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# Stock Price Prediction Using Long Short-Term Memory

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**Abstract**: This document states the study of Long Short-Term Memory (LSTM) algorithms, for stock prediction to predict the stock price effectively to minimize the difficulty of an individual in stock prediction. The main goal of this study is to use the LSTM algorithm with parameters to create a line graph that compares the real and forecasted stock prices. To train the algorithm, the project employs the Python programming language in Jupyter Notebook and uses Cross-Industry Standard Process for Data Mining (CRISP-DM) process methodology. There are two datasets used in the research which are Maxis and Maybank Stock price allocated from 2 November 2020 to 1 November 2021. To analyze the performance of the algorithms, the results would include a line graph and an indicator table such as Mean Square Error (MSE) and Mean Absolute Error (MAE). An individual or a firm can have a better understanding of prediction methods and how they affect the predictive result by conducting research. It found that LSTM model have high accuracy in the aspect of stock price prediction and can predict the trend of the stock price in the future. However, LSTM model still cannot predict the stock price perfectly but just near the exact value. This is because there are many unpredictable and external factors will affect the stock price such as political issues and news. Therefore, this research suggests that LSTM model prediction should act as an assistance role or reference for an investor in decision making process instead of fully depend on it.

**Keywords**: Long Short-Term Memory, Stock Market, Stock Prediction System

## 1. Introduction

Stock market is made up of a multitude of investors and traders who buy and sell stock and push the price up or down. The prices of stocks are determined by the principles of bid and offer, and the ultimate goal of purchases is to make money by buying shares of companies whose perceived is expected to increase[1]. In fact, sock price is influenced by many indicators like closing price and volume. Due to the volatility of factors that play an important role in price movement, it is almost

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impossible to predict stock prices up to the truly exact value. However, it is possible to make an educated guess from prices. Stock prices never change in isolation: the movement of 4,444 stocks tends to have an avalanche effect on several other 4,444 stocks. This aspect of stock price movement can be used as an important tool for predicting the prices of many stocks at once. Due to the large cash volume and the number of transactions that take place every minute, there is a trade-off between the accuracy and the volume of the predictions made.

For many years, whether or not in monetary or educational aspects, inventory rate forecast has been a totally essential studies topic. Stock market prediction aims to determine the future movement of the stock value of a financial exchange. The accurate prediction of share price movement will lead to more profit investors can make. Predicting how the stock market will move is one of the most challenging issues due to many factors that involved in the stock prediction[2]. There are so many algorithms and models can be used to make a prediction for the stock price. However, Recurrent Neural Network (RNN) has been proven that it is one of the powerful models for processing the prediction in it. Because of vanishing gradient problem that occurs in RNN which longer the time processing and effectiveness, a enhanced version, Long Short-Term Memory (LSTM) neural community has been introduced[3].

This project is dedicated to the stock forecasting system due to the high difficulty with the manual calculation method. Predictive findings are visualized in line graphs for ease of understanding. This is because enormous of information is needed such as company profile, political issue, market trend, supply chains and so on to analyze and predict the price. Even an individual predicted the price by referring previous stock price, it still needs to refer 1 or 2 year of the data. Hence, it is hard for an individual to do the prediction manually. The algorithm is able to predict the stock price according to the indicator that been chosen and provided. Moreover, effectiveness of LSTM will also be discussed in this project by evaluating and analyze the result.

This article is divided into five sections. An introduction that outlines the project's context is included in the first section. The second section describes the analysis of the pertinent work. The third section presents the solution strategy, which will also be detailed. The results and discussions are presented in the fourth part. The final segment gives the conclusion.

## 2. Literature Review

### 2.1 Stock Price prediction

With the continuous expansion of the stock market over the last few decades, an increasing number of people have conducted research on stock price forecasting. They attempt to analyze and forecast stock market fluctuations and price changes. Stock prices have a high degree of dynamism, nonlinearity, and noise. Many factors influence individual stock prices, including the global economy, politics, government policies, natural or man-made disasters, investor behavior, and so on. It is one of the most difficult problems in time series forecasting [4].

Some studies have shown that stock market is based on Random Walk Theory and Efficient Market Hypothesis[5]. Previous studies believed that stock price fluctuations were random and thus could not be predicted. Stock prices, according to the efficient market hypothesis, are driven by news rather than current or historical prices. Because news is unpredictable, stock prices will move in a random walk pattern. It is difficult to forecast the stock price with greater than 50% accuracy. However, more and more studies in recent years have shown that the stock market's price is not random and can be predicted to some extent. This is because stock price estimates are still useful in guiding a person's judgement on whether a stock has promise or not. As previously said, the flow of stock prices is influenced by a variety of elements; therefore, we require a machine learning to assist us in simplifying the analysis as much as feasible.

## 2.2 Long Short-Term Memory (LSTM)

One of the RNN's derivatives is the LSTM neural network. It not only compensates for RNN's lack of long-term memory, but also prevents gradient disappearance. The LSTM neural network can learn and decide whether a particular output should be the next recursive input in real time. It gives a useful reference and application for creating a predictive model for this study based on this process that can retain essential information.[6].

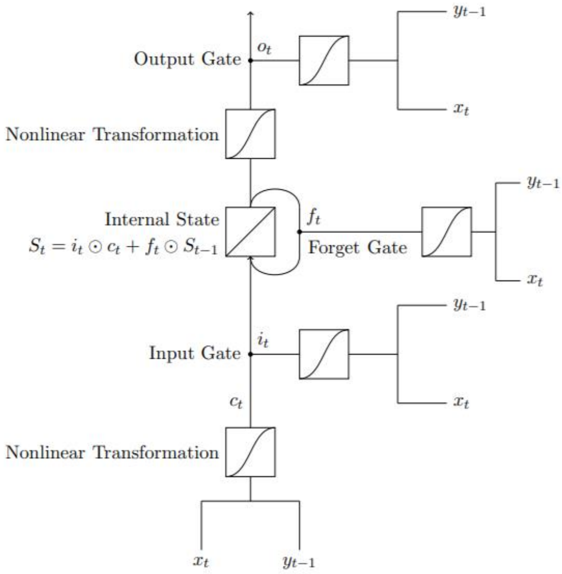


**Figure 2: LSTM Architecture**

Cells having sigmoidal input, output, and forget gates make up the LSTM hidden layers. This enables the network to figure out when it should forget, take input, and output. The internal state of the LSTM cell is updated based on previous layer activations and inputs via connections to the prior layer and self-connections.

A layer of LSTM cells takes a sequence of vectors as

$$\text{Input } x = (x_1, x_2, x_3, \ldots x_T) \quad (1)$$

and outputs a sequence of vectors

$$y = (y_1, y_2, y_3, \ldots y_T) \quad (2)$$

The output vectors are calculated by iterating through the following equations from t = 1 to T:

$$f_t = 6(W_{fx}x_t + W_{fy}y_{t-1} + b_f) \quad (3)$$

LSTM networks are built by first identifying the data that is not necessary and will be removed from the cell at that time. The sigmoid function σ(x), which uses the output of the previous LSTM unit ($y_{t-1}$) at time t-1 and the current input ($x_t$) at time t, determines the process of detecting and excluding data. The sigmoid function also decides whether portion of the previous output should be deleted. The forget gate (or $f_t$) is the name of this gate. Each number in the cell state, $s_t$, is represented by a vector with values ranging from 0 to 1. 6 is the sigmoid function, and $W_f$ and $b_f$ are the weight matrices and bias, respectively, of the forget gate.

$$6(x) = \begin{cases} 0, & x \leq -2.5 \\ 0.2x + 0.5, & -2.5 \leq x \leq 2.5 \\ 1, & 2.5 \geq x \end{cases} \quad (4)$$

σ(x) in (4) is defined as a hard sigmoid function which can output 0 and 1. This means that the gates can fully close or open.

$$c_t = \tanh(W_{cx}x_t + W_{cy}y_{t-1} + b_c) \quad (5)$$

$$i_t = 6(W_{ix}x_t + W_{iy}y_{t-1} + b_i) \quad (6)$$

$$s_t = i_t * c_t + f_t * s_{t-1} \quad (7)$$

The next step is to make a decision, save the data from the new input ($x_t$) in the cell state, and update the cell state. The sigmoid layer and the second component of this step are the tanh layer. The sigmoid layer first determines whether or not the new information should be updated (0 or 1), and then the tanh function assigns weight to the data that passed by, determining their level of relevance (1 to 1). In Equation (7), the new cell state is updated by multiplying the two values. Then, the old memory $s_{t-1}$ is joined to the new memory, yielding $s_t$. Here, $s_{t-1}$ and $s_t$ are the cell states at time t−1 and t, while W and b are the weight matrices and bias, respectively, of the cell state.

$$o_{t =} 6(W_{ox}x_t + W_{oy}y_{t-1} + b_o) \quad (8)$$

$$y_t = o_t * \tanh(S_t) \quad (9)$$

The output values ($y_t$) in the last step are based on the output cell state ($o_t$), which show in (8) however they are a filtered version. A sigmoid layer makes the initial determination of which components of the cell state are output. The new values produced by the tanh layer from the cell state ($s_t$) are then multiplied by the output of the sigmoid gate ($o_t$), with a value between 1 and 1. Here, $W_o$ and $b_o$ are the weight matrices and bias, respectively, of the output gate.

### 2.3 Comparison of Existing Algorithms

The comparison of the proposed algorithms is shown in **Table 1**. The implementation of algorithms has provided an example of the changes in how the algorithms would be implemented based on the research of existing algorithms in other applications. The existing researches studied including Indian stock prediction using artificial neural networks on tick data[7] , predicting stock price direction using support vector machines [8] and stock price prediction using K-Nearest neighbour (kNN) Algorithm[9]. **Table 1** has shown the comparison between each of the algorithms about its strengthens and weakness.

**Table 1: Comparison between ANN, LSTM, KNN and SVM**

| Method | Type | Method type | Advantage | Disadvantage |
|---|---|---|---|---|
| ANN | Deep Learning | Model | - High ability to tackle complex nonlinear patterns<br>- High accuracy for modelling the relationship in data groups Model can support both linear and non-linear processes | - Over fitting<br>- Sensitive to parameter selection (ANNs just give predicted target values for some unknown data without any variance information to assess the prediction) |
| LSTM | Deep Learning | Model | - Makes good predictions because it analyses the interactions and hidden patterns within the data<br>- Good in remembering information for long time | - Lacks a mechanism to index the memory while writing and reading the data The number of memory cells is linked to the size of the recurrent weight matrices |
| SVM | Machine Learning | Algorithms | - Can provide the optimal global solution and has excellent predictive accuracy capability | - Sensitive to outliers<br>- Sensitive to parameter selection |
| KNN | Machine Learning | Algorithms | - Very efficient if the training data is large<br>- Robust to noisy training data | - The number of nearest neighbours must first be determined<br>- Memory limitation |

| | | |
|---|---|---|
| | | - Sensitive to the local structure of the data |

In short, both algorithms have different advantage and disadvantage when apply it. However, it cannot deny that both methods can predict stock price respectively. In this study, LSTM has been chosen in the study due to good remembering information for long time and can make good prediction based on historical data. SVM and KNN method is too simple and because there has huge limitation when using to predict stock price. It is because KNN need to determine the number of nearest neighbours before carry out while SVM is very sensitive to outlier which often occur in stock price. ANN is a good algorithm but it is very sensitive to parameter selection and has data overfitting problem. Therefore, LSTM is the most suitable algorithm to predict the stock price and chosen to carry out the research.

## 3. Research Methodology

The Cross-Industry Standard Process for Data Mining (CRISP-DM) was employed in this study. Business understanding, data understanding, data preparation, modelling, evaluation, and finally deployment are the phases covered in this study. These phases will serve as the foundation for how this study is carried out and will ensure that the research is completed within the specified time frame. **Table 2** shows the tasks and the outputs for each phases.

**Table 2: CRISP-DM activities and their task**

| Phase | Task | Output |
|---|---|---|
| Business Understanding | • Proposed the project<br>• Determine the project schedule, activities and output | • Project proposal<br>• Gantt Chart |
| Data Understanding | • Select data for modelling<br>• Describe data<br>• Explore the data<br>• Verify the quality of data | • Dataset description table<br>• Data Collection report<br>• Data Exploration Report<br>• Data quality report |
| Data Preparation | • Clean the data<br>• Integrate the data<br>• Construct the data<br>• Format the data | • Clean and quality dataset in excel table |
| Modelling | • Construct the LSTM model<br>• Generate the training and testing of LSTM<br>• Build Model | • Modelling technique<br>• Parameter settings model<br>• Model assessment<br>• Output graph |

| | | |
|---|---|---|
| Evaluation | • Evaluate the result<br>• Visualize the result by graphs<br>• Determine the next step whether to improve the modelling or move to next phase | • Review report of the result<br>• Efficiency report of the project |
| Deployment | • Plan deployment and maintenance<br>• Review the model<br>• Produce final report | • Deployment schedule and plan<br>• Maintenance report<br>• Final report |

## 4. Result and Discussion

In this section, a LSTM model is constructed by training and testing it. The prediction models have been presented.

### 4.1 Experiment Design

Designing the experiment design phases is one of the important phases to ensure the research can be run as smooth as possible. **Figure 3** has shown the flowchart of the whole research will be carried out. In this experiment, there are 2 datasets which are Maybank stock price and Maxis stock price will be used. the dataset goes through data pre-processing process to ensure there are no error in the dataset. After that, min-max scaling method had chosen to normalise the data in order to get better result. When the datasets are ready, LSTM model will be carried out. The train- test split ratio in this research is 60:40. The result will be evaluated independently and make comparison between two datasets.

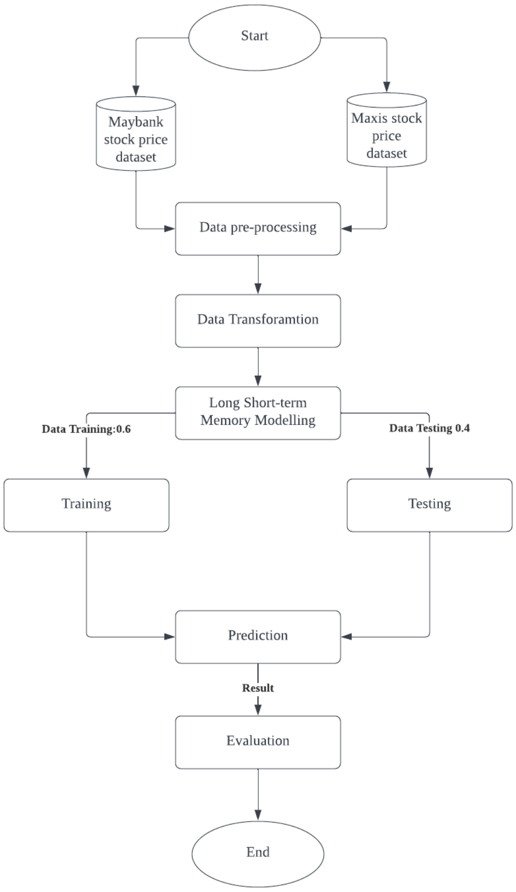


**Figure 3: Flowchart of the Experiment Phases**

The detail of the hyperparameters setup have shown in the **Table 3** below.

**Table 3: Hyperparameter**

| Categories | Hyperparameters |
|---|---|
| Optimizer | Adam |
| Number of hidden layers | 4 |
| Number of neurons | 50 |
| Number of epochs | 100 |
| Batch size | 32 |
| Dropout | 0.2 |

LSTM model will be set up with 50 neurons and 4 hidden layers. 1 neuron will be assigned in the output layer for predicting the normalized stock price. For the optimiser, Adam optimiser with default parameters provided by Keras was employed in our experiment due to it is the most suitable optimiser for deep learning problem with large datasets.

### 4.2 Parameter and Testing Method

This section will discuss the parameter used in this project. In order to analyze the effect of model more comprehensively, two type of evaluation measure were used which were Mean Square Error (MSE) and Mean Absolute Error (MAE) to evaluate the difference between the predicted and practical data.

The MSE is a loss function given by Equation (10) [10]:

$$L_{MSE} = 1/n \sum_{(i=0)}^{n} ((y)^{i}_{true} - y^{i}_{pred})^2 \tag{10}$$

The MAE is a loss loss function given by Equation (11) [11]:

$$L_{MAE} = \frac{1}{n} \sum_{i=1}^{n} | y^{i}_{true} - y^{i}_{pred} | \tag{11}$$

### 4.3 Prediction and Evaluation

The prediction of Maxis stock price and Maybank stock price are evaluated with basic graphical analysis by employing a line graph. **Figure 4** and **5** shows the actual stock price and predicted stock price of Maxis and Maybank. It shows that the predicted graph was quite accurate and had succeed to predict the pattern. even the line seems not really move closely. It was because the range of the change of stock price for everyday is very less from 0.1 to 0.01. Hence, due to graph enlarged, it illustrated a misperception of graph physically. However, from the graph we also can observe that some of the details pattern cannot be predicted successfully. This is because in year of 2021, Malaysia's economy has affected by pandemic COVID-19 as an external factor which was unpredictable. As result, LSTM algorithm cannot consider the reality factor which make it have some uncertainty issue.

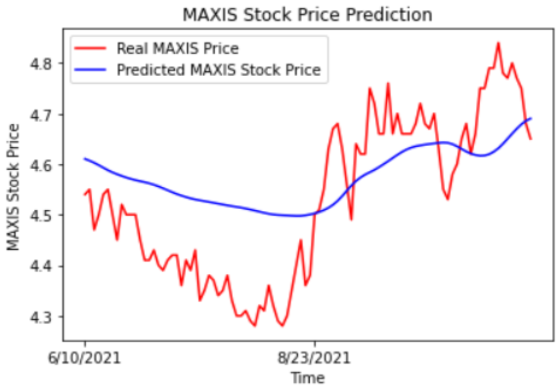


**Figure 4: Predicted Stock Price of Maxis**

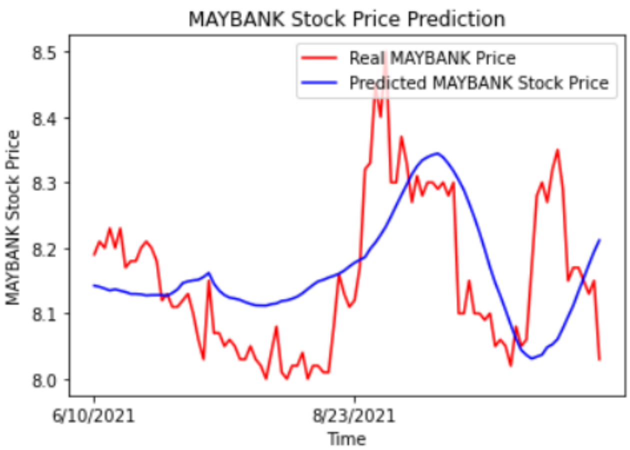


**Figure 5: Predicted Stock Price of Maybank**

Beside graphical analysis, different evaluation measure had been used to evaluate the result more clearly and detail. In this project, mean square error and mean absolute error were chosen to evaluate the system. **Table 4** had displayed the value of each parameter.

**Table 4: MSE and MAE of Predicted Maxis and Maybank Stock Price**

| Evaluation Measure | Predicted Maxis Stock Price | Predicted Maybank Stock Price |
|---|---|---|
| Mean Square Error (MSE) | 0.016 | 0.019 |
| Mean Absolute Error (MAE) | 0.110 | 0.120 |

Based on the **Table 4**, it shows both datasets have low value of MSE, which are 0.016 for Maxis's stock price and 0.019 for Maybank's stock price. We can conclude that LSTM algorithm produce consistent ability in prediction due to similar MSE in both datasets. Besides, it also can predict with high accuracy which bring to low MSE. The value of MAE also proves the same inference with MSE.

## 5. Conclusion

In conclusion, all the objectives for the study were met, and significant contributions could be defined in depth. In this paper, the LSTM neural network had been carried out by using two different datasets of stock price. Each node in an LSTM is a memory cell that can store contextual data. As a result, LSTMs outperform other models because they can keep track of context-specific temporal connections between stock values for longer periods of time while making forecasts. Due to low MAE and MSE that found in this research, it concludes that LSTM has the ability and high accuracy to predict the stock price and the pattern of the graph of stock price based on historical stock price data.

However, stock markets are difficult to follow, and interpreting and forecasting price movements requires a lot of contexts. Because of this, LSTM also cannot predict the stock prices perfectly which show in this study too. It is because stock price will be effect by many external factors. For example, in our study, it found that the prediction did not manage to predict the exact stock price because of pandemic COVID-19 that effect economy of Malaysia. LSTM only can predict the stock price according to the history of it but cannot handle unpredictable factor that might influence the flow of stock price. Therefore, stock prediction system using LSTM model should act as assistance role or a reference for an investor in the process of decision making instead of rely it fully. The investors still need to consider other external and unpredictable factor such as government policy, political issues or market news which the algorithms are unable to predict it.

It was suggested that the future studies analyze a bigger dataset to get more accurate output because the dataset in this study only contain 256 data which will affect the efficiency of learning for LSTM algorithm. Besides, changes in timestep, batch size and epoch also be encouraged because it might make the system has a better performance.

## Acknowledgment

The authors would like to thank the Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia for its support.

## Appendix

| | Name | Duration | Start | Finish |
|---|---|---|---|---|
| | **⊟) Bussiness Understanding Phase** | 7 days? | **11/10/21 8:00 AM** | **11/18/21 5:00 PM** |
| | 1.1 Identifying the problem | 2 days? | 11/10/21 8:00 AM | 11/11/21 5:00 PM |
| | 1.2 Identifying the objective | 2 days? | 11/10/21 8:00 AM | 11/11/21 5:00 PM |
| | 1.3 Identifying the requirement | 3 days? | 11/12/21 8:00 AM | 11/16/21 5:00 PM |
| | 1.4 Identifying the methodology | 3 days? | 11/13/21 8:00 AM | 11/17/21 5:00 PM |
| | 1.5 Identifying the scope | 4 days? | 11/13/21 8:00 AM | 11/18/21 5:00 PM |
| | 1.6 Submit the Proposal | 7 days? | 11/10/21 8:00 AM | 11/18/21 5:00 PM |
| | **⊟2.0 Data Understanding Phase** | 40 days? | **11/22/21 8:00 AM** | **1/14/22 5:00 PM** |
| | 2.1 Identifying about the data | 40 days? | 11/22/21 8:00 AM | 1/14/22 5:00 PM |
| | 2.2 Identifying the techniques | 40 days? | 11/22/21 8:00 AM | 1/14/22 5:00 PM |
| | 2.3 Identifying the application | 40 days? | 11/22/21 8:00 AM | 1/14/22 5:00 PM |
| | 2.4 Explore te dataset | 40 days? | 11/22/21 8:00 AM | 1/14/22 5:00 PM |
| | 2.5 Verify the data quality | 40 days? | 11/22/21 8:00 AM | 1/14/22 5:00 PM |
| | **⊟3.0 Data Preparation Phase** | 30 days? | **1/17/22 8:00 AM** | **2/25/22 5:00 PM** |
| | 3.1 Data Retrieving | 30 days? | 1/17/22 8:00 AM | 2/25/22 5:00 PM |
| | 3.2 Data transformaiton | 30 days? | 1/17/22 8:00 AM | 2/25/22 5:00 PM |
| | 3.3 Construct the data | 30 days? | 1/17/22 8:00 AM | 2/25/22 5:00 PM |
| | **⊟4.0 Modelling Phase** | 50 days? | **2/26/22 8:00 AM** | **5/6/22 5:00 PM** |
| | 4.1 Select Modelling Techniques | 50 days? | 2/26/22 8:00 AM | 5/6/22 5:00 PM |
| | 4.2 Parameter Preparation | 50 days? | 2/26/22 8:00 AM | 5/6/22 5:00 PM |
| | 4.3 Requirement Analysis | 50 days? | 2/26/22 8:00 AM | 5/6/22 5:00 PM |
| | 4.4 Training Analysis | 50 days? | 2/26/22 8:00 AM | 5/6/22 5:00 PM |
| | 4.5 Testing Analysis | 50 days? | 2/26/22 8:00 AM | 5/6/22 5:00 PM |
| | **⊟5.0 Evaluation Phase** | 18 days? | **6/6/22 8:00 AM** | **6/29/22 5:00 PM** |
| | 5.1 Data Evaluation | 18 days? | 6/6/22 8:00 AM | 6/29/22 5:00 PM |
| | 5.2 Accuracy Evaluation | 18 days? | 6/6/22 8:00 AM | 6/29/22 5:00 PM |
| | 5.3 Root Mean Square Error Evaluati | 18 days? | 6/6/22 8:00 AM | 6/29/22 5:00 PM |
| | **⊟6.0 Deployment Phase** | 7 days? | **6/30/22 8:00 AM** | **7/8/22 5:00 PM** |
| | 6.1 Training Data | 7 days? | 6/30/22 8:00 AM | 7/8/22 5:00 PM |
| | 6.2 Discussion on Data Accuracy | 7 days? | 6/30/22 8:00 AM | 7/8/22 5:00 PM |
| | 6.3 Produce Final Report | 7 days? | 6/30/22 8:00 AM | 7/8/22 5:00 PM |

**Figure 6: Gantt Chart Activity**

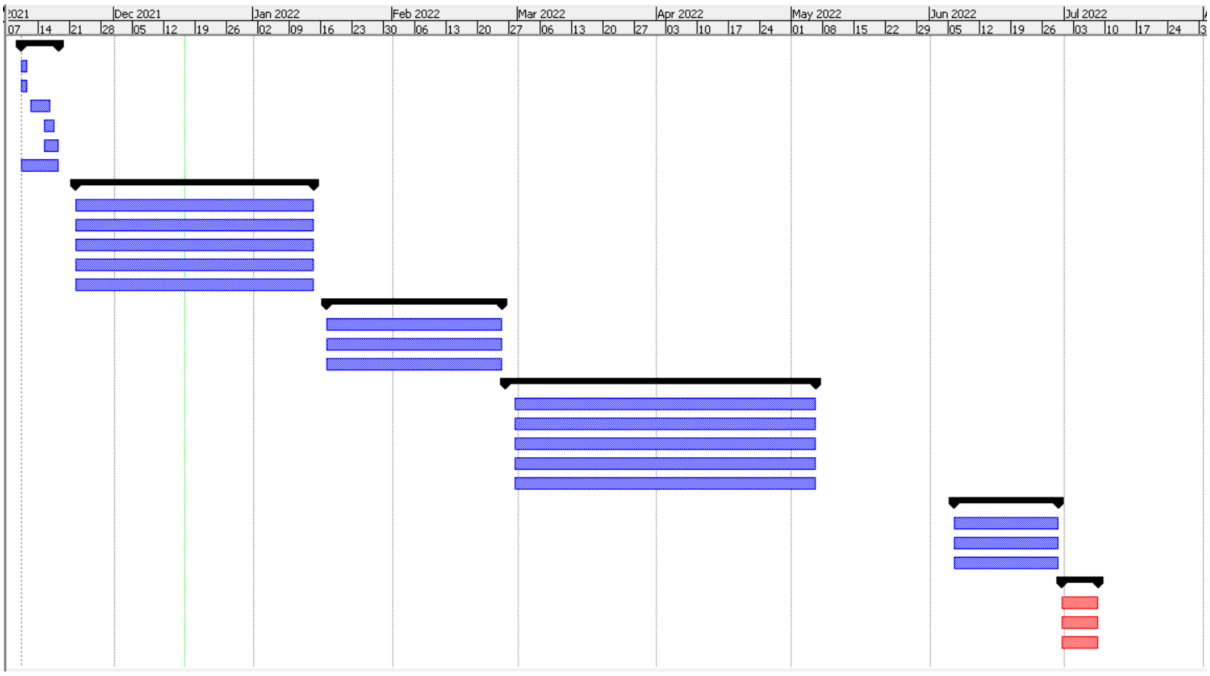

**Figure 7: Gantt Chart**

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 11/2/2020 | 7 | 7.03 | 6.96 | 7.01 | 6.36226 | 4829300 |
| 11/3/2020 | 7.01 | 7.04 | 6.97 | 7 | 6.353183 | 6801700 |
| 11/4/2020 | 7.02 | 7.09 | 6.99 | 7 | 6.353183 | 2220100 |
| 11/5/2020 | 7.03 | 7.08 | 7.02 | 7.08 | 6.425791 | 4913900 |
| 11/6/2020 | 7.08 | 7.19 | 7.06 | 7.18 | 6.516551 | 5184100 |
| 11/9/2020 | 7.18 | 7.26 | 7.07 | 7.12 | 6.462094 | 4107900 |
| 11/10/2020 | 7.23 | 7.66 | 7.23 | 7.66 | 6.952197 | 30397300 |
| 11/11/2020 | 7.66 | 7.69 | 7.45 | 7.69 | 6.979426 | 11143500 |
| 11/12/2020 | 7.68 | 7.85 | 7.6 | 7.8 | 7.079261 | 17048000 |
| 11/13/2020 | 7.75 | 7.93 | 7.66 | 7.93 | 7.197248 | 10653600 |
| 11/16/2020 | 7.93 | 8.15 | 7.83 | 8.14 | 7.387845 | 12784100 |
| 11/17/2020 | 8.18 | 8.35 | 8.16 | 8.3 | 7.53306 | 15747400 |
| 11/18/2020 | 8.3 | 8.3 | 8.12 | 8.23 | 7.469528 | 13471400 |

**Figure 8: Part of the Dataset of Maybank Stock Price**

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 11/2/2020 | 4.8 | 4.85 | 4.76 | 4.84 | 4.710916 | 813700 |
| 11/3/2020 | 4.84 | 4.92 | 4.83 | 4.89 | 4.759583 | 717000 |
| 11/4/2020 | 4.93 | 4.94 | 4.86 | 4.93 | 4.798515 | 598200 |
| 11/5/2020 | 4.93 | 5.03 | 4.93 | 5.02 | 4.886115 | 1402700 |
| 11/6/2020 | 5 | 5.15 | 4.98 | 5.15 | 5.012648 | 2525800 |
| 11/9/2020 | 5.15 | 5.3 | 5.11 | 5.3 | 5.158648 | 1955800 |
| 11/10/2020 | 5.28 | 5.28 | 5.18 | 5.2 | 5.061315 | 3074100 |
| 11/11/2020 | 5.26 | 5.26 | 5.11 | 5.19 | 5.051581 | 1232700 |
| 11/12/2020 | 5.19 | 5.24 | 5.12 | 5.2 | 5.061315 | 2828900 |
| 11/13/2020 | 5.1 | 5.23 | 5.1 | 5.2 | 5.061315 | 762100 |
| 11/16/2020 | 5.15 | 5.2 | 5.1 | 5.14 | 5.002915 | 1056200 |
| 11/17/2020 | 5.18 | 5.2 | 5.12 | 5.2 | 5.061315 | 636200 |
| 11/18/2020 | 5.2 | 5.21 | 5.1 | 5.13 | 4.993181 | 1455200 |
| 11/19/2020 | 5.17 | 5.17 | 5.05 | 5.05 | 4.915315 | 1461800 |
| 11/20/2020 | 5.05 | 5.14 | 5.04 | 5.11 | 4.973715 | 743600 |
| 11/23/2020 | 5.1 | 5.18 | 5.08 | 5.12 | 4.983448 | 1121200 |

**Figure 9: Part of the Dataset of Maxis Stock Price**

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