | 2.18 | -4.45 |
| 150 | 1.76 | 0.93 | 0.26 | 4.46 | -77.58 | 8.64 | -75.06 |
| 50 | 20 | 3.38 | 0.75 | 1.44 | 0.64 | -1.04 | 1.52 | -1.96 |
| 50 | 3.84 | 0.72 | 2.04 | 1.17 | -4.59 | 1.51 | -2.01 |
| 100 | 1.94 | 0.92 | 0.72 | 1.2 | -4.52 | 2.04 | -3.43 |
| 150 | 1.92 | 0.92 | 0.94 | 0.43 | 0.16 | 0.79 | 0.08 |

Table 19: Model-2 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 3.64 | 0.83 | 2.85 | 7.69 | -47.76 | 9.26 | -13.69 |
| 50 | 5.6 | 0.66 | 0.26 | 1.48 | -1.35 | 1.49 | 0.5 |
| 100 | 2.47 | 0.92 | 0.37 | 1.45 | -1.63 | 4.49 | -4.9 |
| 150 | 2.22 | 0.93 | -1.21 | 1.34 | -0.64 | 3.09 | -1.66 |
| 25 | 20 | 3.47 | 0.84 | 1.61 | 4.09 | -12.86 | 4.37 | -2.34 |
| 50 | 5.34 | 0.68 | 1.89 | 3.79 | -13.62 | 8.08 | -14.31 |
| 100 | 2.82 | 0.89 | 0.26 | 1.36 | -1.27 | 3.94 | -3.46 |
| 150 | 2.19 | 0.94 | 2.68 | 6.36 | -32.46 | 7.21 | -7.94 |
| 50 | 20 | 3.16 | 0.88 | 1.26 | 1.1 | -0.35 | 2.38 | -0.61 |
| 50 | 3.07 | 0.88 | 0.29 | 0.9 | 0.14 | 1.58 | 0.18 |
| 100 | 2.42 | 0.92 | 1.08 | 1.42 | -1.16 | 1.52 | 0.41 |
| 150 | 2.23 | 0.93 | 1.82 | 2.74 | -5.22 | 2.44 | -0.11 |

Table 20: Model-2 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 3.99 | 0.6 | 2.98 | 5.38 | -20.72 | 11.24 | -85.45 |
| 50 | 5.97 | 0.23 | 0.88 | 0.9 | 0.38 | 2.23 | -3.28 |
| 100 | 2.28 | 0.84 | 0.23 | 5.34 | -19.29 | 7.5 | -32.86 |
| 150 | 2.08 | 0.86 | 0.59 | 2.75 | -4.31 | 2.53 | -3.25 |
| 25 | 20 | 3.31 | 0.67 | 2.5 | 2.79 | -5.09 | 6.59 | -30.58 |
| 50 | 4.92 | 0.41 | 1.47 | 6.48 | -27.78 | 9.12 | -48.23 |
| 100 | 2.67 | 0.79 | 0.05 | 3.54 | -7.83 | 3.88 | -8.0 |
| 150 | 2.05 | 0.86 | 2.05 | 2.12 | -2.75 | 6.56 | -33.93 |
| 50 | 20 | 3.32 | 0.68 | 0.04 | 2.02 | -1.97 | 1.69 | -1.0 |
| 50 | 3.22 | 0.72 | 0.09 | 2.92 | -5.02 | 2.79 | -3.99 |
| 100 | 2.27 | 0.84 | 1.03 | 1.58 | -0.91 | 1.44 | -0.46 |
| 150 | 2.14 | 0.85 | 0.96 | 2.04 | -1.97 | 1.69 | -0.91 |

Table 21: Model-3 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 3.04 | 0.87 | 0.67 | 3.35 | -5.38 | 6.35 | -23.26 |
| 50 | 1.75 | 0.95 | 0.58 | 1.94 | -0.9 | 1.59 | -0.71 |
| 100 | 1.43 | 0.97 | 1.64 | 8.39 | -33.86 | 13.32 | -100.66 |
| 150 | 1.48 | 0.97 | 0.34 | 1.56 | -0.32 | 3.15 | -5.14 |
| 25 | 20 | 2.42 | 0.92 | 1.15 | 8.27 | -35.7 | 17.92 | -209.0 |
| 50 | 1.76 | 0.96 | 1.32 | 7.9 | -31.13 | 14.71 | -132.47 |
| 100 | 1.43 | 0.97 | 1.26 | 6.75 | -22.26 | 12.46 | -96.0 |
| 150 | 1.49 | 0.97 | 0.77 | 2.67 | -2.38 | 2.79 | -3.52 |
| 50 | 20 | 2.56 | 0.92 | 0.38 | 2.2 | -1.33 | 2.12 | -1.8 |
| 50 | 1.83 | 0.95 | 0.81 | 3.62 | -5.22 | 5.01 | -13.38 |
| 100 | 1.48 | 0.97 | 0.75 | 2.44 | -1.86 | 2.34 | -2.3 |
| 150 | 1.95 | 0.95 | 0.06 | 3.99 | -9.35 | 10.93 | -82.45 |

Table 22: Model-3 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 2.71 | 0.83 | 0.57 | 3.01 | -33.48 | 4.72 | -19.9 |
| 50 | 1.55 | 0.95 | 1.77 | 0.93 | -2.63 | 1.09 | -0.48 |
| 100 | 1.33 | 0.96 | 2.97 | 9.08 | -317.97 | 14.78 | -210.82 |
| 150 | 1.4 | 0.95 | 1.56 | 0.91 | -2.91 | 2.11 | -4.2 |
| 25 | 20 | 2.15 | 0.9 | 2.09 | 5.58 | -129.94 | 13.86 | -238.29 |
| 50 | 1.76 | 0.93 | 2.6 | 8.61 | -306.35 | 18.05 | -356.03 |
| 100 | 1.35 | 0.96 | 2.39 | 5.74 | -129.46 | 10.83 | -124.14 |
| 150 | 1.4 | 0.96 | 1.97 | 2.29 | -18.69 | 3.33 | -10.39 |
| 50 | 20 | 2.5 | 0.87 | 1.2 | 0.81 | -2.04 | 2.17 | -4.57 |
| 50 | 1.97 | 0.92 | 1.82 | 1.96 | -13.77 | 2.96 | -8.52 |
| 100 | 1.43 | 0.95 | 1.88 | 1.53 | -7.19 | 1.95 | -3.34 |
| 150 | 1.94 | 0.92 | 1.07 | 5.86 | -152.0 | 12.2 | -154.89 |

Table 23: Model-3 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 3.52 | 0.83 | 0.18 | 0.95 | -0.11 | 2.37 | -0.7 |
| 50 | 2.24 | 0.93 | 0.04 | 1.48 | -2.12 | 3.83 | -3.0 |
| 100 | 1.68 | 0.96 | 0.79 | 9.62 | -93.23 | 17.89 | -67.22 |
| 150 | 1.58 | 0.97 | 0.83 | 1.92 | -2.43 | 1.77 | 0.37 |
| 25 | 20 | 3.03 | 0.87 | 0.15 | 3.64 | -13.56 | 7.54 | -12.29 |
| 50 | 1.88 | 0.95 | 0.53 | 6.61 | -44.7 | 15.16 | -54.83 |
| 100 | 1.52 | 0.97 | 0.21 | 5.02 | -26.84 | 10.8 | -26.1 |
| 150 | 1.65 | 0.96 | 0.15 | 2.55 | -7.24 | 6.09 | -8.27 |
| 50 | 20 | 3.02 | 0.87 | 1.65 | 3.93 | -11.74 | 3.66 | -1.43 |
| 50 | 1.89 | 0.95 | 0.68 | 1.08 | -0.1 | 2.19 | -0.42 |
| 100 | 1.5 | 0.95 | 0.36 | 1.38 | -1.72 | 3.91 | -3.31 |
| 150 | 2.09 | 0.95 | 1.71 | 7.43 | -45.85 | 7.43 | -8.64 |

Table 24: Model-3 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 4.92 | 0.29 | 0.39 | 3.3 | -6.39 | 2.98 | -4.61 |
| 50 | 3.11 | 0.7 | 0.54 | 4.4 | -11.98 | 4.74 | -11.88 |
| 100 | 2.41 | 0.79 | 1.45 | 12.17 | -104.61 | 18.21 | -197.9 |
| 150 | 1.93 | 0.88 | 0.05 | 1.79 | -1.41 | 1.75 | -1.14 |
| 25 | 20 | 4.61 | 0.37 | 0.64 | 6.26 | -25.79 | 8.08 | -36.73 |
| 50 | 2.52 | 0.79 | 1.05 | 8.94 | -55.55 | 15.17 | -147.79 |
| 100 | 1.7 | 0.9 | 0.85 | 7.78 | -41.51 | 11.38 | -76.56 |
| 150 | 1.97 | 0.88 | 0.52 | 5.51 | -19.94 | 6.96 | -26.96 |
| 50 | 20 | 4.79 | 0.29 | 0.99 | 1.03 | 0.18 | 2.56 | -4.22 |
| 50 | 2.45 | 0.8 | 0.05 | 3.18 | -6.02 | 2.92 | -4.45 |
| 100 | 1.69 | 0.91 | 0.36 | 4.35 | -11.96 | 4.98 | -13.36 |
| 150 | 2.6 | 0.79 | 0.89 | 3.65 | -9.65 | 5.8 | -20.29 |

Table 25: Model-3 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.53 | 0.97 | 0.6 | 1.81 | -0.76 | 1.36 | -0.38 |
| 50 | 1.58 | 0.96 | 1.33 | 6.15 | -17.83 | 9.37 | -49.15 |
| 100 | 1.6 | 0.96 | 1.32 | 6.76 | -22.09 | 11.11 | -71.54 |
| 150 | 1.51 | 0.97 | 2.76 | 19.7 | -200.45 | 38.71 | -933.43 |
| 25 | 20 | 1.82 | 0.95 | 1.8 | 11.15 | -61.15 | 18.21 | -184.94 |
| 50 | 1.41 | 0.97 | 0.52 | 1.48 | -0.2 | 1.3 | -0.11 |
| 100 | 1.41 | 0.97 | 1.3 | 6.86 | -22.82 | 11.51 | -77.54 |
| 150 | 1.4 | 0.97 | 0.69 | 8.57 | -39.8 | 17.39 | -185.87 |
| 50 | 20 | 1.44 | 0.97 | 0.12 | 1.45 | -0.06 | 2.7 | -3.4 |
| 50 | 1.5 | 0.97 | 0.7 | 2.65 | -2.33 | 2.78 | -3.46 |
| 100 | 1.5 | 0.97 | 0.12 | 2.33 | -2.74 | 5.53 | -19.21 |
| 150 | 1.42 | 0.97 | 0.74 | 2.88 | -2.88 | 3.3 | -5.16 |

Table 26: Model-3 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 1.4 | 0.95 | 1.67 | 0.62 | -1.05 | 0.84 | 0.06 |
| 50 | 1.65 | 0.94 | 2.53 | 5.98 | -135.86 | 9.83 | -94.36 |
| 100 | 1.63 | 0.94 | 2.52 | 6.65 | -173.51 | 11.74 | -139.23 |
| 150 | 1.5 | 0.95 | 4.09 | 21.07 | -1854.3 | 42.46 | -1920.97 |
| 25 | 20 | 2.07 | 0.91 | 0.94 | 13.53 | -719.3 | 21.0 | -409.01 |
| 50 | 1.32 | 0.96 | 1.59 | 0.6 | -0.83 | 1.26 | -1.05 |
| 100 | 1.34 | 0.96 | 2.48 | 6.57 | -170.73 | 11.9 | -145.01 |
| 150 | 1.33 | 0.96 | 0.28 | 10.78 | -491.16 | 20.32 | -417.28 |
| 50 | 20 | 1.36 | 0.96 | 1.18 | 1.44 | -7.86 | 3.24 | -10.41 |
| 50 | 1.44 | 0.95 | 1.84 | 1.67 | -9.69 | 2.25 | -4.57 |
| 100 | 1.43 | 0.95 | 1.21 | 3.46 | -49.04 | 6.77 | -45.67 |
| 150 | 1.34 | 0.96 | 1.88 | 1.91 | -12.93 | 2.77 | -7.29 |

Table 27: Model-3 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 1.6 | 0.97 | 0.01 | 1.63 | -2.78 | 4.15 | -3.61 |
| 50 | 1.51 | 0.97 | 0.59 | 5.94 | -34.76 | 11.57 | -28.52 |
| 100 | 1.61 | 0.97 | 0.29 | 5.23 | -28.98 | 11.36 | -29.18 |
| 150 | 1.54 | 0.97 | 1.46 | 15.59 | -249.26 | 34.07 | -266.74 |
| 25 | 20 | 1.71 | 0.96 | 2.57 | 10.06 | -84.62 | 12.62 | -26.7 |
| 50 | 1.46 | 0.97 | 0.52 | 1.01 | -0.03 | 1.69 | 0.12 |
| 100 | 1.46 | 0.97 | 0.21 | 4.89 | -25.73 | 10.81 | -26.52 |
| 150 | 1.45 | 0.97 | 1.89 | 10.25 | -93.23 | 14.92 | -40.18 |
| 50 | 20 | 1.54 | 0.97 | 1.15 | 2.54 | -4.6 | 2.55 | -0.2 |
| 50 | 1.56 | 0.97 | 0.23 | 1.97 | -4.25 | 5.09 | -5.81 |
| 100 | 1.56 | 0.97 | 0.79 | 2.62 | -5.06 | 2.7 | -0.36 |
| 150 | 1.47 | 0.97 | 0.35 | 1.29 | -1.16 | 3.56 | -2.61 |

Table 28: Model-3 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 1.51 | 0.93 | 0.19 | 3.09 | -5.53 | 2.67 | -3.7 |
| 50 | 1.42 | 0.94 | 1.03 | 7.96 | -42.8 | 11.27 | -73.92 |
| 100 | 1.5 | 0.93 | 0.97 | 8.37 | -48.43 | 12.72 | -97.29 |
| 150 | 1.43 | 0.94 | 2.4 | 20.94 | -329.35 | 40.1 | -1075.99 |
| 25 | 20 | 1.68 | 0.92 | 2.29 | 9.4 | -65.18 | 16.28 | -167.0 |
| 50 | 1.36 | 0.94 | 0.1 | 2.27 | -2.65 | 1.82 | -1.23 |
| 100 | 1.35 | 0.94 | 0.92 | 8.28 | -47.62 | 12.76 | -98.6 |
| 150 | 1.34 | 0.94 | 1.17 | 7.42 | -45.19 | 16.33 | -186.7 |
| 50 | 20 | 1.4 | 0.94 | 0.4 | 1.22 | -0.15 | 2.27 | -3.13 |
| 50 | 1.43 | 0.94 | 0.37 | 4.2 | -11.05 | 4.61 | -11.27 |
| 100 | 1.45 | 0.94 | 0.24 | 1.34 | -0.28 | 4.16 | -13.14 |
| 150 | 1.35 | 0.94 | 0.35 | 4.02 | -10.32 | 4.41 | -10.32 |

Table 29: Model-4 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 3.54 | 0.83 | 2.53 | 4.34 | -7.67 | 5.2 | -13.41 |
| 50 | 2.66 | 0.89 | 0.63 | 3.36 | -4.33 | 4.12 | -8.37 |
| 100 | 2.0 | 0.94 | 0.15 | 1.84 | -0.72 | 1.61 | -0.74 |
| 150 | 1.75 | 0.95 | 0.16 | 1.74 | -0.56 | 1.54 | -0.63 |
| 25 | 20 | 2.7 | 0.9 | 1.27 | 4.58 | -9.25 | 6.14 | -19.83 |
| 50 | 2.01 | 0.94 | 1.11 | 4.94 | -11.06 | 6.95 | -26.04 |
| 100 | 1.94 | 0.94 | 0.01 | 1.32 | 0.05 | 1.27 | -0.03 |
| 150 | 1.71 | 0.95 | 0.76 | 3.64 | -5.34 | 4.52 | -10.25 |
| 50 | 20 | 2.29 | 0.92 | 1.48 | 4.75 | -9.99 | 6.71 | -24.21 |
| 50 | 1.98 | 0.94 | 0.11 | 1.62 | -0.42 | 1.3 | -0.22 |
| 100 | 1.75 | 0.95 | 0.19 | 2.1 | -1.17 | 1.91 | -1.31 |
| 150 | 1.58 | 0.96 | 0.75 | 3.07 | -3.49 | 3.39 | -5.37 |

Table 30: Model-4 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 3.36 | 0.76 | 3.21 | 3.26 | -35.44 | 4.39 | -17.23 |
| 50 | 2.51 | 0.87 | 1.92 | 3.47 | -46.11 | 5.5 | -29.13 |
| 100 | 1.79 | 0.93 | 1.18 | 1.02 | -3.83 | 1.76 | -3.27 |
| 150 | 1.62 | 0.94 | 1.28 | 1.0 | -3.54 | 1.68 | -2.99 |
| 25 | 20 | 2.35 | 0.88 | 1.69 | 2.23 | -19.16 | 3.78 | -14.62 |
| 50 | 1.9 | 0.92 | 2.37 | 5.47 | -114.31 | 8.62 | -70.99 |
| 100 | 1.82 | 0.93 | 1.48 | 1.58 | -9.1 | 2.29 | -4.9 |
| 150 | 1.7 | 0.93 | 1.74 | 2.67 | -27.59 | 4.63 | -21.91 |
| 50 | 20 | 2.16 | 0.89 | 2.12 | 3.21 | -39.04 | 5.54 | -31.39 |
| 50 | 1.91 | 0.92 | 1.34 | 1.1 | -4.01 | 1.54 | -2.18 |
| 100 | 1.64 | 0.94 | 1.7 | 2.86 | -29.95 | 4.04 | -14.88 |
| 150 | 1.51 | 0.95 | 2.23 | 4.21 | -64.88 | 5.9 | -31.38 |

Table 31: Model-4 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 4.2 | 0.77 | 2.5 | 3.13 | -8.06 | 5.65 | -6.05 |
| 50 | 3.67 | 0.82 | 0.18 | 1.88 | -3.96 | 5.37 | -6.97 |
| 100 | 2.29 | 0.93 | 0.74 | 1.59 | -2.62 | 4.66 | -5.11 |
| 150 | 2.15 | 0.94 | 1.12 | 1.29 | -0.72 | 1.61 | 0.21 |
| 25 | 20 | 3.79 | 0.8 | 0.18 | 1.78 | -3.28 | 4.16 | -3.45 |
| 50 | 2.77 | 0.89 | 0.17 | 4.29 | -20.32 | 10.03 | -23.32 |
| 100 | 2.72 | 0.8 | 0.36 | 2.25 | -5.53 | 5.59 | -7.0 |
| 150 | 2.03 | 0.94 | 0.56 | 1.5 | -2.3 | 4.54 | -4.88 |
| 50 | 20 | 3.24 | 0.85 | 0.35 | 1.19 | -0.63 | 3.04 | -1.63 |
| 50 | 2.49 | 0.91 | 0.76 | 1.13 | -0.2 | 2.52 | -0.82 |
| 100 | 2.39 | 0.92 | 0.07 | 5.47 | -30.92 | 10.07 | -20.8 |
| 150 | 1.98 | 0.95 | 0.1 | 4.57 | -22.46 | 9.79 | -21.19 |

Table 32: Model-4 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 5.51 | 0.16 | 2.1 | 5.51 | -18.61 | 6.09 | -19.57 |
| 50 | 5.12 | 0.26 | 0.22 | 4.75 | -14.82 | 6.31 | -22.67 |
| 100 | 3.41 | 0.62 | 0.11 | 4.42 | -12.86 | 5.65 | -17.87 |
| 150 | 3.29 | 0.63 | 0.37 | 2.51 | -3.43 | 2.07 | -1.96 |
| 25 | 20 | 5.48 | 0.16 | 0.2 | 4.26 | -11.47 | 4.64 | -11.5 |
| 50 | 4.18 | 0.45 | 0.57 | 7.08 | -34.67 | 10.7 | -68.63 |
| 100 | 3.98 | 0.51 | 0.21 | 5.11 | -17.2 | 6.43 | -23.0 |
| 150 | 3.03 | 0.67 | 0.1 | 4.5 | -13.15 | 5.68 | -17.99 |
| 50 | 20 | 5.13 | 0.12 | 0.09 | 3.53 | -7.7 | 3.67 | -7.07 |
| 50 | 3.93 | 0.49 | 0.32 | 3.11 | -5.72 | 3.01 | -4.68 |
| 100 | 4.09 | 0.41 | 0.67 | 8.3 | -46.72 | 10.69 | -64.46 |
| 150 | 2.99 | 0.69 | 0.71 | 7.46 | -38.1 | 10.53 | -64.46 |

Table 33: Model-4 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 2.76 | 0.88 | 2.67 | 3.36 | -4.27 | 3.4 | -5.87 |
| 50 | 2.45 | 0.91 | 0.26 | 1.59 | -0.51 | 3.42 | -6.47 |
| 100 | 2.12 | 0.93 | 1.4 | 5.62 | -14.65 | 8.01 | -34.66 |
| 150 | 2.14 | 0.93 | 0.38 | 1.4 | -0.07 | 1.2 | -0.02 |
| 25 | 20 | 2.43 | 0.91 | 3.91 | 8.08 | -28.64 | 11.06 | -64.14 |
| 50 | 2.2 | 0.93 | 1.34 | 3.47 | -4.68 | 4.2 | -8.74 |
| 100 | 2.17 | 0.93 | 0.12 | 1.47 | -0.19 | 1.23 | -0.08 |
| 150 | 1.79 | 0.95 | 0.19 | 2.11 | -1.13 | 2.17 | -1.97 |
| 50 | 20 | 3.7 | 0.82 | 1.38 | 2.29 | -1.64 | 1.83 | -1.12 |
| 50 | 2.41 | 0.91 | 0.65 | 1.87 | -0.8 | 1.47 | -0.52 |
| 100 | 2.09 | 0.93 | 1.77 | 4.15 | -7.82 | 6.66 | -23.87 |
| 150 | 2.53 | 0.91 | 0.23 | 2.66 | -2.33 | 2.82 | -3.54 |

Table 34: Model-4 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 2.52 | 0.85 | 3.35 | 2.42 | -19.07 | 2.89 | -7.08 |
| 50 | 2.46 | 0.88 | 0.62 | 2.28 | -19.33 | 4.37 | -18.32 |
| 100 | 2.17 | 0.89 | 2.66 | 5.48 | -114.56 | 8.52 | -68.59 |
| 150 | 2.54 | 0.86 | 0.71 | 0.42 | 0.14 | 0.8 | 0.05 |
| 25 | 20 | 2.18 | 0.89 | 4.98 | 7.86 | -218.9 | 11.52 | -120.88 |
| 50 | 1.99 | 0.91 | 2.35 | 2.68 | -25.78 | 3.93 | -14.42 |
| 100 | 2.02 | 0.91 | 0.9 | 0.41 | 0.13 | 0.77 | 0.09 |
| 150 | 1.78 | 0.93 | 1.29 | 1.24 | -5.51 | 1.94 | -3.72 |
| 50 | 20 | 3.85 | 0.73 | 2.01 | 0.84 | -2.2 | 0.94 | -0.09 |
| 50 | 2.14 | 0.9 | 1.56 | 0.55 | -0.72 | 0.81 | 0.07 |
| 100 | 1.97 | 0.91 | 1.01 | 5.51 | -112.06 | 7.89 | -54.75 |
| 150 | 2.36 | 0.89 | 1.27 | 1.55 | -8.86 | 2.22 | -4.61 |

Table 35: Model-4 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 3.04 | 0.88 | 2.81 | 2.46 | -4.9 | 4.69 | -4.12 |
| 50 | 2.83 | 0.9 | 0.96 | 1.95 | -2.52 | 1.78 | 0.35 |
| 100 | 2.18 | 0.94 | 0.73 | 5.93 | -36.64 | 11.92 | -30.69 |
| 150 | 2.09 | 0.94 | 0.67 | 2.64 | -7.65 | 6.25 | -8.67 |
| 25 | 20 | 2.76 | 0.9 | 4.37 | 8.6 | -62.69 | 14.07 | -38.44 |
| 50 | 2.66 | 0.91 | 1.32 | 3.69 | -12.87 | 7.32 | -11.13 |
| 100 | 2.62 | 0.91 | 1.2 | 1.32 | -0.82 | 1.57 | 0.29 |
| 150 | 2.03 | 0.95 | 1.04 | 1.47 | -1.2 | 4.03 | -3.55 |
| 50 | 20 | 4.58 | 0.75 | 1.02 | 1.18 | -0.71 | 2.78 | -1.17 |
| 50 | 3.12 | 0.87 | 0.4 | 1.03 | -0.19 | 1.46 | 0.29 |
| 100 | 2.23 | 0.93 | 1.42 | 1.26 | -0.61 | 1.94 | -0.13 |
| 150 | 3.22 | 0.88 | 0.66 | 1.69 | -3.16 | 4.86 | -5.52 |

Table 36: Model-4 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 2.94 | 0.73 | 1.96 | 4.41 | -11.56 | 4.49 | -10.41 |
| 50 | 2.59 | 0.8 | 1.24 | 0.82 | 0.44 | 2.69 | -5.42 |
| 100 | 2.16 | 0.86 | 0.79 | 7.62 | -39.74 | 10.46 | -63.02 |
| 150 | 1.98 | 0.88 | 0.75 | 3.19 | -6.1 | 3.26 | -5.5 |
| 25 | 20 | 2.69 | 0.78 | 3.33 | 9.69 | -60.58 | 12.91 | -93.85 |
| 50 | 2.47 | 0.81 | 0.55 | 4.77 | -14.6 | 5.77 | -18.2 |
| 100 | 2.41 | 0.83 | 0.9 | 2.43 | -3.17 | 2.15 | -2.18 |
| 150 | 1.84 | 0.9 | 0.56 | 3.59 | -8.13 | 4.27 | -9.87 |
| 50 | 20 | 4.2 | 0.53 | 0.39 | 2.91 | -4.73 | 2.32 | -2.71 |
| 50 | 2.91 | 0.75 | 0.32 | 2.44 | -3.19 | 2.0 | -1.72 |
| 100 | 2.26 | 0.85 | 2.62 | 2.07 | -2.42 | 4.09 | -10.61 |
| 150 | 3.03 | 0.77 | 0.23 | 4.33 | -12.06 | 4.94 | -13.18 |

Table 37: Model-5 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.94 | 0.94 | 0.27 | 1.41 | -0.03 | 1.91 | -1.14 |
| 50 | 1.45 | 0.97 | 0.53 | 1.52 | -0.11 | 2.87 | -4.01 |
| 100 | 1.53 | 0.97 | 0.97 | 3.94 | -6.36 | 5.75 | -18.13 |
| 150 | 1.46 | 0.97 | 0.63 | 1.89 | -0.8 | 1.55 | -0.63 |
| 25 | 20 | 1.95 | 0.94 | 0.61 | 2.43 | -1.74 | 2.74 | -3.38 |
| 50 | 1.66 | 0.96 | 0.95 | 3.12 | -3.59 | 4.11 | -8.74 |
| 100 | 1.43 | 0.97 | 0.53 | 1.34 | 0.05 | 1.22 | 0.03 |
| 150 | 1.43 | 0.97 | 0.59 | 1.39 | 0.02 | 1.6 | -0.53 |
| 50 | 20 | 1.93 | 0.94 | 0.5 | 2.89 | -2.92 | 3.17 | -4.6 |
| 50 | 1.45 | 0.97 | 0.62 | 1.56 | -0.34 | 2.04 | -1.44 |
| 100 | 1.44 | 0.97 | 0.96 | 2.28 | -1.64 | 1.97 | -1.52 |
| 150 | 1.44 | 0.97 | 0.83 | 1.43 | -0.02 | 2.25 | -1.93 |

Table 38: Model-5 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 1.87 | 0.92 | 1.45 | 0.52 | -0.24 | 1.16 | -0.74 |
| 50 | 1.37 | 0.96 | 1.49 | 1.93 | -15.91 | 4.74 | -24.18 |
| 100 | 1.44 | 0.95 | 1.96 | 2.21 | -17.72 | 3.49 | -12.13 |
| 150 | 1.38 | 0.96 | 1.81 | 1.28 | -5.63 | 1.66 | -2.44 |
| 25 | 20 | 1.87 | 0.92 | 1.74 | 1.28 | -5.86 | 2.03 | -4.18 |
| 50 | 1.58 | 0.94 | 2.1 | 2.47 | -21.67 | 3.99 | -15.75 |
| 100 | 1.36 | 0.96 | 1.69 | 0.53 | -0.67 | 0.94 | -0.48 |
| 150 | 1.36 | 0.96 | 1.66 | 0.59 | -0.54 | 0.96 | -0.19 |
| 50 | 20 | 1.87 | 0.92 | 2.02 | 4.09 | -62.77 | 5.97 | -32.92 |
| 50 | 1.37 | 0.96 | 1.19 | 3.79 | -60.22 | 7.52 | -57.13 |
| 100 | 1.37 | 0.96 | 1.94 | 1.44 | -6.54 | 1.59 | -2.01 |
| 150 | 1.38 | 0.96 | 1.64 | 1.18 | -5.47 | 3.11 | -10.19 |

Table 39: Model-5 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 2.1 | 0.94 | 0.69 | 1.15 | -0.26 | 2.68 | -1.05 |
| 50 | 1.52 | 0.97 | -1.01 | 3.47 | -9.52 | 4.24 | -2.21 |
| 100 | 1.86 | 0.95 | 0.59 | 1.01 | 0.01 | 2.16 | -0.4 |
| 150 | 1.48 | 0.97 | 0.45 | 1.29 | -1.22 | 3.55 | -2.57 |
| 25 | 20 | 2.18 | 0.94 | 0.45 | 1.4 | -1.72 | 3.97 | -3.36 |
| 50 | 1.73 | 0.96 | 0.13 | 2.54 | -7.17 | 6.24 | -8.77 |
| 100 | 1.47 | 0.97 | 0.77 | 1.25 | -0.85 | 3.44 | -2.31 |
| 150 | 1.47 | 0.97 | 0.69 | 1.17 | -0.6 | 3.41 | -2.31 |
| 50 | 20 | 2.18 | 0.94 | 0.57 | 6.95 | -47.38 | 12.29 | -30.6 |
| 50 | 1.57 | 0.97 | -1.16 | 3.73 | -10.78 | 3.55 | -1.32 |
| 100 | 1.52 | 0.97 | 0.58 | 1.15 | -0.49 | 2.9 | -1.42 |
| 150 | 1.48 | 0.97 | 1.11 | 3.96 | -13.24 | 5.09 | -3.69 |

Table 40: Model-5 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 2.08 | 0.87 | 0.07 | 3.46 | -7.26 | 3.42 | -6.1 |
| 50 | 1.45 | 0.94 | 0.24 | 0.95 | 0.14 | 3.13 | -7.54 |
| 100 | 2.03 | 0.89 | 0.18 | 3.41 | -6.9 | 3.1 | -5.03 |
| 150 | 1.37 | 0.94 | 0.29 | 4.2 | -11.01 | 4.62 | -11.37 |
| 25 | 20 | 2.21 | 0.85 | 0.24 | 4.04 | -10.37 | 4.68 | -11.8 |
| 50 | 1.68 | 0.92 | 0.54 | 5.37 | -18.8 | 6.9 | -26.51 |
| 100 | 1.39 | 0.94 | 0.03 | 3.76 | -8.69 | 4.07 | -8.66 |
| 150 | 1.36 | 0.94 | 0.07 | 3.65 | -8.12 | 3.99 | -8.33 |
| 50 | 20 | 2.27 | 0.84 | 1.17 | 9.4 | -60.02 | 12.64 | -91.1 |
| 50 | 1.59 | 0.92 | 0.37 | 0.98 | 0.16 | 2.55 | -4.34 |
| 100 | 1.49 | 0.93 | 0.2 | 3.69 | -8.24 | 3.67 | -7.06 |
| 150 | 1.47 | 0.93 | 0.27 | 1.41 | -0.42 | 4.1 | -12.61 |

Table 41: Model-5 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.75 | 0.96 | 0.39 | 1.55 | -0.21 | 3.14 | -5.08 |
| 50 | 1.48 | 0.97 | 0.71 | 2.54 | -2.08 | 2.47 | -2.62 |
| 100 | 1.45 | 0.97 | 0.62 | 1.79 | -0.71 | 1.3 | -0.3 |
| 150 | 1.45 | 0.97 | 0.43 | 1.58 | -0.31 | 3.28 | -5.73 |
| 25 | 20 | 1.55 | 0.97 | 0.61 | 7.44 | -29.62 | 15.44 | -148.24 |
| 50 | 1.45 | 0.97 | 1.16 | 4.79 | -10.29 | 7.47 | -31.65 |
| 100 | 1.56 | 0.96 | 0.79 | 2.73 | -2.52 | 3.12 | -4.62 |
| 150 | 1.42 | 0.97 | 0.51 | 1.63 | -0.37 | 3.28 | -5.63 |
| 50 | 20 | 1.4 | 0.97 | 0.11 | 2.46 | -3.16 | 6.13 | -24.21 |
| 50 | 1.46 | 0.97 | 1.08 | 4.07 | -6.98 | 5.71 | -17.45 |
| 100 | 1.45 | 0.97 | 0.87 | 2.78 | -2.68 | 3.03 | -4.3 |
| 150 | 1.42 | 0.97 | 0.53 | 1.65 | -0.43 | 3.51 | -6.76 |

Table 42: Model-5 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 1.83 | 0.93 | 1.5 | 1.57 | -10.28 | 3.67 | -13.9 |
| 50 | 1.41 | 0.95 | 1.83 | 1.49 | -7.44 | 1.84 | -2.92 |
| 100 | 1.38 | 0.96 | 1.73 | 0.57 | -0.86 | 0.79 | 0.13 |
| 150 | 1.37 | 0.96 | 1.5 | 1.76 | -12.38 | 3.87 | -15.11 |
| 25 | 20 | 1.51 | 0.95 | 0.31 | 9.95 | -412.42 | 18.81 | -358.52 |
| 50 | 1.4 | 0.96 | 2.37 | 4.47 | -74.81 | 7.72 | -59.94 |
| 100 | 1.5 | 0.95 | 1.92 | 1.72 | -10.09 | 2.5 | -5.98 |
| 150 | 1.34 | 0.96 | 1.6 | 1.77 | -14.06 | 4.02 | -16.63 |
| 50 | 20 | 1.33 | 0.96 | 1.12 | 3.76 | -57.76 | 7.72 | -60.93 |
| 50 | 1.41 | 0.95 | 2.18 | 3.5 | -45.63 | 5.69 | -31.81 |
| 100 | 1.39 | 0.96 | 1.98 | 1.96 | -12.81 | 2.58 | -6.07 |
| 150 | 1.34 | 0.96 | 1.62 | 1.64 | -11.52 | 3.95 | -16.3 |

Table 43: Model-5 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 1.8 | 0.96 | 0.63 | 2.02 | -2.83 | 2.1 | 0.14 |
| 50 | 1.53 | 0.97 | 0.38 | 1.21 | 0.82 | 3.2 | -1.91 |
| 100 | 1.5 | 0.97 | 0.53 | 1.01 | 0.01 | 1.88 | -0.09 |
| 150 | 1.51 | 0.97 | 0.63 | 1.45 | -1.2 | 1.44 | 0.55 |
| 25 | 20 | 1.61 | 0.97 | 1.81 | 10.28 | -94.1 | 16.38 | -50.72 |
| 50 | 1.5 | 0.97 | 0.08 | 3.22 | -11.49 | 7.95 | -14.85 |
| 100 | 1.66 | 0.96 | 0.34 | 1.19 | -0.75 | 3.43 | -2.41 |
| 150 | 1.48 | 0.97 | 0.66 | 2.35 | -4.16 | 2.16 | 0.05 |
| 50 | 20 | 1.47 | 0.97 | 0.96 | 3.91 | -12.26 | 5.31 | -4.08 |
| 50 | 1.51 | 0.97 | 0.08 | 2.95 | -9.87 | 7.12 | -12.07 |
| 100 | 1.49 | 0.97 | 0.2 | 1.49 | -2.21 | 4.19 | -3.93 |
| 150 | 1.47 | 0.97 | 0.6 | 1.3 | -0.91 | 1.46 | 0.49 |

Table 44: Model-5 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 1.71 | 0.91 | 0.03 | 1.29 | -0.39 | 2.46 | -3.84 |
| 50 | 1.42 | 0.94 | 0.32 | 3.79 | -8.7 | 3.78 | -7.45 |
| 100 | 1.38 | 0.94 | 0.18 | 2.82 | -4.44 | 2.23 | -2.41 |
| 150 | 1.39 | 0.94 | 0.05 | 1.24 | -0.25 | 2.36 | -3.48 |
| 25 | 20 | 1.5 | 0.93 | 1.12 | 6.6 | -35.34 | 15.23 | -166.24 |
| 50 | 1.38 | 0.94 | 0.78 | 6.3 | -26.52 | 9.04 | -47.79 |
| 100 | 1.54 | 0.93 | 0.35 | 3.82 | -8.97 | 4.21 | -9.35 |
| 150 | 1.36 | 0.94 | 0.06 | 1.09 | -0.14 | 2.57 | -4.57 |
| 50 | 20 | 1.36 | 0.94 | 0.32 | 1.55 | -0.75 | 5.18 | -21.2 |
| 50 | 1.39 | 0.94 | 0.64 | 5.38 | -18.95 | 7.08 | -28.36 |
| 100 | 1.37 | 0.94 | 0.47 | 4.02 | -9.9 | 4.3 | -9.76 |
| 150 | 1.35 | 0.94 | 0.08 | 1.12 | -0.14 | 2.58 | -4.49 |

Table 45: Model-6 Metrics of BP With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.5 | 0.97 | 0.76 | 2.85 | -2.83 | 3.35 | -5.42 |
| 50 | 1.5 | 0.97 | 0.81 | 3.17 | -3.74 | 3.76 | -6.83 |
| 100 | 1.42 | 0.97 | 0.74 | 2.23 | -1.41 | 1.97 | -1.44 |
| 150 | 1.41 | 0.97 | 0.84 | 3.28 | -4.0 | 4.76 | -12.51 |
| 25 | 20 | 1.5 | 0.96 | 0.16 | 2.04 | -1.93 | 5.23 | -17.57 |
| 50 | 1.43 | 0.97 | 0.71 | 2.12 | -1.19 | 2.03 | -1.61 |
| 100 | 1.42 | 0.97 | 0.42 | 1.66 | -0.55 | 3.46 | -6.51 |
| 150 | 1.41 | 0.97 | 0.53 | 1.53 | -0.28 | 1.29 | -0.14 |
| 50 | 20 | 1.57 | 0.96 | 0.47 | 1.38 | 0.05 | 2.05 | -1.44 |
| 50 | 1.41 | 0.97 | 0.54 | 1.39 | 0.02 | 1.96 | -1.23 |
| 100 | 1.44 | 0.97 | 0.81 | 2.73 | -2.45 | 3.1 | -4.48 |
| 150 | 1.13 | 0.97 | 0.6 | 1.43 | -0.06 | 2.32 | -2.16 |

Table 46: Model-6 Metrics of SHEL With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 1.42 | 0.95 | 1.8 | 0.98 | -2.95 | 1.13 | -0.53 |
| 50 | 1.41 | 0.95 | 2.05 | 3.08 | -35.21 | 4.71 | -21.04 |
| 100 | 1.34 | 0.96 | 1.86 | 1.25 | -5.15 | 1.52 | -1.89 |
| 150 | 1.34 | 0.96 | 1.73 | 1.21 | -5.07 | 1.73 | -2.9 |
| 25 | 20 | 1.43 | 0.95 | 1.09 | 4.13 | -71.5 | 7.82 | -60.73 |
| 50 | 1.36 | 0.96 | 1.68 | 0.54 | -0.35 | 0.82 | 0.09 |
| 100 | 1.34 | 0.96 | 1.6 | 0.91 | -3.01 | 1.91 | -3.32 |
| 150 | 1.34 | 0.96 | 1.57 | 0.6 | -0.98 | 0.94 | -0.42 |
| 50 | 20 | 1.48 | 0.95 | 1.47 | 0.9 | -2.79 | 2.09 | -4.07 |
| 50 | 1.33 | 0.96 | 1.51 | 0.93 | -3.03 | 2.35 | -5.44 |
| 100 | 1.37 | 0.96 | 1.75 | 0.63 | -1.04 | 0.89 | 0.0 |
| 150 | 1.36 | 0.96 | 1.59 | 0.52 | -0.25 | 1.33 | -1.4 |

Table 47: Model-6 Metrics of XOM With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 1.62 | 0.96 | 0.53 | 1.03 | -0.12 | 1.7 | 0.06 |
| 50 | 1.53 | 0.97 | 0.02 | 3.74 | -15.34 | 8.19 | -14.86 |
| 100 | 1.46 | 0.97 | 0.45 | 1.22 | -0.75 | 3.22 | -1.94 |
| 150 | 1.45 | 0.97 | 0.65 | 1.1 | -0.39 | 1.24 | 0.61 |
| 25 | 20 | 1.68 | 0.96 | 1.23 | 4.78 | -18.79 | 5.57 | -4.43 |
| 50 | 1.47 | 0.97 | 0.64 | 1.01 | -0.02 | 2.2 | -0.45 |
| 100 | 1.45 | 0.97 | 0.56 | 1.25 | -0.97 | 3.49 | -2.43 |
| 150 | 1.46 | 0.97 | 0.53 | 1.56 | -2.59 | 4.57 | -4.68 |
| 50 | 20 | 1.68 | 0.96 | 0.64 | 1.11 | -0.31 | 1.62 | 0.16 |
| 50 | 1.47 | 0.97 | -0.78 | 1.28 | -0.84 | 1.39 | 0.51 |
| 100 | 1.47 | 0.97 | 0.79 | 1.24 | -0.67 | 1.38 | 0.5 |
| 150 | 1.45 | 0.97 | -0.62 | 1.13 | -0.23 | 2.37 | -0.61 |

Table 48: Model-6 Metrics of CVX With StandardScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 1.64 | 0.92 | 0.2 | 2.89 | -4.76 | 2.4 | -2.94 |
| 50 | 1.39 | 0.94 | 0.75 | 6.79 | -30.99 | 9.1 | -47.18 |
| 100 | 1.35 | 0.94 | 0.3 | 3.96 | -9.67 | 4.19 | -9.27 |
| 150 | 1.39 | 0.94 | 0.13 | 2.66 | -3.88 | 2.04 | -1.83 |
| 25 | 20 | 1.7 | 0.91 | 0.52 | 1.84 | -1.61 | 4.48 | -13.91 |
| 50 | 1.37 | 0.94 | 0.06 | 2.8 | -4.45 | 2.52 | -3.19 |
| 100 | 1.39 | 0.94 | 0.25 | 4.02 | -9.95 | 4.32 | -9.81 |
| 150 | 1.43 | 0.94 | 0.23 | 4.44 | -12.6 | 5.3 | -15.22 |
| 50 | 20 | 1.57 | 0.92 | 0.14 | 2.82 | -4.5 | 2.23 | -2.4 |
| 50 | 1.39 | 0.94 | 0.01 | 2.24 | -2.59 | 1.81 | -1.28 |
| 100 | 1.45 | 0.94 | 0.02 | 2.4 | -3.04 | 1.9 | -1.46 |
| 150 | 1.37 | 0.94 | 0.1 | 3.01 | -5.24 | 2.59 | -3.49 |

Table 49: Model-6 Metrics of BP With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| BP | 10 | 20 | 1.4 | 0.97 | 0.25 | 2.0 | -1.73 | 5.34 | -18.61 |
| 50 | 1.69 | 0.96 | 1.3 | 6.52 | -20.42 | 10.19 | -58.75 |
| 100 | 1.44 | 0.97 | 0.16 | 2.02 | -1.84 | 5.18 | -17.24 |
| 150 | 1.49 | 0.97 | 1.35 | 7.11 | -24.7 | 11.89 | -82.43 |
| 25 | 20 | 1.51 | 0.97 | 1.01 | 4.44 | -8.58 | 6.17 | -20.3 |
| 50 | 1.44 | 0.97 | 1.33 | 6.74 | -21.73 | 10.18 | -57.67 |
| 100 | 1.42 | 0.97 | 0.67 | 2.04 | -1.16 | 1.58 | -0.76 |
| 150 | 1.44 | 0.97 | 1.01 | 3.85 | -6.17 | 5.32 | -15.18 |
| 50 | 20 | 1.5 | 0.97 | 1.09 | 4.52 | -8.94 | 6.55 | -23.36 |
| 50 | 1.42 | 0.97 | 0.84 | 3.09 | -3.45 | 3.77 | -6.97 |
| 100 | 1.43 | 0.97 | 0.97 | 3.65 | -5.27 | 4.87 | -12.26 |
| 150 | 1.42 | 0.97 | 1.05 | 2.78 | -2.66 | 2.95 | -3.93 |

Table 50: Model-6 Metrics of SHEL With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| SHEL | 10 | 20 | 1.33 | 0.96 | 1.33 | 2.98 | -37.32 | 6.68 | -47.26 |
| 50 | 1.65 | 0.94 | 2.49 | 6.38 | -158.29 | 10.74 | -113.87 |
| 100 | 1.39 | 0.96 | 1.25 | 2.97 | -37.08 | 6.39 | -42.34 |
| 150 | 1.43 | 0.95 | 2.61 | 7.12 | -201.17 | 12.71 | -163.69 |
| 25 | 20 | 1.43 | 0.95 | 2.16 | 3.77 | -53.44 | 6.02 | -35.07 |
| 50 | 1.35 | 0.96 | 2.49 | 6.63 | -169.92 | 10.77 | -112.06 |
| 100 | 1.34 | 0.96 | 1.71 | 0.9 | -2.4 | 1.0 | -0.21 |
| 150 | 1.39 | 0.96 | 2.25 | 3.2 | -36.07 | 5.05 | -24.79 |
| 50 | 20 | 1.46 | 0.95 | 2.14 | 3.94 | -59.34 | 6.42 | -40.45 |
| 50 | 1.34 | 0.96 | 1.82 | 2.09 | -15.82 | 3.04 | -8.71 |
| 100 | 1.37 | 0.96 | 2.01 | 2.97 | -32.8 | 4.62 | -20.63 |
| 150 | 1.35 | 0.96 | 2.04 | 1.88 | -11.97 | 2.38 | -4.85 |

Table 51: Model-6 Metrics of XOM With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| XOM | 10 | 20 | 1.45 | 0.97 | 0.95 | 4.19 | -14.57 | 6.25 | -6.3 |
| 50 | 1.77 | 0.96 | 0.29 | 5.62 | -33.1 | 11.7 | -30.22 |
| 100 | 1.5 | 0.97 | 0.92 | 3.17 | -7.91 | 3.93 | -1.78 |
| 150 | 1.58 | 0.97 | 0.33 | 5.74 | -35.09 | 12.46 | -35.16 |
| 25 | 20 | 1.59 | 0.97 | 0.08 | 3.59 | -14.15 | 8.01 | -14.32 |
| 50 | 1.51 | 0.97 | 0.38 | 6.73 | -46.29 | 13.18 | -37.29 |
| 100 | 1.49 | 0.97 | 0.56 | 1.0 | 0.04 | 2.25 | -0.54 |
| 150 | 1.5 | 0.97 | 0.38 | 1.57 | -2.36 | 4.41 | -4.34 |
| 50 | 20 | 1.53 | 0.97 | 0.03 | 2.92 | -9.8 | 7.07 | -11.49 |
| 50 | 1.48 | 0.97 | 0.55 | 1.21 | -0.44 | 2.86 | -1.31 |
| 100 | 1.49 | 0.97 | 0.15 | 2.22 | -5.65 | 5.75 | -7.62 |
| 150 | 1.51 | 0.97 | 0.2 | 1.35 | -1.48 | 3.57 | -2.54 |

Table 52: Model-6 Metrics of CVX With MinMaxScaler

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Test metrics | | 1 day Forecast metrics | 15 days Forecast metrics | | 30 days Forecast metrics | |
| Stock | Look Back | Epochs | MAPE | R2 | MAPE | MAPE | R2 | MAPE | R2 |
| CVX | 10 | 20 | 1.34 | 0.94 | 0.16 | 1.35 | -0.32 | 4.83 | -19.06 |
| 50 | 1.67 | 0.92 | 0.96 | 8.31 | -47.38 | 12.1 | -86.47 |
| 100 | 1.39 | 0.94 | 0.22 | 1.25 | -0.16 | 4.24 | -14.28 |
| 150 | 1.46 | 0.94 | 1.0 | 8.82 | -54.45 | 13.69 | -113.92 |
| 25 | 20 | 1.47 | 0.93 | 0.65 | 6.01 | -23.95 | 7.89 | -35.19 |
| 50 | 1.39 | 0.94 | 0.97 | 8.67 | -51.71 | 12.39 | -89.8 |
| 100 | 1.36 | 0.94 | 0.11 | 3.03 | -5.3 | 2.51 | -3.25 |
| 150 | 1.37 | 0.94 | 0.57 | 5.04 | -16.19 | 6.32 | -22.04 |
| 50 | 20 | 1.4 | 0.94 | 0.68 | 6.05 | -24.38 | 8.04 | -36.74 |
| 50 | 1.36 | 0.94 | 0.3 | 4.19 | -11.1 | 4.64 | -11.57 |
| 100 | 1.36 | 0.94 | 0.59 | 5.1 | -16.89 | 6.31 | -22.0 |
| 150 | 1.39 | 0.94 | 0.57 | 4.11 | -10.41 | 4.24 | -9.49 |

## Programme

Programming used for this project is attached below.

# -\*- coding: utf-8 -\*-

###Importing Necessary Libraries

"""

#Importing necessary libraries

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import yfinance as yf

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, GRU, Bidirectional, Dense, Dropout, Input

from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator

from sklearn.preprocessing import StandardScaler, MinMaxScaler

from sklearn.metrics import mean\_absolute\_percentage\_error as mape

from sklearn.metrics import r2\_score, mean\_squared\_error

from keras.utils import plot\_model

from keras.callbacks import History

"""###Defining Necessary Functions"""

def data\_download(ticker, start\_date, end\_date):

'''

This function generates array of close prices of given ticker stock between

start\_date and end\_date and from end\_date to considered date

Parameters

----------

ticker : STR

Ticker resembles the stock chosen and is used to download the stock data.

start\_date : STR

Starting date from when the stock data to be collected.

end\_date : STR

Ending date till when the stock data to be collected.

Returns

-------

numpy.array, numpy.array

Stock close prices between given dates, Stock close prices from end date

to considered date

'''

#Downloading stock data between start\_date and end\_date

data = yf.download(ticker,start = start\_date, end = end\_date)

data = np.array(data['Close'])

#Downloading stock data from end\_date to today

data\_forecast = yf.download(ticker, start = end\_date, end = '2024-03-27')

data\_forecast = np.array(data\_forecast['Close'])

#Returning close price from the downloaded stock data

return data, data\_forecast

def train\_test\_gen(data, scaler, look\_back):

'''

This function scales the data using the given scaler and also generates

timeseries data from the scaled data for given look\_back

Parameters

----------

data : numpy.array

Data that to be scaled and transformed to timeseries data.

scaler : sklearn.preprocessor

Scaler used to scale the given data.

look\_back : INT

Window period to genrate timeseries data.

Returns

-------

numpy.array, numpy.array, timeseries, timeseries, timeseries

Scaled train data, Scaled test data, Scaled timeseries data, Scaled

timeseries train data, Scaled timeseries test data of the given data

'''

#Transforming data with given scaler

data = scaler.fit\_transform(data.reshape(-1,1))

#Splitting data into 80:20 for train and test

size = int(len(data) \* 0.80)

train = data[:size]

test = data[size - look\_back:]

#Transforming scaled data into timeseries with look\_back

data\_ts = TimeseriesGenerator(data, data,

length=look\_back, batch\_size = 32)

train\_ts = TimeseriesGenerator(train, train,

length=look\_back, batch\_size = 32)

test\_ts = TimeseriesGenerator(test, test,

length=look\_back, batch\_size = 1)

#Returning scaled data and scaled timeseries data

return train, test, data\_ts, train\_ts, test\_ts

def evaluate(model, test, test\_ts, scaler, ticker):

'''

This function predicts using the given model and plots the predicted and

actual values from the given dataset. Performance metrics are evaluated and

printed.

Parameters

----------

model : tensorflow.keras.model

Tensorflow model built.

test : numpy.array

Scaled test data.

test\_ts : timeseries

SCaled timeseries test data.

scaler : sklearn.preprocessor

Scaler used to inverse transform the predicted data.

ticker : STR

Ticker resembles the stock chosen.

'''

#Prediction using test data with given model

model\_predictions = model.predict(test\_ts, verbose = 0)

model\_predictions = scaler.inverse\_transform(model\_predictions)

actual\_prices = scaler.inverse\_transform(test[look\_back:])

#Plotting the actual and predicted values of given test data

plt.figure(figsize=(10,5))

plt.plot(actual\_prices, color='blue', label='Actual '+ticker+' Stock Price')

plt.plot(model\_predictions, color='green', label='Predicted '+ticker+

' Stock Price')

plt.title(ticker+' Stock Price Prediction')

plt.xlabel('Forecast/Test index')

plt.ylabel(ticker+' Stock Price')

plt.legend()

plt.show()

#Evaluating the model prediction perfromance

print('Prediction Performance Metrics on test data:')

print('MAPE is ', np.round(mape(actual\_prices,model\_predictions)\*100,2),'%')

print('R2 Score is ', np.round(r2\_score(actual\_prices,model\_predictions),2))

def forecast(model, data\_forecast, test, scaler, look\_back, ticker):

'''

This function forecasts the stock close price with the given model and

evaluates its perfromance with the actual prices.

Parameters

----------

model : tensorflow.keras.model

Tensorflow model built.

data\_forecast : numpy.array

Data gathered to compare with forecast predictions.

test : numpy.array

Scaled test data.

scaler : sklearn.preprocessor

Scaler used to inverse transform the predicted data.

look\_back :

Window size to feed the data to model for predicting next day close price.

ticker : STR

Ticker resembles the stock chosen.

'''

#Creating timeseries data from the last look\_back days

input\_data = test[-look\_back:].reshape(1, look\_back, 1)

#Calculating number of days to predict future stock price

days\_to\_predict = len(data\_forecast)

#List to store the future predictions

future\_predictions = []

for \_ in range(days\_to\_predict):

#Predicting for the next day

prediction = model.predict(input\_data, verbose = 0)

#Appending the prediction

future\_predictions.append(prediction[0, 0])

#Updating the input data with new prediction

input\_data = np.append(input\_data[:, 1:, :],

prediction.reshape(1, 1, 1), axis=1)

#Transforming predicted values

future\_predictions = scaler.inverse\_transform(np.array(future\_predictions).

reshape(-1, 1))

#Plotting the actual and forecasted values

plt.figure(figsize=(10,5))

plt.plot(data\_forecast, color='blue', label='Actual '+ticker+' Stock Price')

plt.plot(future\_predictions, color='green',

label='Forecasted '+ticker+' Stock Price')

plt.title(ticker+' Stock Price Forecast')

plt.xlabel('Forecast/Test index')

plt.ylabel(ticker+' Stock Price')

plt.legend()

plt.show()

#Evaluating the model forecast performance for 1 day

print('Forecast Performance for 1 day:')

print('MAPE is ',

np.round(((data\_forecast[0]-future\_predictions[0])/data\_forecast[0]

)\*100,2)[0],'%')

#Evaluating the model forecast performance for 15 days

print('Forecast Performance for 15 day:')

print('MAPE is ', np.round(mape(data\_forecast[:15],

future\_predictions[:15])\*100,2),'%')

print('R2 Score is ', np.round(r2\_score(data\_forecast[:15],

future\_predictions[:15]),2))

#Evaluating the model forecast performance for 30 days

print('Forecast Performance for 30 day:')

print('MAPE is ', np.round(mape(data\_forecast[:30],

future\_predictions[:30])\*100,2),'%')

print('R2 Score is ', np.round(r2\_score(data\_forecast[:30],

future\_predictions[:30]),2))

"""###Look Back and Epochs set-up"""

#Setting Look Back

look\_back = 10

#Setting Epochs

epoch = 20

#Setting keras seed

tf.random.set\_seed(19)

"""###Data Gathering and Pre-Processing"""

#BP stock data gathering

bp,bp\_forecast = data\_download('BP.L', "2014-02-01", "2024-02-01")

#Scalers, that to be used for scaling BP stock data

bp\_scaler\_min = MinMaxScaler()

bp\_scaler\_std = StandardScaler()

#Generating scaled and timeseries data for training and testing data from BP

#stock data.

bp\_train\_std, bp\_test\_std, bp\_ts\_std, bp\_train\_ts\_std, bp\_test\_ts\_std=train\_test\_gen(

bp, bp\_scaler\_std, look\_back)

bp\_train\_min, bp\_test\_min, bp\_ts\_min, bp\_train\_ts\_min, bp\_test\_ts\_min=train\_test\_gen(

bp, bp\_scaler\_min, look\_back)

#Plotting BP performance over last 10 years

plt.figure(figsize=(10,5))

plt.plot(bp,label='Daily Close Price',color='m')

plt.xlabel('Days from February 2014')

plt.ylabel('BP Stock Price')

plt.title('BP Stock Performance')

plt.legend()

#plt.savefig('bp')

plt.show()

#SHEL stock data gathering

shel,shel\_forecast = data\_download('SHEL', "2014-02-01", "2024-02-01")

#Scalers, that to be used for scaling SHEL stock data

shel\_scaler\_min = MinMaxScaler()

shel\_scaler\_std = StandardScaler()

#Generating scaled and timeseries data for training and testing data from SHEL

#stock data.

shel\_train\_std, shel\_test\_std, shel\_ts\_std, shel\_train\_ts\_std, shel\_test\_ts\_std = train\_test\_gen(

shel, shel\_scaler\_std, look\_back)

shel\_train\_min, shel\_test\_min, shel\_ts\_min, shel\_train\_ts\_min, shel\_test\_ts\_min = train\_test\_gen(

shel, shel\_scaler\_min, look\_back)

#Plotting SHEL performance over last 10 years

plt.figure(figsize=(10,5))

plt.plot(shel,label='Daily Close Price',color='m')

plt.xlabel('Days from February 2014')

plt.ylabel('SHEL Stock Price')

plt.title('SHEL Stock Performance')

plt.legend()

#plt.savefig('shel')

plt.show()

#XOM stock data gathering

xom,xom\_forecast = data\_download('XOM', "2014-02-01", "2024-02-01")

#Scalers, that to be used for scaling XOM stock data

xom\_scaler\_min = MinMaxScaler()

xom\_scaler\_std = StandardScaler()

#Generating scaled and timeseries data for training and testing data from XOM

#stock data.

xom\_train\_std, xom\_test\_std, xom\_ts\_std, xom\_train\_ts\_std, xom\_test\_ts\_std = train\_test\_gen(

xom, xom\_scaler\_std, look\_back)

xom\_train\_min, xom\_test\_min, xom\_ts\_min, xom\_train\_ts\_min, xom\_test\_ts\_min = train\_test\_gen(

xom, xom\_scaler\_min, look\_back)

#Plotting XOM performance over last 10 years

plt.figure(figsize=(10,5))

plt.plot(xom,label='Daily Close Price',color='m')

plt.xlabel('Days from February 2014')

plt.ylabel('XOM Stock Price')

plt.title('XOM Stock Performance')

plt.legend()

#plt.savefig('xom')

plt.show()

#CVX stock data gathering

cvx,cvx\_forecast = data\_download('CVX', "2014-02-01", "2024-02-01")

#Scalers, that to be used for scaling CVX stock data

cvx\_scaler\_min = MinMaxScaler()

cvx\_scaler\_std = StandardScaler()

#Generating scaled and timeseries data for training and testing data from CVX

#stock data.

cvx\_train\_std, cvx\_test\_std, cvx\_ts\_std, cvx\_train\_ts\_std, cvx\_test\_ts\_std = train\_test\_gen(

cvx, cvx\_scaler\_std, look\_back)

cvx\_train\_min, cvx\_test\_min, cvx\_ts\_min, cvx\_train\_ts\_min, cvx\_test\_ts\_min = train\_test\_gen(

cvx, cvx\_scaler\_min, look\_back)

#Plotting CVX performance over last 10 years

plt.figure(figsize=(10,5))

plt.plot(cvx,label='Daily Close Price',color='m')

plt.xlabel('Days from February 2014')

plt.ylabel('CVX Stock Price')

plt.title('CVX Stock Performance')

plt.legend()

#plt.savefig('cvx')

plt.show()

"""###Model-1 building and evaluation"""

#LSTM model

model\_1 = Sequential()

model\_1.add(LSTM(units=50,activation='sigmoid', return\_sequences=True,

input\_shape=(look\_back, 1)))

model\_1.add(LSTM(units=50,activation='sigmoid', return\_sequences=True))

model\_1.add(LSTM(units=25, return\_sequences=True))

model\_1.add(LSTM(units=10))

model\_1.add(Dense(1))

#Compiling model-1

model\_1.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_1.summary()

plot\_model(model\_1)

#Compiling the model

model\_1.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_1.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_1, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_1, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_1, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_1, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_1.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_1.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_1, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_1, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_1, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_1, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_1.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_1.fit(bp\_train\_ts\_min, epochs=epoch,verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_1, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_1, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_1, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_1, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_1.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_1.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_1, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_1, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_1, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_1, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Model-2 Building and evaluation"""

#LSTM model with Dropout layers

model\_2 = Sequential()

model\_2.add(LSTM(units=50,activation='sigmoid', return\_sequences=True,

input\_shape=(look\_back, 1)))

model\_2.add(Dropout(0.2))

model\_2.add(LSTM(units=50,activation='sigmoid', return\_sequences=True))

model\_2.add(Dropout(0.1))

model\_2.add(LSTM(units=25, return\_sequences=True))

model\_2.add(Dropout(0.05))

model\_2.add(LSTM(units=10))

model\_2.add(Dense(1))

#COmpiling the model

model\_2.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_2.summary()

plot\_model(model\_2)

#Compiling the model

model\_2.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_2.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_2, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_2, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_2, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_2, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_2.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_2.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_2, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_2, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_2, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_2, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_2.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_2.fit(bp\_train\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_2, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_2, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_2, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_2, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_2.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_2.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_2, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_2, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_2, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_2, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Model-3 building and evaluation"""

#GRU model

model\_3 = tf.keras.models.Sequential()

model\_3.add(tf.keras.layers.GRU(units=50,activation='sigmoid',

return\_sequences=True,

input\_shape=(look\_back, 1)))

model\_3.add(tf.keras.layers.GRU(units=25))

model\_3.add(tf.keras.layers.Dense(1))

#Compiling the model

model\_3.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_3.summary()

plot\_model(model\_3)

#Compiling the model

model\_3.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_3.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_3, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_3, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_3, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_3, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_3.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_3.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_3, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_3, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_3, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_3, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_3.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_3.fit(bp\_train\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_3, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_3, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_3, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_3, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_3.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_3.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_3, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_3, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_3, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_3, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Model-4 Building and evaluation"""

#GRU model with Dropout layers

model\_4 = tf.keras.models.Sequential()

model\_4.add(tf.keras.layers.GRU(units=50,activation='sigmoid',

return\_sequences=True,

input\_shape=(look\_back, 1)))

model\_4.add(tf.keras.layers.Dropout(0.2))

model\_4.add(tf.keras.layers.GRU(units=25,activation='sigmoid'))

model\_4.add(tf.keras.layers.Dropout(0.2))

model\_4.add(tf.keras.layers.Dense(1))

#Compiling the model

model\_4.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_4.summary()

plot\_model(model\_4)

#Compiling the model

model\_4.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_4.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_4, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_4, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_4, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_4, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_4.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_4.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_4, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_4, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_4, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_4, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_4.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_4.fit(bp\_train\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_4, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_4, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_4, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_4, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_4.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_4.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_4, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_4, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_4, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_4, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Model-5 Building and Evaluation"""

#Bi-Directional LSTM model

model\_5 = Sequential()

model\_5.add(Input(shape=(look\_back, 1)))

model\_5.add(Bidirectional(LSTM(units=50, return\_sequences=False)))

model\_5.add(Dense(units=1))

#COmpiling the model

model\_5.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_5.summary()

plot\_model(model\_5)

#Compiling the model

model\_5.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_5.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_5, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_5, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_5, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_5, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_5.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_5.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_5, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_5, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_5, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_5, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_5.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_5.fit(bp\_train\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_5, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_5, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_5, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_5, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_5.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_5.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_5, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_5, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_5, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_5, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Model-6 Building and Evaluation"""

#Bi-Directional GRU layer

model\_6 = Sequential()

model\_6.add(Input(shape=(look\_back, 1)))

model\_6.add(Bidirectional(GRU(units=50, return\_sequences=False)))

model\_6.add(Dense(units=1))

#Compiling the model

model\_6.compile(optimizer='adam', loss='mean\_squared\_error')

#Plotting model summary and the model

model\_6.summary()

plot\_model(model\_6)

#Compiling the model

model\_6.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_6.fit(bp\_train\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_6, bp\_test\_std, bp\_test\_ts\_std, bp\_scaler\_std, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_6, shel\_test\_std, shel\_test\_ts\_std, shel\_scaler\_std, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_6, xom\_test\_std, xom\_test\_ts\_std, xom\_scaler\_std, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_6, cvx\_test\_std, cvx\_test\_ts\_std, cvx\_scaler\_std, 'CVX')

#Compiling the model

model\_6.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_6.fit(bp\_ts\_std, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_6, bp\_forecast, bp\_test\_std, bp\_scaler\_std, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_6, shel\_forecast, shel\_test\_std, shel\_scaler\_std, look\_back,

'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_6, xom\_forecast, xom\_test\_std, xom\_scaler\_std, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_6, cvx\_forecast, cvx\_test\_std, cvx\_scaler\_std, look\_back, 'CVX')

#Compiling the model

model\_6.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries training data

model\_6.fit(bp\_train\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model with BP timeseries test data

evaluate(model\_6, bp\_test\_min, bp\_test\_ts\_min, bp\_scaler\_min, 'BP')

#Evaluating the model with SHEL timeseries test data

evaluate(model\_6, shel\_test\_min, shel\_test\_ts\_min, shel\_scaler\_min, 'SHEL')

#Evaluating the model with XOM timeseries test data

evaluate(model\_6, xom\_test\_min, xom\_test\_ts\_min, xom\_scaler\_min, 'XOM')

#Evaluating the model with CVX timeseries test data

evaluate(model\_6, cvx\_test\_min, cvx\_test\_ts\_min, cvx\_scaler\_min, 'CVX')

#Compiling the model

model\_6.compile(optimizer='adam', loss='mean\_squared\_error')

#Training the model with BP timeseries data

model\_6.fit(bp\_ts\_min, epochs=epoch, verbose=2)

#Evaluating the model Forecast Performance with BP data

forecast(model\_6, bp\_forecast, bp\_test\_min, bp\_scaler\_min, look\_back, 'BP')

#Evaluating the model Forecast Performance with SHEL data

forecast(model\_6, shel\_forecast, shel\_test\_min, shel\_scaler\_min, look\_back, 'SHEL')

#Evaluating the model Forecast Performance with XOM data

forecast(model\_6, xom\_forecast, xom\_test\_min, xom\_scaler\_min, look\_back, 'XOM')

#Evaluating the model Forecast Performance with CVX data

forecast(model\_6, cvx\_forecast, cvx\_test\_min, cvx\_scaler\_min, look\_back, 'CVX')

"""###Results analysis"""

results = pd.read\_excel('/content/drive/MyDrive/dat.xlsx')

results.head()

results.describe()

results[(results['lookback']==25)].describe()

print(results[results['30 day mape']==results['30 day mape'].max()])

print(results[results['r2']>=0.95].count())

print(results.groupby(['lookback','model'])['r2'].max())

print(results.groupby(['scaler','stock'])['r2'].min())

#MAPE variation plots

res = results[(results['model']=='m6') & (results['scaler']=='min') & (results['lookback']==10)]

plt.figure(figsize = (10,5))

df\_pivot = pd.pivot\_table(res,

values="fmape",

index="stock",

columns="epoch",

aggfunc=np.mean)

df\_pivot.plot.bar()

plt.ylabel('MAPE')

plt.xlabel('Stock')

plt.legend(title = 'Epochs', loc='center left', bbox\_to\_anchor=(1, 0.75))

plt.title('Model - 6 performance with 10 lookbacks and MinMaxScaler')