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An Improved LSTM technique using Three-Point Moving Gradient for Stock Price Forecasting

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***Abstract*: Everybody desires to see the future. The understanding of the time ahead can create enormous prospects, clout and fortune. For soothsayers who can predict the future financial developments, they are be able to command immense fortune. Therefore, predicting the financial stock market is always a great attraction with financiers and opportunists. Massive finance and equipment have been devoted into exploring the stock prices movements, hoping of realizing the best method to hit paydirt in this endervour. Analysts utilize numerous methodologies as well as employ a variety of hypotheses to solve this artful task, but not any has accomplished with a satisfactory margin of errors. The need to make informed choices causes correct and accurate information to be a desired and highly valued commodity. One encouraging Artificial Intelligence technique is the Long Short-Term Memory (LSTM) technique. Although LSTM is excellent in recognizing patterns, it places no considerable importance to the intense relationship that connects the past and its ensuing values within a time series. It does not take into account the association between the past and the later values. This research offers an optional LSTM method which contemplates the past, current and subsequent prices by predicting the Three-Point Moving Gradient of the stock market prices. The precise forecast price can be calculated with adequate accuracy by employing reversed Linear Regression (LR) and its mean price. The results is just as precise as the conventional LSTM method.**

Keywords: Time Series Forecasting, Long Short-Term Memory (LSTM), Linear Regression, Deep Learning, Three Point Moving Gradient

I. Introduction

Stock forecasting using the LSTM methods has been utilised for a considerable time and has attained amazing outcomes. LSTM has been coded to teach the computer to best match the past values to predict the succeeding value.

Time Series stock price prediction is a key topic in finance since precise forecasting of stock market price is essential [1][2]. It is essential as this information of future developments would help speculators in getting the best profit for their investments. Puspitaningtyas describes stock prices are determined by the interaction of market participants on the demand and supply of shares [3]. Puspitaningtyas further states that the price reflects the stock price that occurs in the stock market at a given moment [3]. A company's worth may be reflected by changes in stock price. Market strengths oversee stock market prices, and these prices vary day by day according to their supply and demand [4]. If the number of purchasers (demand) surpasses the number of offerors (supply), the stock value will increase. Equally, the stock price will plummet if there were lesser purchasing actions than offering. In short, when many people desire it, it will be more costly but when less people desire of it, it will be less costly.

The place for this intention of arrangement is the stock market. The primary function of stock markets is to be a tool for turning savings into financing for the real sector [5]. The function of a country's stock market is essential for the economy of the country as it is the swiftest and highly effective way for capitalists to gain more investment. The amassing of investment is able to be conducted in an orderly, legal, swift and safe conduct through this market.

Stock prices changes do not act arbitrary [6]. Nor stock prices do not change uncontrollably. They show some guided ups and downs. They display highs and lows. Stock prices possess momentums. Therefore, stock prices are understood to display some unknown patterns and seasonal movements. The real world is being inundated with data and comprehending and translating this data is a formidable task for the lot of 21st century experts [7]. Therefore, predicting the stock market prices to a reasonable extent of precision, is considered rationally plausible if a person is able to decode their patterns and trend paths. The virtuosity of predicting stock prices is of the field of Time Series Forecasting. A lot of the work was committed over the previous years for the advancement and enhancement of Time Series Forecasting techniques including the employment of many statistical and non-statistical methodologies. Nevertheless, the financial stock market prediction is still obscure among uncertain outcomes [8]. Pandey signifies that stock market prediction is a method which employs past information as feedbacks to construct educated estimations that are foretelling in deciding the direction of future traditional methods [9]. Donahue et. al. notes that LSTMs are not confined to fixed length inputs or outputs thus making it a better accommodating yet flexible method [10]. Cabrera, Guamán, Zhang, Cerrada, Sánchez, Cevallos, Long and Li stated that LSTMs resolve extended elaborate period lag jobs that were never resolved by other techniques [11]. Gers, Schmidhuber and Cummins also observes that LSTM enhanced through 'peephole relationships' from the inner cells to the multiplicative gateways, is able to discover the subtle discrepancy between orders of points set either 49 or 50 period stages apart minus the assistance of brief training exemplars [12].

Pascanu, Mikolov and Bengio conveys that LSTMs unravels the Vanishing Gradient and Exploding Gradient challenges encountered by more Recurrent Neural Networks (RNNs) [13]. Pham, Bluche, Kermorvant and Louradour argued that the application of dropouts in LSTMs thwart overfitting and enhances execution [14].

Various methodologies are utilized in stock market time series prediction. Some are purely statistical whereas some are not. Marcellino, Stock & Watson, M. W. catalogued including techniques applied in Time Series prediction are vector autoregressions (VARs), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA) [15] and Autoregression Moving Average (ARMA).

Shah, Isah and Zulkernine acknowledged that numerous issues exist in stock market forecasting [16]. Rackauckas denotes that ARIMA and ARMA are mainly appropriate for predicting straight revised standards whereas LSTMs and RNNs are basically for non-straight standards [17]. Shewalkar, Nyavanandi & Ludwig claim that LSTMs/RNNs are more precise than traditional methods [18]. Refer to Figure 1 for a basic prediction process using LSTM.

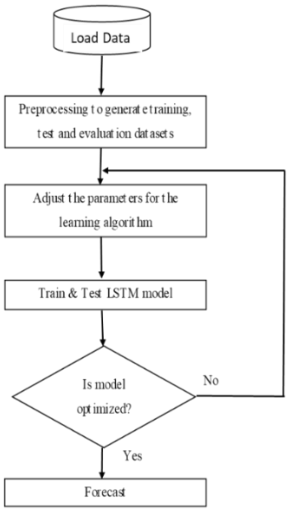

Figure 1. A basic prediction procedure using LSTM

Zhou informed that LSTM has been used in stock market price prediction for a while and accomplished some extraordinary achievements [19]. LSTM is devised to teach the computer to best match the historical information to predict the succeeding value. LSTM understands from its past information and manipulates it to work out the systems. It checks the forecasts against previous information to facilitate prediction of future values. However, the trouble with traditional LSTM is it contemplates not the hidden associations between the current value, the direct past value and the direct succeeding value. It predicts not the subsequent gradient in a time sequence. LSTM only seeks the model that can excellently match the entire subsequent data devoid of contemplating the gradients of the previous, current and succeeding values. Thus, a different technique that applies LTSM Three-point Moving Gradient groups that are the past, current and succeeding prices, is projected to generate better precise predictions.

The primary purpose of the research is to investigate the reliability of stock market price trend with LSTM supported Three-Point Moving Gradients. The rest of the paper is arranged as follows. We present the experimentation plan in Section 2. The experimentation results are displayed in Section 3. We will be drawing some conclusion in Section 4.

II. Methods

A. Three-Point Moving Gradient

The proposed Three-Point Moving Gradient is the gradient of three moving last price points. It takes 3 last prices points to form a linear regression line and thus its gradient is calculated. The next gradient can be calculated from the next 3 moving last prices points. The first gradient is calculated from the last price Y_t , Y_{t+1} and Y_{t+2}. The second gradient is calculated from Y_{t+1}, Y_{t+2} and Y_{t+3} and the next gradient is calculated from Y_{t+2}, Y_{t+3} and Y_{t+4} and so on. All the gradients are then fed into a LSTM network to predict the next gradient. The next price can be determined from the forecasted gradient and mean price. The proposed Three-Point Moving Gradient (TPMG) is an improved version of the simple LSTM. Instead of feeding pure values into LSTM, Three-Point Moving Gradients are being fed into LSTM. So instead of forecasting real values, the gradient is being forecasted.

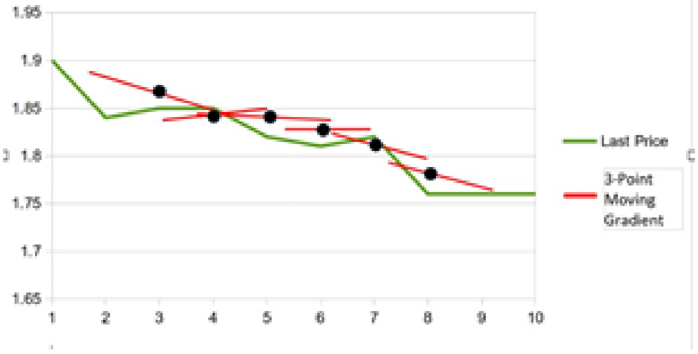

Figure 2. Example of Last Price and Gradients

This research utilizes Deep Learning to predict the day-to-day stock market last prices of Main Market Kuala Lumpur Stock Exchange (KLSE). The last offering and purchasing prices will be automatically mined from a financial stock market portal. The system utilises Deep Learning in a different variation of LSTM system to predict values. Instead of using real prices themselves, the LSTM will predict utilizing Linear Regression (LR) of three point moving price gradient. Then next price can be easily computed by forecasting the gradient.

The objective of the research is to discover if a stock market price prediction achieved utilizing LSTM of Three Point Moving LR gradients. This is also to discover the precision of this LSTM technique prediction contrasted to a standard LSTM prediction. The research is to build a dependable software using this technique.

The research is focused upon the utilisation of Three Point Moving Gradients. The assumption of utilisation of Three-Point Moving Gradient is that the value of a present stock market price will vary not a lot from its direct past values in the usual condition. Similarly, its the next day price will not vary a lot from the current price. With the exception of very odd abnormalities, stock price changes are slow and in continuum. Thus, believing the three price points (past, present and the next day) are linear, reversed LR can be utilised to determine the next stock price point. Therefore, the three day prices are applied in LR model. LR is a statistical technique that describes the correlation amid two uninterrupted variables in a simple linear equation as demonstrated in Equation 1.

$$y = bx + c \quad (1)$$

where;

x = independent variable
y = dependent variable.
b = gradient
c = initial value of y when x = 0

For stock forecasting, x refers to the time (day) while y is the stock price. Given in equation 2 and 3,

$$S_{xy} = n\sum xy - \sum x \sum y \quad (2)$$

$$S_{xx} = n\sum x^2 - (\sum x)^2 \quad (3)$$

where n implies the number of values and

$$b = \frac{S_{xy}}{S_{xx}} \quad (4)$$

Thus, the Regression Line Equation is:

$$y = \overline{y} - b\overline{x} \quad (5)$$

where are mean x and mean y respectively.

The regression line is drawn and protracted for the subsequent x and the subsequent y value. It is able to remain projected. In the research, LSTM is employed to forecast the three-point gradient of the final prices. Reversed LR is utilized from this gradient to compute the next last price. Making use of the final two gradient points and forecast gradient, reversed LR method is employed to calculate the third point that is the computed price.

Reverse LR evaluation establishes the direction the price is moving – rising, plunging or stay unmoved. These networks can predict the next gradient by entering Three Point moving gradients to be taught and checked against past data. Subsequently the next price is calculated through reversed LR method from this gradient and its mean.

The gradient forecasted may either be positive or negative. This differs from LSTM prediction of the next price that it is only positive as prices cannot have negative values. The subsequent price can be computed from either positive or negative forecast gradient. Thus, the conceptual model of Enhanced LSTM by a Three-Point Moving Gradient technique in stock price prediction is explained as in Figure 2.2. The last prices are entered into the LSTM network as well as into past gradients computation. The past gradients are subsequently entered into the LSTM Gradient network. Thus, the subsequent price is computed from the forecasted next gradient. Essentially LSTM forecasts and the computed next price are compared via RA, R2, RAE and RMSE. Both prices are then compared using Residual Analysis (RA), Coefficient of Determination (R2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to determine which is nearer to the actual value. Figure 3 illustrates the conceptual model of improved LSTM with three-point moving gradient method.

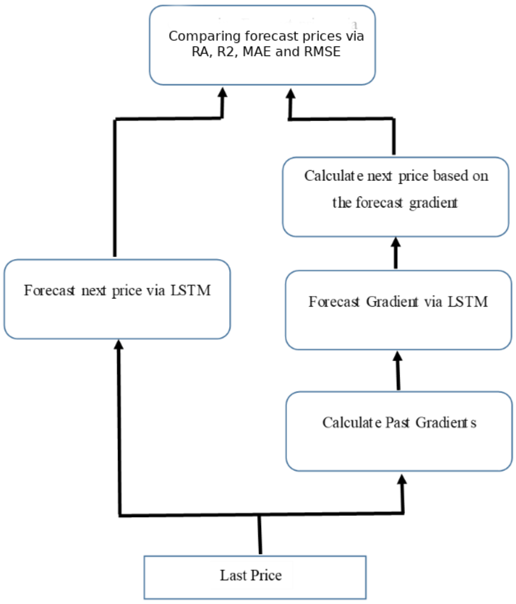

Figure 3. The Conceptual Model of Improved LSTM with Three-point Moving Gradient method.

B. Coefficient of Determination R2

The R2 statistic calculates multivariate association between the repeated outcomes and the fixed effects in the linear mixed model [20]. It is a statistical measure that signifies the percentage of the variance for a dependent variable that is clarified by an independent variable or variables in a regression model. R-squared describes the extent of the variance of one variable clarifies the variance of the second variable. The formula for R2 is

$$SS_{tot} = \sum (y_i - \overline{y})^2$$

$$SS_{res} = \sum (y_i - y)^2$$

$$R^2 = 1 - \frac{Unexplained\ Variation}{Total\ Variation}$$
$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$
$$R^2 = 1 - \frac{\Sigma(y_i - y)^2}{\Sigma(y_i - \overline{y})^2} \quad (6)$$

Where $\overline{y}$ = mean of observed value
y_i = observed value
y = predicted value

When R2 = 1, the predicted values exactly matches the observed values, whereas when R2 = 0, the predicted values does not match and a poor fit to the observed values. The more negative R2 value is the poorer fit the predicted values is to the observed values.

C. Residual Analysis

The contrast between the observed value and the predicted value is known as the residual. Each data point has a residual. In this study, the mean of the total residuals is calculated.

e = observed value – predicted value

$$e = y_i - \hat{y} \quad (7)$$

where y_i = observed value
$\hat{y}$ = predicted value

D. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is widely used in evaluating the accuracy of a prediction system [21]. MAE can be calculated using the formula below:

$$MAE = \frac{\Sigma(|y - y_i|)}{N} \quad (8)$$

Where y = predicted value
y_i = observed value
N = number of values

The smaller MAE value, the closer the predicted value to the observed value.

E. Root Mean Square Error (RMSE)

Root Mean Square Error is a statistical method applied to measure the discrepancies between values predicted by a model and the actual observed values. In this case, RMSE is used to calculate the differences between LSTM and the actual values, and TPMG and the actual values. RMSE is the square root of the mean of the squared differences between corresponding elements of forecasts and observations. [22].

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{N}} \quad (9)$$

Where:
$\hat{y}_t$ = LSTM value at t time
y_t = actual observed value at t time
N = Number of Values
t = the maximum number of values
Note: The lower the RMSE, the closer the data is to the actual observed values.

III. Results and Analysis

The evaluation has been performed on the prices of 245 KLSE stocks from 13th May 2019 till 14th October 2019. As they have more than 80 historical stock prices, these counters are selected. The final price and gradient data are fed through the identical LSTM network except LSTM for the final price is determined with sigmoid activation whereas the LSTM for gradient (TPMG) is determined with tanh activation. LSTM for the final price is predicted with sigmoid activation because its forecasted data is only positive values, being the predicted prices. LSTM for gradient (Three-Point Moving Gradient) is predicted with tanh activation as its forecasted data consists of both positive and negative values, being the forecasted gradients. The additional similar settings are optimizer = adam, loss = mean square error and three consecutive dropouts of 0.2. In order to determine how much dispersion each against the actual last price, RMSE, R2, RA and MAE are calculated for both LSTM and TPMG.

A. Results

Rec	No. Code	Name	LSTM RA	TPMG RA	LSTM R2	TPMG R2	LSTM MAE	TPMG MAE	LSTM RMSE	TPMG RMSE
10	0106	REXIT	0.0613	0.0028	-0.2533	0.5022	0.0177	0.0112	0.0217	0.0137
20	0823EA	CIMBC50	-0.0149	-0.0092	-1.8858	0.7701	0.0665	0.0170	0.0764	0.0216
30	1899	BKAWAN	-0.0801	-0.1167	-0.3506	0.8569	0.4227	0.1415	0.5000	0.1627
40	2593	UMCCA	-0.0506	-0.0581	-0.8204	-0.2471	0.0650	0.0581	0.0784	0.0649
50	3107	FIMACOR	0.0300	-0.0132	-0.4165	0.9567	0.0560	0.0109	0.0828	0.0145
60	3867	MPI	-1.0030	0.0444	-3.8026	0.3828	0.4959	0.1671	0.5734	0.2055
70	4758	ANCOM	0.0075	0.0037	-0.9148	-1.7111	0.0040	0.0046	0.0053	0.0063
80	5012	TAANN	-0.1063	-0.0113	-4.8900	0.2111	0.1261	0.0402	0.1344	0.0492
90	5065	ORNA	-0.0284	-0.0012	-9.4287	0.5607	0.0664	0.0126	0.0727	0.0149
100	5112	THPLANT	-0.0117	-0.0488	-1.0947	0.8840	0.0724	0.0196	0.0935	0.0220
110	5139LA	AEONCR-LA	0.0056	-0.0156	-0.8327	0.8928	0.0887	0.0239	0.1209	0.0292
120	5208	EITA	0.0230	-0.0203	-1.4354	0.6617	0.0805	0.0328	0.0982	0.0366
130	5436	PERSTIM	-0.0200	-0.0028	-1.6413	0.8472	0.2175	0.0506	0.2540	0.0611
140	5908	DKSH	0.1043	0.0862	-1.0328	-6.2620	0.0336	0.0631	0.0392	0.0742
150	6262	INNO	-0.0165	0.0156	-2.3940	0.5680	0.0583	0.0173	0.0613	0.0219
160	6971	KOBAY	0.0607	0.0289	-4.7932	-0.0791	0.0966	0.0405	0.1123	0.0485
170	7090	AHEALTH	-0.6926	0.2374	-1.8984	0.8825	3.4526	0.5879	4.5229	0.9108

180	7169	DOMINAN	-0.0197	-0.0029	-0.7259	0.6823	0.0223	0.0092	0.0264	0.0113
190	7203	WANGZNG	-0.0702	-0.0084	-3.6501	0.6573	0.0762	0.0168	0.0768	0.0209
200	7237WA	PWROOT-WA	0.0209	-0.0089	-2.6077	0.9164	0.3007	0.0353	0.3399	0.0518
210	7757	UPA	-0.0051	-0.0089	-0.8490	0.4697	0.0437	0.0218	0.0510	0.0273
220	8362	KYM	-0.0507	-0.0020	-22.9454	-3.4993	0.0438	0.0159	0.0440	0.0191
230	8966	PRLEXUS	-0.0132	-0.0054	-3.9886	0.8341	0.0841	0.0148	0.0884	0.0161
240	9687	IDEAL	-0.0576	0.0169	-1.7009	0.8772	0.1709	0.0327	0.1894	0.0404
		MEAN 245 Counters	-0.0760	-0.0176	-4.1052	-0.4783	0.1517	0.0482	0.1399	0.0486

Table 1. Results of 24 Systematic randomly Selected Counters

The above are the results of several tests for systematic randomly selected 24 counters and have been truncated into 4 decimal points. The LSTM mean for Residual Analysis is -0.0760 while the TPMG mean for Residual Analysis is -0.0176. This shows that Residual Analysis for TPMG is smaller and TPMG is much closer to the observed data than LSTM. The LSTM mean for Coefficient of Determination R2 is -4.1052 while the TPMG mean for Coefficient of Determination R2 is -0.4783. The results reveal that TPMG is much nearer to the observed data than LSTM. The LSTM mean for Mean Absolute Error is 0.1517 while the TPMG mean for Mean Absolute Error is 0.0482. Again, this indicates that TPMG is much nearer to the observed data than LSTM. The LSTM mean for Root Mean Square Error for all the 245 counters is 0.1399 while the TPMG mean for all the 245 counters is 0.0486. This also reveals that TPMG is much nearer to the observed data than LSTM.

From the results calculated above, we can conclude that on average, forecasts with TPMG are closer to the real data compared to forecasts with LSTM alone. Therefore, TPMG forecasts are more accurate compared to LSTM forecasts.

B. The Graphs

The graphs below are 24 previously selected counters displaying the actual last price, LSTM and the TPMG.

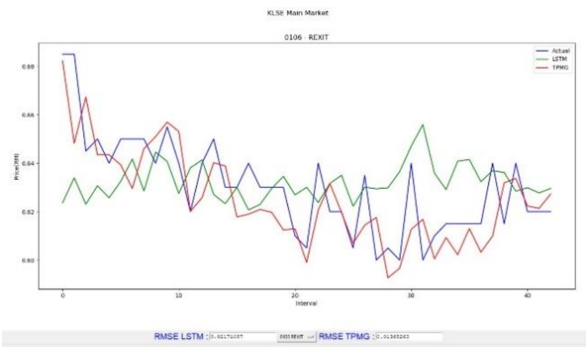

Figure 4. Rexit Counter

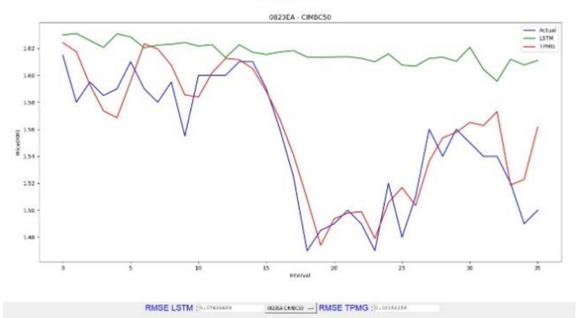

Figure 5. CIMBC50 Counter

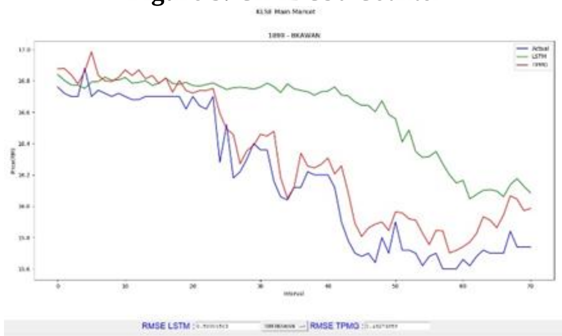

Figure 6. BKAWAN Counter

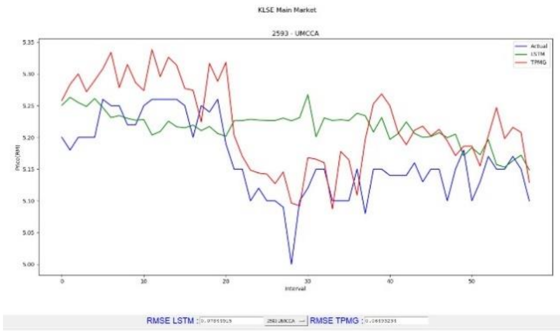

Figure 7. UMCCA Counter

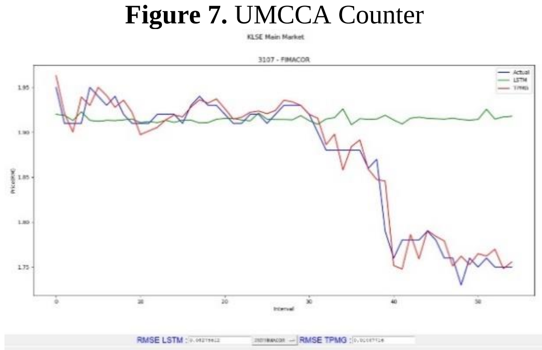

Figure 8. FIMACOR Counter

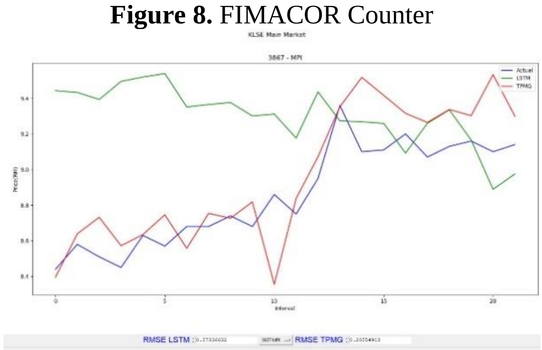

Figure 9. MPI Counter

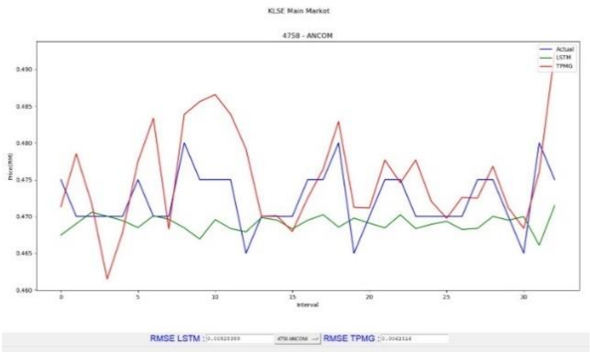

Figure 10. ANCOM Counter

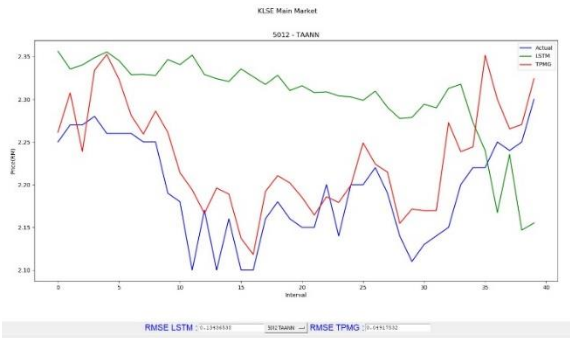

Figure 11. TAANN Counter

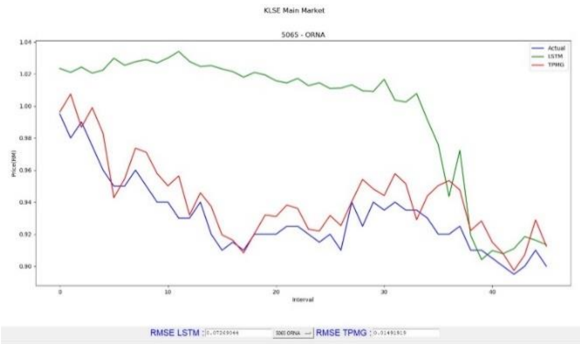

Figure 12. ORNA Counter

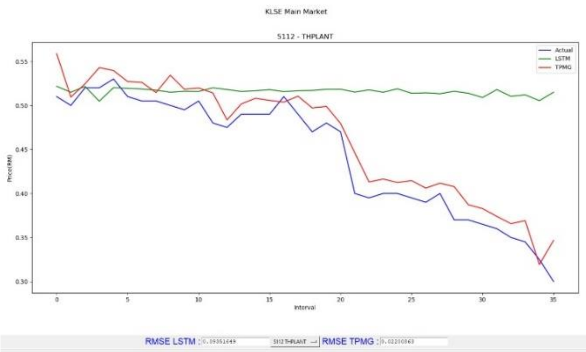

Figure 13. THPLANT Counter

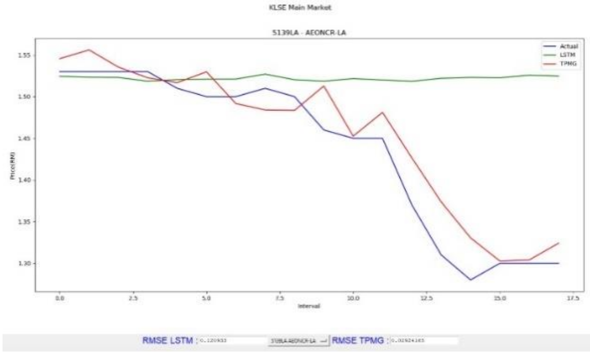

Figure 14. AEONCR-LA Counter

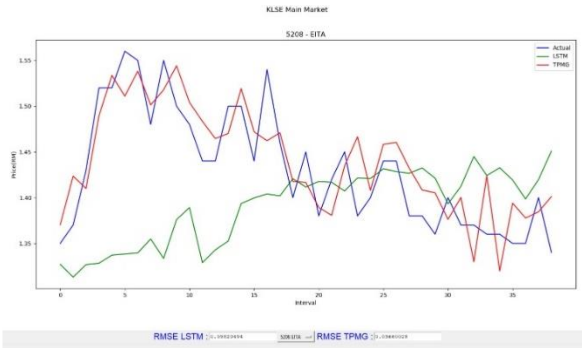

Figure 15. EITA Counter

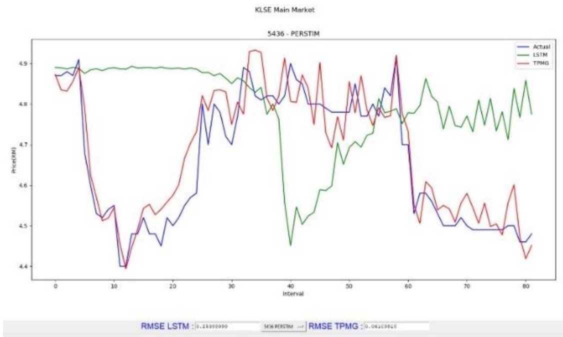

Figure 16. PERSTIM Counter

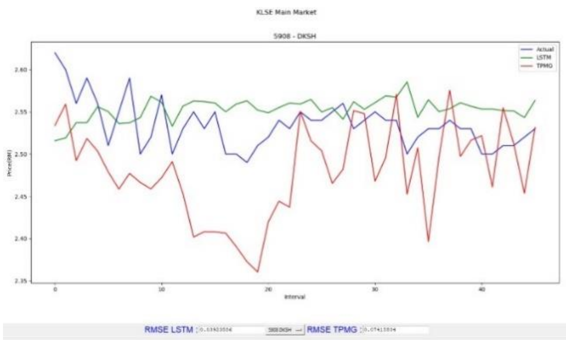

Figure 17. DKSH Counter

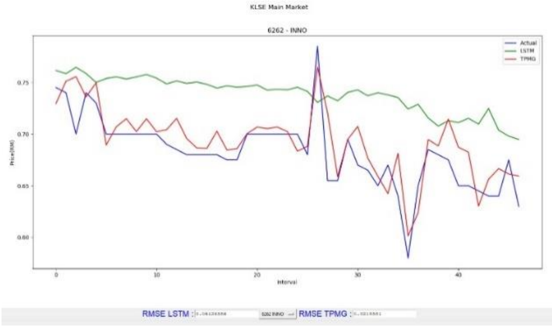

Figure 18. INNO Counter

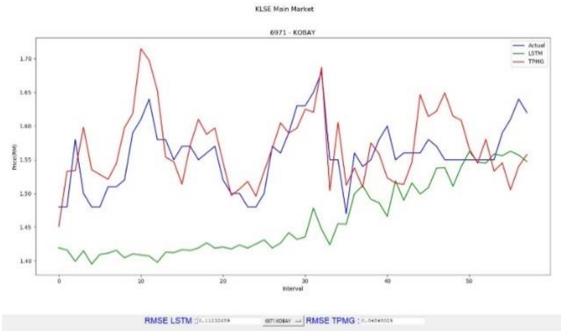

Figure 19. KOBAY Counter

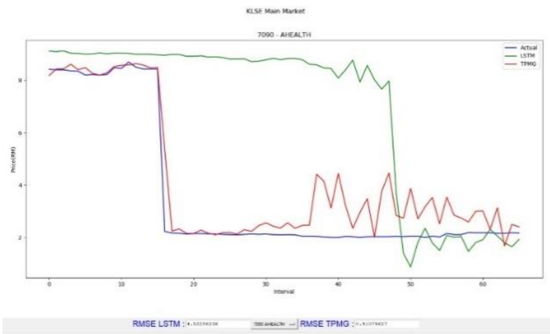

Figure 20. AHEALTH Counter

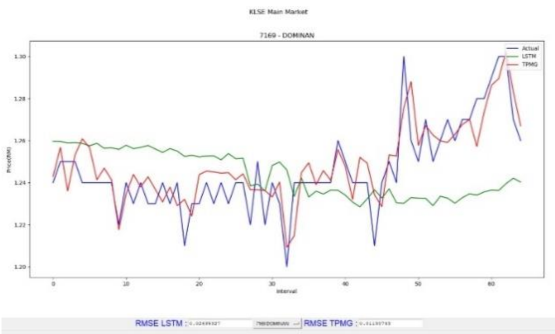

Figure 21. DOMINAN Counter

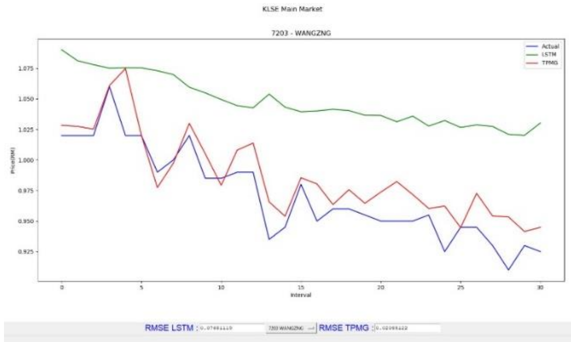

Figure 22. WANGZNG Counter

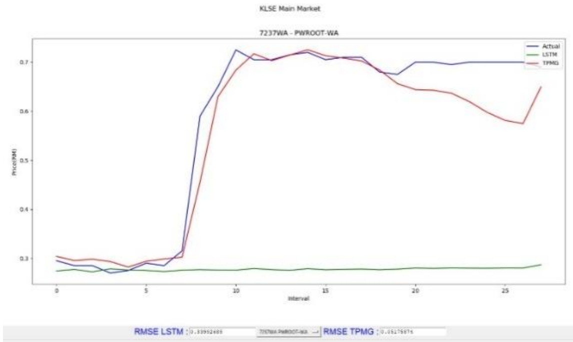

Figure 23. PWROOT-WA Counter

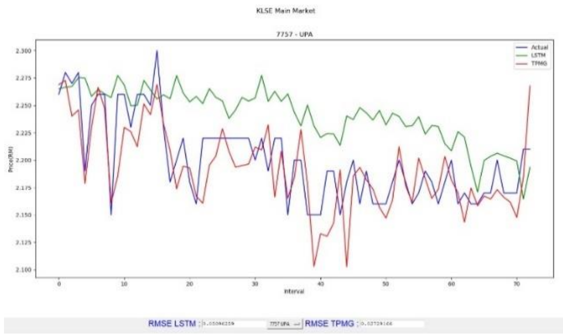

Figure 24. UPA Counter

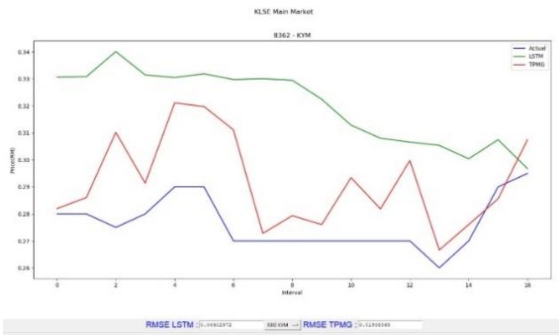

Figure 25. KYM Counter

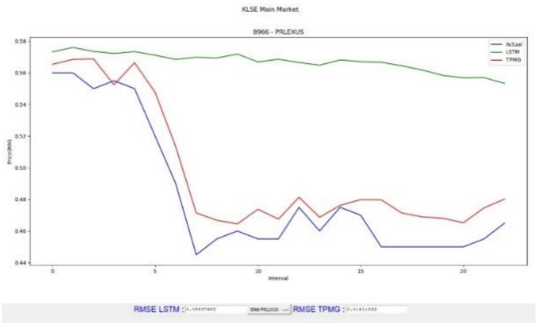

Figure 26. PRLEXUS Counter

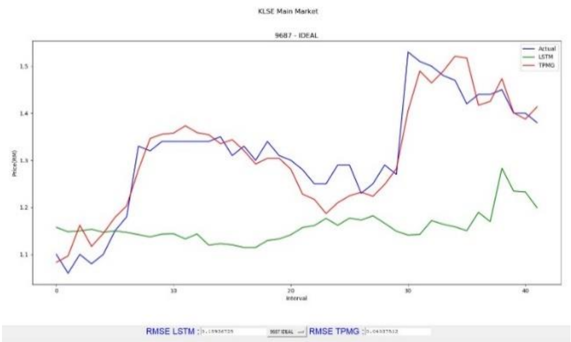

Figure 27. IDEAL Counter

IV. The Conclusion

The method of using Three Point Moving Gradients in LSTM generates a better prediction in contrasted with the standard LSTM as TPMG graphs are closer in spread to the original price points compare with LSTM.

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