Share Buyback Prediction using LSTM on Malaysian Stock Market

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***Abstract*—Share buyback is a strategy for companies to repurchase their outstanding shares to reduce the number of shares from the open markets. With buyback, it indirectly increases the shares proportion and earning per shares (EPS) of a company. The aim of this study is to investigate the trend of share buyback strategy, and to design a simple prediction model for stock market price movement before initiating any buyback action. This study finds the use of Long Short-Term Memory (LSTM) as prediction algorithm has demonstrated that stock market price movement can be predicted using associated stock indicators, namely MACD and RSI which have an impact to the stock market price movement. The study also finds that the "Open" parameter based on the MAE, MSE and RMSE have been found to be the lowest value as compared to "High", "Low" and "Close" parameters.**

***Keywords*—Share buyback, LSTM, stock trading indicators, highest, lowest, opening and closing.**

I. INTRODUCTION

Stocks buyback happened when a market shares of a company is considered "undervaluation" [1-3]. To reacquire their share, company will initiate stock buyback in the open market [4] [5] and this will indirectly increase their earnings per share (EPS). Furthermore, it will indirectly shows that the company is financially stable to buy back their shares [5-7]. With buyback, company can reduce dividend paid to outside entities and have more cash reserves circulating inside the company. Hence, the company can focus on investing internally.

The benefit of buyback according to [6], company can reduce equity financing cost, capitalize on undervalued shares and consolidate ownership. While this activity is legal in many countries, there is a growing concern on this perplexed and that the cash used to repurchase shares is at the expense of capital reinvestment for future growth. The companies would be better off focusing on improving wages and benefits for their employees, and to invest in R&D rather than buying back shares.

Research has shown that buyback announcements have positive effects on the price returns in Malaysian [10] and South Korean [11] stock market, but not for Indian stock market [3, 12]. Abnormal returns were also not found in Indian market [3, 12] and this also applied to Malaysian market [2]. Nevertheless, this does not mean that there were no positive effects.

Share buyback that has been happening in the US may not project the same outcome as what happen to other countries. Different company structures may have different share buyback outcomes [3]. As for Malaysian cases, due to restricted number of shares for buyback purchase, it was found that it does not have any correlation with the increases of share price [2]. In terms of performance, Albaity and Said [2] found that short term performance yield was better than long term performance to the companies and investors.

Stock market and prediction modeling continue to be an active research area with many researchers developing numerous prediction models to predict the future trend of a particular stock market [13-17]. However, the prediction for stock market is very challenging as there are many factors that need to be considered [18].

This study addresses three main questions namely (1) What is the trend of share buyback strategy/decision as practice by companies? (2) How to predict the share market price movement? And (3) When is the appropriate time for buyback? This study proposes the use of prediction model with appropriate data type and trading patterns, trends and level of indicators that will be designed to assist company in the decision for buyback. It will generate predicted future stock price by creating multiple forecasts of the future price progression development.

Hence, the objectives of this study are (1) To investigate the trend of share buyback strategy/decision as practice by companies. (2) To design a prediction model in relation to the share price movement during the share repurchase event period, and (3) To predict stock market price movement that will initiate buyback action using prediction algorithm. The remainder of this paper is organized as follows: Section 2 briefly reviews the literature, Section 3 provides a research methodology, including identification of suitable approach/techniques, development of models, and validation of results. Section 4 presents findings and discussions, and Section 5 provides a conclusion.

II. LITERATURE REVIEW

2.1 *Why companies' buyback their shares?*

Stock buyback is a way for company to start to invest on themselves when they have more cash to be used instead of paying the dividend. Hayes and Scott [4] reported that companies buyback their shares: (i) to reduce available outstanding shares (ii) to reduce dividend payment, (iii) to increase shares' value and Earning per Shares (EPS), (iv) to show to their shareholders that the company is doing well, and (v) to eliminate any threats by shareholders who might want to control the stake. Moin et al. [19] study the association between share buyback and several affecting variables consisting of dividends overpayment, overcash, underleverage, underpricing and regulations. The study finds that those variables except underpricing have significant association with the stock buyback decision. Nath [7] also mentioned that, with buyback companies: (i) can improve the shareholders' value, (ii) can increase the share price (iii) shows that the company is doing well by having extra cash to spend on buyback, and (iv) can give benefits to investors from tax reduction.

2.2 *Stock Analysis*

Stock analysis is a way to evaluate the stock market future before deciding either to buy or sell their shares [8], namely fundamental analysis and technical analysis. Fundamental analysis is based on data about a company such as its assets and economic reports, while technical analysis is an analysis based on historical data and the chart trend [8, 20]. There are three trend patterns namely pennants, flags and wedges in which it was used to determine the company stock market trend [4]. With those patterns, trends and level indicators, traders can predict future stock market price.

2.3 *Stock Indicators*

Stock indicators were used by traders as an assistance during trading as well as to predict stock market price movement such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Exponential Moving Average (EMA), etc. One of the popular trading sites to trade is tradingview.com which offers to their traders with every available stock indicator.

Vargas et al. [21] uses two different sets of indicators. The first set consist of seven technical indicators arranged chronologically and the second set consist of five most common used technical indicators based on Kirkpatrick & Dahlquist book [20].

2.4 *Data*

Selvamuthu et al. [14] compared the different in prediction accuracy of using tick data and 15-minutes data in which they learned that tick data achieved better prediction accuracy of 99.9% while the 15-minutes data managed to give them the best results of 98.9% owing to tick data have more information compared with 15-minutes data - tick data registers every change, while 15-minutes data only register one data at the end of 15-minutes cycle.

Ding and Qin [17] found that the highest price of next day is related with the parameters of 1) historical price, 2) opening price and 3) lowest price of the same day. They also found that the daily opening price, the lowest price, and the highest price are related to each other. Their findings mentioned that the three parameters were associated with each other's when running the prediction model experiments. With this information, a prediction model can be developed with multiple parameters to get better prediction accuracy.

Roondiwala et al. [16] design a prediction model using LSTM by taking four variables which are highest price, lowest price, opening price and closing price with 250 and 500 epochs. Those two types of epochs approach were then run through a series variable combination. They achieved the best results in RMSE with combining all four variables in both training and testing. As such, the number of parameters does contribute to the prediction accuracy.

To choose only the most impactful parameter might be the most challenging since the higher the number of parameters used, the higher the processing power and time needed in which the prediction accuracy might suffer for over fitting which can reduce the prediction accuracy compared to the lesser parameter. It also will depend on the case studies in which if the case study favours the fastest respond, some parameters may need to be removed, hence prediction accuracy will be reduced.

2.5 *Prediction Algorithm*

Selvamuthu et al. [14] in their research compared the accuracy of three prediction models namely Levenberg-Marquardt (LM), Scale Conjugate Gradient (SCG), Bayesian Regularization (BR). Each of the prediction model achieved 99.9% prediction accuracy using tick data. The only different between those three prediction models are the time taken to produce an output. To get better accuracy with lesser error, it will take longer time to train the model. The prediction model SCG can be trained within few minutes, while LM model need hours of training, and BR model need few days of training to produce output. It can be applied according to different case study depending on time constrain since all the models provide high accuracy.

If tick data is not available, Selvamuthu et al. [14] also did research on 15-min data in which they achieved more than 95% prediction accuracy. LM achieved 96.2% while SCG achieved 97.0% and BR achieved the highest prediction accuracy using 15-min data with 98.9% prediction accuracy rate. This provides an alternative for any researchers with less data option.

Vargas et al. [21] compared between CNN (Convolutional Neural Network) and LSTM using two sets of stock indicators. It was found that both algorithms provide a good prediction accuracy but in different ways. With CNN algorithm, it can get the semantic information while RNN (Recurrent Neural Network) algorithm can get the context information and can model a complex temporal characteristic. Depending on the use cases, both algorithms can be applied.

Karmiani et al. [15] found that LSTM achieved highest accuracy compared to SVM and Backpropagation. They mentioned that, if the requirement was to achieved highest accuracy, LSTM should be the best choice, but if the requirement is on speed, Backpropagation was the best choice. They concluded that the higher the number of parameters used to develop the prediction model, the better the accuracy. The number of epochs also affect the accuracy percentage in which they found that the higher the number of epochs, the higher the prediction accuracy.

Abdoli et al. [13] compared the prediction accuracy between LSTM and Auto-Regressive Integrated Moving Average (ARIMA) to find which model achieved higher accuracy. It was found that both models achieved high accuracy only for short time. As the prediction time increases, the prediction accuracy decreases. LSTM performed better than ARIMA even though the prediction accuracy decreases by 3.22% while ARIMA prediction decreases by 9.32% for 20 days prediction. They max out the epoch by 25 since adding more epochs does not improved the predictions. The behavior of epochs is somehow act randomly as stated by Abdoli et al. [13].

Ding and Qin [17] stated that there are two ways of predicting stock namely the statistical methods and the artificial intelligence. They designed a prediction model based on Artificial Neural Network (ANN) that can handle multiple inputs to produce multiple associate outputs based on Recurrent Neural Network (RNN) variant LSTM. They also separated the network into three different networks with opening price as the first network, lowest price as second network and highest price as the last network. Hence, they managed to reduce error rate, but the proposed solution needed more training to compensate for higher accuracy.

2.6 Proposed Solution

The proposed solution will be having five components which consist of:

1. LSTM algorithm as prediction model.
2. Multiple inputs with multiple neural networks for better prediction of stock price movement.
3. Historical data in the form of tick data.
4. Stock market technical indicators such as trading patterns, trends and level indicators as supporting data and news on the Malaysian companies on buyback.
5. Compare all the different case studies with each other to find the best case.

This prediction model will have three sets of action namely 1) to buyback at the lowest price possible to achieve higher profit margin, 2) to sell back before the price drop to reduce lost and 3) to stay idle until there is a need to buy or sell. The goal is to predict stock price movement based on previous price movement using historical data and to proceed either action number 1, 2 or 3 based on the outcome of the prediction model.

III. RESEARCH METHODOLOGY

3.1 Structured Literature Review

Strategy and decision will be made based on the previous literature. Those literature can provide us with a general overview on how to conduct this research. It was divided into several section and being done chronologically since basic information is needed as a base before starting this research.

Below are the steps conducted in this research study:

1. Buyback background information.
2. Prediction model that can predict stock market price movement with high accuracy.
3. Data/Variables/Parameters that can be used to design and develop the prediction model.
4. Stock indicators that can provide useful information and insight on the stock market price movement.

3.2 Identification of Suitable Approach/Techniques

To design the proposed solution, the followings are required:

1. Identify what company to choose.

The first requirement is the company must be Public Limited Company (PLC) in Bursa Malaysia (BM). The reason was simply that company that are listed in BM is an established company that had met a standard in terms of quality, size and operations and is regulated by Security Commission Malaysia (SCM) [22]. Those companies that are listed also can raise their capital. With big capital, they can spend on buyback. Second requirement is the companies must be available in Yahoo Finance (YF) since YF provide historical data that can be used to develop the prediction model and the last requirement is whether the companies initiate any buyback for the last 5 years or less so that the patterns and factors of buyback can be learned.

The Malaysian companies that fit with the requirements are Top Glove Corporation Berhad (TOPGLOV), 7-Eleven Malaysia Holdings Berhad (SEM) and Unimech Group Berhad (UNIMECH). All of these comes from different business background and initiated multiple buyback action in the last six months in year 2020. These three companies have different buyback volume ranging from million to hundred thousand to thousand buyback shares respectively in single purchase (klse.i3investor.com).

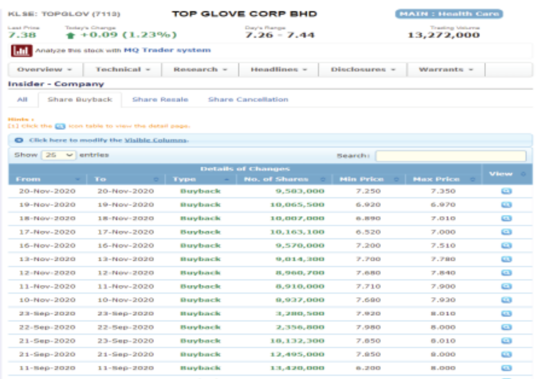
Based on Fig.1, TOPGLOV buyback was around 172 million shares with price ranging from RM6.12 up to RM8.01 from September 2020 until November 2020 with 16 buybacks with the average of 10.75 million per transaction. Based on Fig.2, SEM buyback was around 40 million shares with the price ranging from RM1.29 to RM1.40 for a period between July 2020 until November 2020 with 47 buybacks with the average of 850 thousand shares per transaction. Based on Fig.3, UNIMECH buyback their shares was around 1.2 million shares with price ranging from RM1.09 to RM1.37 from January 2020 until November 2020 with 64 buybacks with the average of 18 thousand shares per transaction. Despite the global pandemic, these three companies still buyback their shares and this showed that these companies are thriving. Even though the price for SEM and UNIMECH did not have a big different, they still consistently buyback. All buyback information of those three companies were collected from Kuala Lumpur Stock

Exchange (KLSE) link klse.i3investor.com as of 19 November 2020.

2. Collect company's data, variables, and parameters.

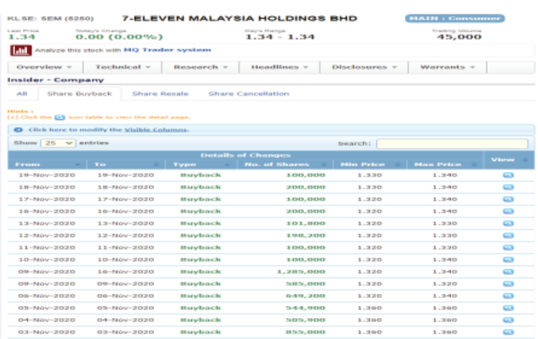
After finalizing the companies, the 10 years historical data from Yahoo Finance of eight variables namely Date, Opening Price, Closing Price, Highest Price, Lowest Price, Adj Close and Volume were gathered. According to Selvamuthu et al. [14], tick data format produces the best prediction accuracy because they managed to achieve 99.9% prediction accuracy. Tick data records the number of price changes within a certain period. For example, 1-minutes price might have one or more price changes before ending the 1-minute period with a price.

Parameters used to develop the prediction model were Opening price, Closing price, Highest price and Lowest price. According to Roondiwala et al. [16], those four parameters can be used in designing the prediction model. Ding and Qin [17] also mentioned that those data are highly related to each other in which can affect the prediction accuracy.



From	To	Type	No. of Shares	Min Price	Max Price	View
20-Nov-2020	20-Nov-2020	Buyback	9,583,000	7.250	7.350	
19-Nov-2020	19-Nov-2020	Buyback	10,065,500	6.920	6.970	
18-Nov-2020	18-Nov-2020	Buyback	10,007,000	6.890	7.010	
17-Nov-2020	17-Nov-2020	Buyback	10,163,100	6.520	7.000	
16-Nov-2020	16-Nov-2020	Buyback	9,570,000	7.200	7.510	
13-Nov-2020	13-Nov-2020	Buyback	9,014,300	7.700	7.780	
12-Nov-2020	12-Nov-2020	Buyback	8,960,700	7.680	7.840	
11-Nov-2020	11-Nov-2020	Buyback	8,910,000	7.710	7.900	
10-Nov-2020	10-Nov-2020	Buyback	8,937,000	7.680	7.930	
23-Sep-2020	23-Sep-2020	Buyback	3,280,500	7.920	8.010	
22-Sep-2020	22-Sep-2020	Buyback	2,356,800	7.980	8.000	
21-Sep-2020	23-Sep-2020	Buyback	10,132,300	7.850	8.010	
21-Sep-2020	21-Sep-2020	Buyback	12,495,000	7.850	8.000	
11-Sep-2020	11-Sep-2020	Buyback	13,420,000	6.200	8.000	
10-Sep-2020	10-Sep-2020	Buyback	14,930,000	6.120	7.400	

Fig.1: TOPGLOV Buyback News



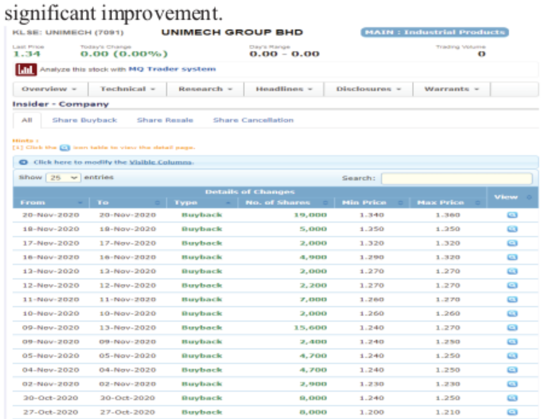
From	To	Type	No. of Shares	Min Price	Max Price	View
19-Nov-2020	19-Nov-2020	Buyback	100,000	1.330	1.340	
18-Nov-2020	18-Nov-2020	Buyback	200,000	1.330	1.340	
17-Nov-2020	17-Nov-2020	Buyback	100,000	1.320	1.340	
16-Nov-2020	16-Nov-2020	Buyback	200,000	1.320	1.340	
13-Nov-2020	13-Nov-2020	Buyback	101,800	1.320	1.330	
12-Nov-2020	12-Nov-2020	Buyback	198,200	1.320	1.330	
11-Nov-2020	11-Nov-2020	Buyback	100,000	1.320	1.330	
10-Nov-2020	10-Nov-2020	Buyback	100,000	1.320	1.340	
09-Nov-2020	16-Nov-2020	Buyback	1,285,000	1.320	1.340	
09-Nov-2020	09-Nov-2020	Buyback	585,000	1.320	1.320	
06-Nov-2020	06-Nov-2020	Buyback	649,200	1.320	1.340	
05-Nov-2020	05-Nov-2020	Buyback	544,900	1.360	1.360	
04-Nov-2020	04-Nov-2020	Buyback	505,900	1.360	1.360	
03-Nov-2020	03-Nov-2020	Buyback	855,000	1.360	1.360	
02-Nov-2020	06-Nov-2020	Buyback	3,684,300	1.320	1.360	

Fig.2: SEM Buyback News

3. Find appropriate stock indicators.

This model will be implemented using the most used stock indicators according to Kirkpatrick & Dahlquist's book [20] namely Exponential Moving Average (EMA), Moving Average Convergence-Divergence (MACD), Relative Strength Index (RSI), On Balance Volume (OBV) and Bollinger Bands (BB)

This research will be focusing on only three indicators which are EMA, MACD and RSI. Each of the chosen stocks' indicators will be compared and tested if there is any significant improvement.



From	To	Type	No. of Shares	Min Price	Max Price	View
20-Nov-2020	20-Nov-2020	Buyback	19,000	1.340	1.360	
18-Nov-2020	18-Nov-2020	Buyback	5,000	1.350	1.350	
17-Nov-2020	17-Nov-2020	Buyback	2,000	1.320	1.320	
16-Nov-2020	16-Nov-2020	Buyback	4,900	1.290	1.320	
13-Nov-2020	13-Nov-2020	Buyback	2,000	1.270	1.270	
12-Nov-2020	12-Nov-2020	Buyback	2,200	1.270	1.270	
11-Nov-2020	11-Nov-2020	Buyback	7,000	1.260	1.270	
10-Nov-2020	10-Nov-2020	Buyback	2,000	1.260	1.260	
09-Nov-2020	13-Nov-2020	Buyback	15,600	1.240	1.270	
09-Nov-2020	09-Nov-2020	Buyback	2,400	1.240	1.250	
05-Nov-2020	05-Nov-2020	Buyback	4,700	1.240	1.250	
04-Nov-2020	04-Nov-2020	Buyback	4,700	1.240	1.250	
02-Nov-2020	02-Nov-2020	Buyback	2,900	1.230	1.230	
30-Oct-2020	30-Oct-2020	Buyback	8,000	1.240	1.250	
27-Oct-2020	27-Oct-2020	Buyback	8,000	1.200	1.210	

Fig.3: UNIMECH Buyback News

4. Find the suitable algorithm.

Based on the literature review, it was found that LSTM is the most suitable with this research study due to its ability to retain previous information. Moreover, according to Karmiani et al. [15], LSTM is the highest prediction accuracy compared to SVM and Backpropagation. Abdoli et al. [13] also found that LSTM has better performance than ARIMA as the prediction number increases. It also can be designed to received multiple input so that it can achieved better prediction of stock market price movement. The LSTM special feature is the ability to retain previous memory and avoid exploding and vanishing gradient that was suffered in RNN.

In this study, the prediction accuracy is compared base on three case studies which are 1) single layer, 2) double layers and 3) quad layers to find which parameter and number of layers have the best accuracy.

5. Find Python libraries to be implemented.

The libraries used to develop the prediction model were Word2vec – for semantic analysis, Sklearn, TensorFlow and Keras – for prediction model development, Pandas – for data analysis, Numpy – for multi-dimensional array, Matplotlib – for data visualization and Yfinance – data source.

6. Trading strategy

The trading strategy depends highly on the company's available resources to buyback and the willingness of their stakeholders to purchase the shares. Usually, big company such as TOPGLOV will purchase more than a million shares per transaction according to klse.i3investor.com as seen in Fig.1. However, if the companies do not make profit for that particular year, they might not buyback despite of the lower stock price. This research will only predict when is the lowest price of stocks for buyback action. For example, buyback for this year might not be possible since pandemic Covid-19 had affected most companies in theory. Nevertheless, for TOPGLOV it may be otherwise since the demand for rubber glove has been skyrocketing due to the pandemic Covid-19.

3.3 *Design and development of share buyback*

In building the LSTM, below were the first steps taken:

1. Import and use data from Yahoo Finance directly into the code according to their tick symbol.
2. Pre-process the collected data and remove any missing rows.
3. Display the data.

Second step was to develop the LSTM Network by setting how many inputs, networks, layers, epochs, and output. Each of those factors can affect the prediction accuracy.

1. Divide training to testing with 80:20 ratio.
2. Number of epochs and batch size.
3. One and multiple inputs.
4. One and multiple stocks indicators.

3.4 *Validating the Proposed Solution*

To validate the proposed solution:

1. Compare LSTM prediction model in:
   a. Between parameters and parameters combination.
   b. Between parameters combination with stocks indicators.
   c. Between parameters combination with stocks indicators and news sentiment.
   d. Between the algorithm with different layers, epochs, and batch sizes.
2. Validate the result using Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE) to check the error rate.

Fig.4 presents the flowchart summarizing the step-by-step of activities that were conducted in this study.

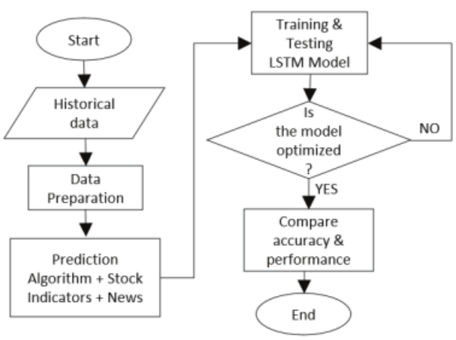


Fig.4: Flowchart

IV. FINDINGS AND DISCUSSIONS

4.1 *Findings*

The earlier findings have indicated that by predicting stock market price data, company can take initiatives to prepare for any upcoming event with the predicted outcome. With the predicted outcome, company can prepare for the next cause of actions either to repurchase their shares or to sell it.

The proposed solution, in theory, will predict stock market price data so that future actions can be taken into consideration before initiating any buying or selling action especially when involving huge financial resources. The goal is to maximize profit and minimize lost.

4.2 *Preliminary Findings*

The training set to test set were set with 80:20 ratio. The results shown were based on TOPGLOV data. Each parameter ran through the LSTM prediction model with three case studies namely 1) single layer, 2) double layers and 3) quad layers to find which parameter and number of layers have the best accuracy. The epochs were set to 50 and batch size at 32. The MAE, MSE and RMSE for each parameter with different case studies are shown on table 1, 2 and 3.

TABLE 1: LSTM Single Layer

Parameter	MAE	MSE	RMSE
High	0.04724	0.00482	0.06941
Low	0.04529	0.00459	0.06772
Open	**0.02937**	**0.00200**	**0.04474**
Close	0.04658	0.00468	0.06840

TABLE 2: LSTM Double Layers

Parameter	MAE	MSE	RMSE
High	0.04501	0.00502	0.07086
Low	0.04481	0.00502	0.07082
Open	**0.03499**	**0.00335**	**0.05790**
Close	0.04599	0.00509	0.07137

TABLE 3: LSTM Quad Layers

Parameter	MAE	MSE	RMSE
High	0.05722	0.00706	0.08401
Low	0.05857	0.00733	0.08563
Open	**0.04155**	**0.00472**	**0.06870**
Close	0.05775	0.00713	0.08443

TABLE 4: LSTM Single Layer

Parameter	MAE	MSE	RMSE
High	0.03642	0.00302	0.05494
Low	0.03642	0.00302	0.05494
Open	**0.02407**	**0.00118**	**0.03435**
Close	0.03697	0.00319	0.05646

TABLE 5: LSTM Double Layers

Parameter	MAE	MSE	RMSE
High	0.04037	0.00383	0.06192
Low	0.04037	0.00383	0.06192
Open	**0.01692**	**0.00059**	**0.02425**
Close	0.03911	0.00352	0.05932

TABLE 6: LSTM Quad Layers

Parameter	MAE	MSE	RMSE

High	0.04292	0.00415	0.06445
Low	0.04210	0.00414	0.06433
Open	**0.03151**	**0.00234**	**0.04837**
Close	0.04125	0.00388	0.06233

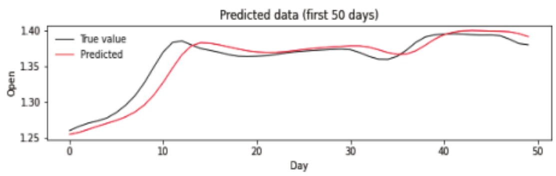


Fig.6: Double Layers "Open" Parameter

Based on table 1, 2 and 3, it can be concluded that the best parameter on all three case studies was "Open" parameter based on the MAE, MSE and RMSE results which has the lowest value of MAE, MSE and RMSE compared to "High", "Low" and "Close" parameters. Additionally, it can be concluded that as the number of layers increases, the prediction accuracy will decrease.

Next, were the results with 100 epochs with the same number of batch size and the same three case studies as shown in table 4, 5 and 6.

Based on table 4, 5 and 6, it can be concluded that the best parameter on all three case studies was and still "Open" parameter based on the MAE, MSE and RMSE results. "Open" parameter has the lowest value of MAE, MSE and RMSE compared to "High", "Low" and "Close" parameters. Based on the results also, the results were different as shown in table 1, 2 and 3. The Double Layers perform the best compared to Single Layer and Quad Layers. As can be seen in Fig.6, the "Red" (Predicted) line is closer to the "Black" line (True value) for "Open" parameter compared to other 3 parameters.

Next experiments will be done on SEM and UNIMECH to verify these initial findings. If the findings are consistent as TOPGLOV, the next stage is to combine parameters that are suitable and significant on the prediction accuracy as compared to only one parameter namely news sentiments and the likes.

V. CONCLUSIONS

Predicting stock market price is very challenging. Many factors can contribute to either improve or reduce the prediction accuracy. Choosing the relevant data type and variables to predict is critical in developing the prediction model. Even though in theory, the higher the number of data, the better the prediction accuracy, there is a need to consider the training time since stock market price movement is dynamic – all in a matter of seconds. It is not practical let alone effective if it takes time to produce a result. The longer the time to process the higher the risk of making losses. As researchers are constantly developing new models to analyze and predict the stock market, more reliable and more precise stock information will be provided to the company and the investors alike. Although our study is preliminary, it is a good start for more interdisciplinary research in this exciting area.

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