

# Stock Price Prediction Based on LSTM-GBM: Evidence from Haier Smart Home

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**Abstract:** In the past few years, stock prices forecasting has been a hot topic due to the non-linear relationships and the uncertainty of the stock prices. In the meantime, machine learning, especially deep learning method, has made great progress. More and more studies show that machine learning models might capture features that are hard for traditional methods to observe, which means these models might be more apposite for forecasting time series. A new model named LSTM-GBM is designed to forecast the share prices of Haier Smart Home. The long short-term memory (LSTM) model is responsible for giving a specific prediction while the Geometric Brownian Motion (GBM) model is in charge of adding uncertainties to the predictions. The final prediction path will be generated through a filtrating mechanism, which makes a secondary screening of the two models. In addition, a possible upgrading model named LSTM-GBM-LSTM is proposed which is adding a LSTM model after the filtrating mechanism. This thesis compares the performances of LSTM-GBM model with LSTM model, GBM model and LSTM-GBM-LSTM model. The results indicate that LSTM-GBM has made the best prediction. These results suggest that it is feasible to project the stock price through LSTM-GBM model. Besides, more effort is needed to improve the performance of LSTM-GBM-LSTM model.

## 1 INTRODUCTION

Equity price forecast is the process of making judgement about future stock price movements based on historical indices such as market data. Stock price market is an essential component of the economy (Zhang et al., 2023). Generally, stock prices are influenced by company conditions, economic environments, market situations and external events (Ji et al., 2021). Due to the huge economic impact on individuals and the challenge of processing non-linear data, stock price prediction is a topic worth discussing (Wang et al., 2021).

Contemporarily, a lot of methods are introduced in the stock market, but many traders and researchers mainly focus on machine learning method. Compared with traditional approaches, using machine learning methods is more likely to interpret the extract information from the data (Mahesh, 2020), which is adapted to the uncertainty of stock market. Therefore, machine learning methods are able to assist traders to make correct predictions (Obthong et al., 2020). However, the machine learning method has gone through a series of updates in a few decades.

Traditional machine learning approaches are mainly applied in earlier years. Among those practices, Naive Bayes, Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbour (KNN) are relatively representative (Soni et al., 2022). Kumar et al. had made comparison between the models above and observed that RF made the most accurate prediction. Models at that time are based on different but independent algorithms, which means the frameworks are relatively simple (Kumar et al., 2018).

With the appearance of advanced learning method, neural networks are applied to forecast stock prices (Nikou et al., 2019). The idea of neural networks is originated from human brain, aiming to process and identify complex information. Generally, a neural network unit features an input layer, several hidden layers, and an output layer. A neural network system may consist of multiple such units. With the cooperation of the nodes, neural networks are able to process non-linear relationships through internal structures and model the changes of stock price more accurately (Rezaei et al., 2021). Some examples of making stock price predictions through neural networks will be presented subsequently.

Many methods of using neural networks have been applied to predict the stock prices, including using single neural network, composing multiple neural networks and combining neural networks with traditional models. Each method has distinct features, contributing to make more accurate predictions.

Ghosh et al. designed a model that includes LSTM (Long Short-Term Memory) to predict the closing prices of 5 companies on Indian market (Ghosh et al., 2019). After acquiring the predicted data of different time spans, the thesis calculated the growth rates and analysed the deviations of closing prices. At last, the thesis found out that the deviations went down with the growth of the time spans, which means the model performed relatively well when predicting shared prices over a long time period. Islam & Nguyen compared the abilities of three models named autoregressive integrated moving average (ARIMA), artificial neural network (ANN), and stochastic process-geometric Brownian motion (GBM) to predict the stock prices (Islam & Nguyen, 2020). The research analysed the residuals and calculated the absolute percentage errors, the average absolute errors, the average relative percentage errors, and the root-mean-square errors of the models. The results illustrated that both ARIMA model and the GBM model were expert in analysing short time series while fusing the existing model may improve the ability of ANN. In other words, a possible way to improve the ability of neural networks is combining different neural network models. Rezaei et al. developed two innovative models, CEEMD-CNN-LSTM and EMD-CNN-LSTM, which combine the deep learning capabilities with the efficiency of the Empirical Mode Decomposition (EMD) and Complete Ensemble Empirical Mode Decomposition (CEEMD) techniques. Deep learning methods and frequency decomposition algorithms were used in the experiment, and performances of those models were evaluated through calculating relevant metrics. The research stated that CEEMD-CNN-LSTM model performs more exact than EMD-CNN-LSTM model. Lu et al. introduced the CNN-BiLSTM-AM framework to project the share prices and compared the performance of the proposed model with other frameworks including MLP, CNN, RNN, LSTM, BiLSTM, CNN-LSTM, and CNN-BiLSTM. After comparing the indexes, the research found that CNN-BiLSTM-AM made the most accurate prediction (Lu et al., 2021). Johansson considered three recurrent neural networks named LSTM-SDE, ESN-SDE and LS-ESN-SDE to predict financial time series. The three proposed model contain parametric neural SDEs, which are the combinations of neural networks

and stochastic differential equation (SDE) models. Compared with traditional LSTM model and geometric Brownian motion model, three experimental models have made more precise predictions (Johansson, 2022).

Throughout the experiments, scientists adopted diverse methods based on the significant advantages of neural networks and the ability of traditional algorithms. The models designed have achieved impressive results in predicting time series. Inspired by the previous progress, this thesis presented a fresh model that combined a recurrent neural network and geometric Brownian motion model. The aim and the framework of this thesis will be presented in next part.

This thesis aims to forecast the share prices of Haier Smart Home via the new framework named LSTM-GBM and discuss a possible direction of improving this model. In order to state the experiment comprehensively, different contents will be presented in different sessions. Section 2 will introduce the basic information, which includes the data, models in need, the way to improve the model and the loss function of this experiment. The results of the research and discussions will be demonstrated in Section 4. Eventually, the conclusion of this experiment will be proposed in Section 4.

## 2 DATA AND METHOD

### 2.1 Data

According to the data requirements and variables used in this research, the primary variable is the closing prices of Haier Smart Home each day from 2019-8-13 to 2024-8-12, which contain 1211 pieces. Therefore, the amount of data is large enough to train the model to make reliable predictions. Besides, the data used in this thesis is up to date, which is able to describe the latest stock movement. In the data, trade date is characteristic variable and daily closing price is object variable. In order to ensure adequate training as well as provide stable evaluation results, the first 80% of the data is allocated to the training set while the remaining 20% is allocated to the test set. To achieve efficient model training, all data is normalized before training LSTM models and denormalized after the training process. This thesis adopts Min-Max Normalization to convert the dataset between 0 and 1 (Johansson, 2022). Through this method, the data is normalized as:

$$Norm(X) = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

In addition, to fit the input shape of LSTM models, the normalized data are sliced with the time span of 60 days, which means the LSTM models will learn to predict the price of next day by processing the prices from previous 60 days. Therefore, the test set will cover 230 nodes.

## 2.2 Models

After processing the data, four models are adopted to forecast the share prices. This section, this thesis will introduce those models, including motivations, frameworks and methods within this section. The models are designed by Python. In addition, it is necessary to introduce the loss function of the experiment. LSTM model is one of the variants of RNN (Recurrent Neural Network), designed to address the vanishing error problem (Ta et al., 2020). Through special gating mechanism, LSTM is able to add new information and forget previous information selectively. According to Hao & Gao, it is feasible that time dependencies in the financial sequence are able to be extracted by this model, which means LSTM has significant advantage in processing time series data like stock prices (Hao & Gao, 2020). The framework of a cycle unit of LSTM can be seen in Fig. 1. It features three gate systems (input, forget, output), cell states, input block, output block and activation functions (Sherstinsky, 2020).

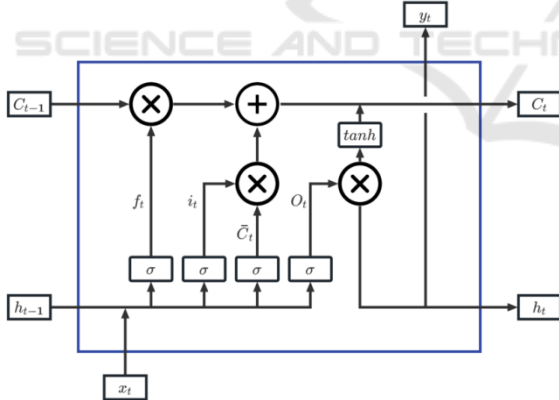


Figure 1: The Organization of a LSTM Cycle Unit (Photo/Picture credit: Original).

It is assumed that in time step  $t$ , the input and output of the unit are  $x_t$  and  $y_t$ . The forget gate system settles what details will be discarded from the cell state and input gate determines what details will be updated.  $y_t$  is mainly affected by the output gate, which contains a *sigmoid* layer and a *tanh* layer. The *sigmoid* layer is able to describe ingredients that pass through by outputting numbers between 0 and 1.

The *tanh* layer is responsible for integrating information through transferring numbers between -1 and 1. Concrete expressions of other functions in need will be presented in Fig. 1. In the experiment, founded on the learning results of the training set data, LSTM outputs a specific target path  $L_{1*N}$  on the test set.

Stochastic Differential Equations (SDEs) are mathematical methods used to simulate changes affected by random factors (Särkkä & Solin, 2019). Since stock price fluctuations are relatively uncertain, SDE models are suitable for describing the changes of stock market. An SDE consists of a certain part and a random part, which is featured in Eq. (2):

$$dX_t = \mu(X_t, t)dt + \sigma(X_t, t)dW_t \quad (2)$$

where  $X_t$  is a stochastic process;  $\mu(X_t, t)$  is the drift term;  $\sigma(X_t, t)$  is the diffusion term;  $W_t$  is a standard Brownian motion. In financial field, another type of SDE called GBM (Geometric Brownian Motion) is the typical simulation in financial modeling due to its concise mathematical model and high prediction accuracy. The general form of a GBM is as follows.

$$dS_t = \mu S_t dt + \sigma S_t dW_t \quad (3)$$

where  $S_t$  is asset price;  $\mu$  is the drift term;  $\sigma$  is the diffusion term;  $W_t$  is a standard Brownian motion. The analytical solution of GBM is:

$$S_t = S_0 \exp \left[ \left( \mu - \frac{1}{2} \sigma^2 \right) t + \sigma W_t \right] \quad (4)$$

where  $S_0$  is the initial asset price. The experiment uses Eq. (3) as the iterative formula and assumes that  $\mu$  and  $\sigma$  is equal to the mean and standard deviation of the logarithmic return on the stock price of the training set.

$$\mu = \frac{1}{N} \sum_{i=1}^N \ln \left( \frac{S_i}{S_{i-1}} \right) \quad (5)$$

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N \left[ \ln \left( \frac{S_i}{S_{i-1}} \right) - \mu \right]^2} \quad (6)$$

The experiment uses the initialized vector  $Z$  to store stock prices simulated by GBM. Besides, this thesis assumes that  $Z_0$  is the last data in the training set. Through solving the equations iteratively, a simulated path  $Z_i$  can be drawn. In the experiment, 100 paths will be generated. The process of GBM is displayed in Fig.2.

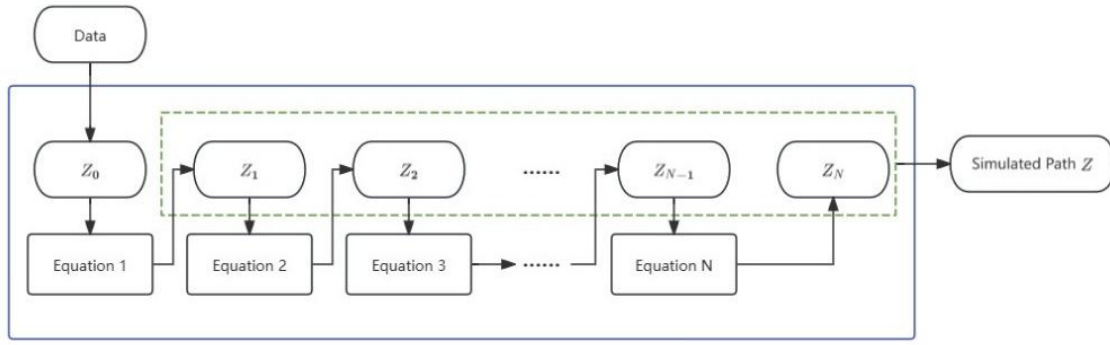


Figure 2: The Flow of GBM Model (Photo/Picture credit: Original).

Considering that LSTM is good at dealing long-time dependence in stock prices and GBM is good at dealing with the potential randomness behind stock prices, this thesis adopts LSTM-GBM model as the experimental model. This model includes a LSTM center, a GBM system and a target path filtering module (TPFM). LSTM center is responsible for generating a prediction path  $L_{1*N}$  and GBM system simulates  $i$  paths  $Z_{i,1*N}$  through iteration. TPFM fits the final path  $P_{1*N}$  through filtering the path generated by GBM system based on  $L$ . For each time point  $t$ , TPFM first calculates the distance between  $L_t$  and every path generated by GBM system  $d_{i,t}$ , then chooses the minimum value of  $d_{i,t}$  as the point of  $P_t$ . All  $P_t$  constitute the final path  $P$ .

$$d_{i,t} = \min |Z_{i,t} - L_t| \quad (7)$$

Eq. (6) represents the screening mechanism of TPFM and the process of LSTM-GBM model is displayed in Fig. 3.

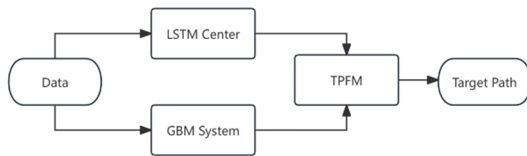


Figure 3: The Flow of LSTM-GBM Model (Photo/Picture credit: Original).

In order to strengthen the performance of the model, this thesis attempts to add a LSTM model after the GBM system, trying to forecast the share prices through LSTM-GBM-LSTM model. In this model, the front LSTM is named as LSTM-1 while the latter is called LSTM-2. On the basis of LSTM-GBM, LSTM-2 mainly responsible for generating a prediction path  $D_{1*N}$  based on learning from LSTM-1 predicted path  $L$  and LSTM-GBM generated path  $P$ . Since the dataset of LSTM-2 is from both training set

and  $P$ , LSTM-2 predicted path  $T_{1*N}$  is not able to cover the test set. Therefore, the part that cannot be covered is replaced by the corresponding part of  $D$  in this experiment. Fig. 4 presents the process of LSTM-GBM-LSTM.

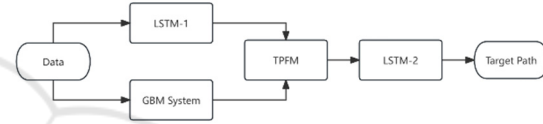


Figure 4: The Process of LSTM-GBM-LSTM Model (Photo/Picture credit: Original).

## 2.3 Models Parameters and Evaluations

In terms of model training, both training times and learning rate are considered in this experiment. LSTM-1 is trained for 50 times and LSTM-2 is trained for 30 times. Both LSTM-1 and LSTM-2 uses 'adam' booster and the learning rate is 0.001. To evaluate the models, this thesis uses the evaluation metrics as detailed in Tabel 1. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MSE) and  $r^2$  score are included in the matrix, which allows this thesis to comprehensively assess accuracy of the predictions. This experiment compares the target path generated by the four models above with true prices on test set. As a result, this experiment uses MSE as the loss function (Hodson, 2022). The equation of MSE is as follows.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (8)$$

where  $y_i$  is true stock price;  $\hat{y}_i$  is predicted stock price;  $N$  is total forecast time. In the experiment, a smaller MSE represents the better performance of the model. The MSE of four models above are calculated in this experiment and the result will be presented in Section 4.

### 3 RESULTS AND DISCUSSION

After using LSTM, GBM, LSTM-GBM and LSTM-GBM-LSTM to forecast the share prices, the result of each model will be presented in this section. This thesis will evaluate the results and analyze the possible reasons, therefore discuss the feasibility of making predictions by LSTM-GBM and LSTM-GBM-LSTM. Finally, limitations of this study will be analyzed and future prospects will be proposed. Fig. 5 contains true prices, LSTM predicted paths, LSTM-GBM simulated path, LSTM-GBM-LSTM predicted

path and MSE of each model. The comparison of those three models can be drawn from Fig. 5. For the readability of the results, the results of GBM will be presented separately in Table 1.

Table 1: Evaluation Metrics of Each Model.

Index	LSTM	GBM	LSTM-GBM	LSTM-GBM-LSTM
MSE	0.96	7.46	0.10	96.46
RMSE	0.98	2.73	0.31	9.82
MAE	0.21	2.22	0.23	9.80
$r^2$	0.84	0.26	0.79	-53402.69

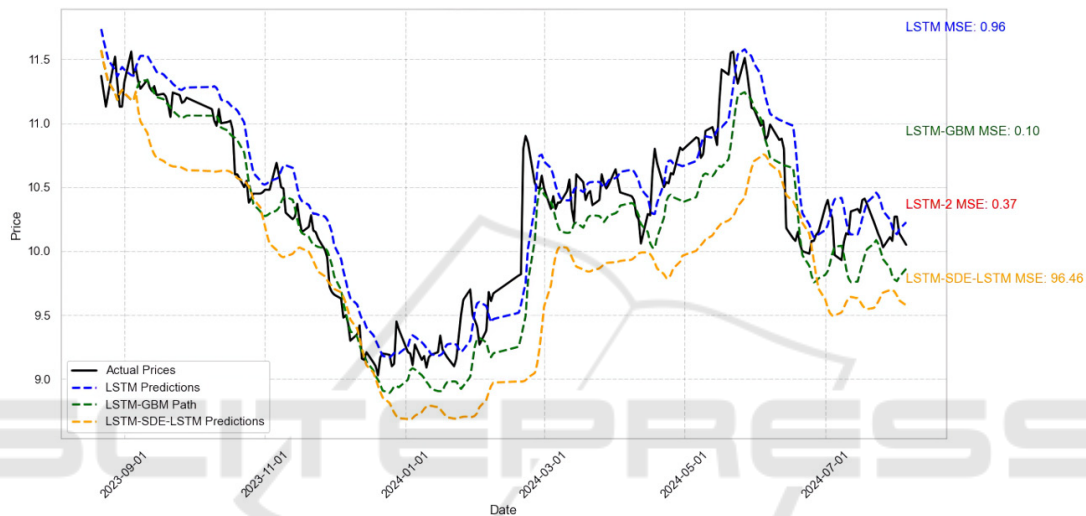


Figure 5: Stock Price Prediction Comparison (Photo/Picture credit: Original).

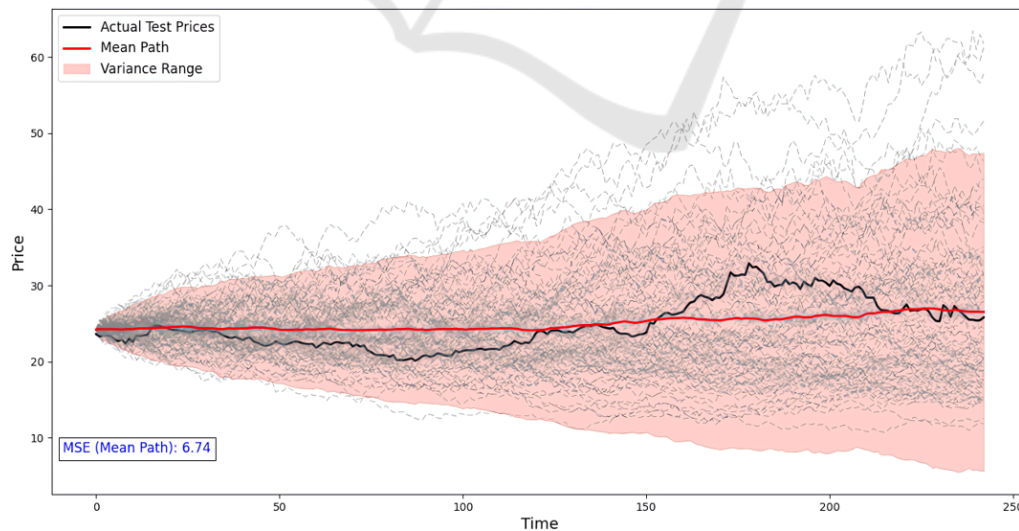


Figure 6: Stock Price Prediction Using GBM (Photo/Picture credit: Original).

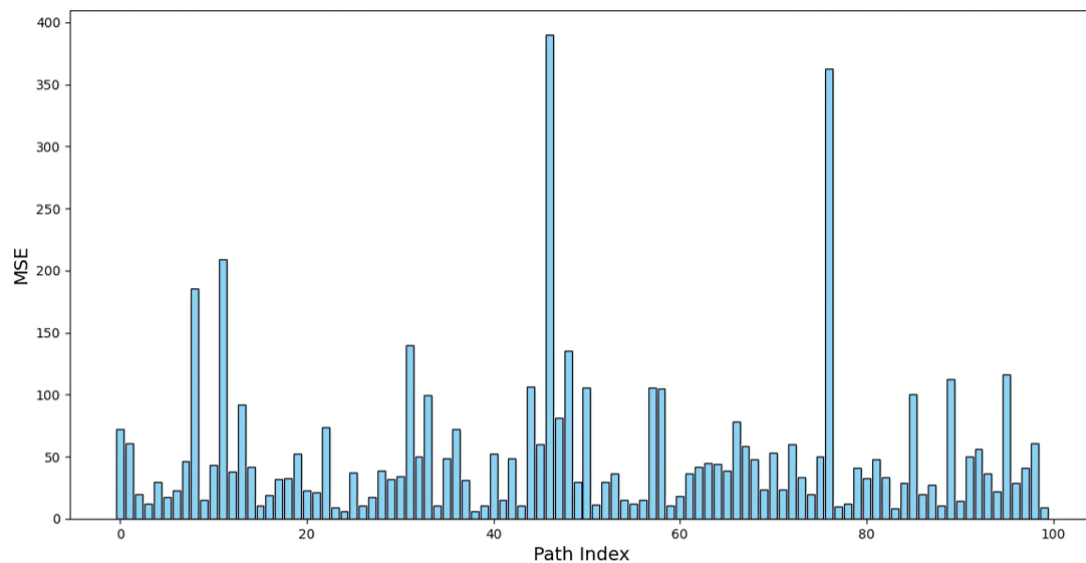


Figure 7: Histogram of MSE for Each Path (Photo/Picture credit: Original).

According to Fig. 5, the MSE of LSTM is 0.96, which is much higher than LSTM-GBM (will be presented later). It seems unsuitable for LSTM alone to forecast the share prices. On the other hand, LSTM seems to perform better with GBM model. Both Fig. 6 and Fig. 7 present the result of GBM model. Fig. 6 contains all simulated path by GBM, the mean path, the variance range and average MSE of GBM model. Fig. 7 presents the MSE of each path. Fig. 6 implies that GBM model may be inappropriate to forecast the share price because the MSE of this model is relatively high. Meanwhile, Fig. 7 demonstrates that different path has distinct MSE, which illustrates the randomness of GBM. The results prove that the GBM model might need some restrictions to perform better. According to Fig. 5, LSTM-GBM model seems to perform best in this experiment because the MSE of this model is the lowest. In addition, the path seems able to describe fluctuations in originate share prices. Founded on the ability of LSTM to simulate the share price data, LSTM-GBM adds possible changes. Besides, the standard of fitting the path seems appropriate. However, in terms of the latter part of the prediction, LSTM-GBM seems to deviate more from the true prices compared with LSTM. It might imply that the long-term forecasting ability of LSTM-GBM needs to be improved. In conclusion, LSTM-GBM is more suitable for predicting stock prices compared with LSTM and GBM, but the model is able to perform better with some improvements.

Although the MSE of LSTM-2 is relatively low, the MSE of LSTM-GBM-LSTM is the highest, which implies that LSTM-GBM-LSTM performs the worst among the four models. Besides, the prediction is

generally lower than the actual prices. There are a number of possible reasons for the results. On the one hand, it is difficult for LSTM to learn effective features that contains randomness. On the other hand, Eq. (7) declines the expectation of the prediction. In addition, after adding LSTM-2, original standard may no longer be appropriate. New ways to generate target paths need to be discovered. Last but not least, the stacking of multi models may lead to overfitting problems. In general, several factors may lead to the bad performance of LSTM-GBM-LSTM. Much more effort needs to be paid to improve the model.

Despite the best performance of LSTM-GBM, there are still limitations to this experiment. Firstly, due to time constraints, this experiment was not able to explore all possible parameters for the models. Better performance of the models may not be presented. Secondly, GBM model makes predictions based on only the last value of training set, which means the model has no idea of historical stock price movements. In this case, simulated path has to limited. Further studies need to make greater efforts in improving methods that allow GBM to learn the whole historical data. Thirdly, there may be more standards rather than Eq.7, which is likely to lead LSTM-GBM to make predictions with low expectations. Further studies could try to find other standards that are more suitable. Lastly, there might be other methods to design LSTM-GBM-LSTM model to make more accurate predictions. Future researches could focus on better ways to combine LSTM and GBM.

## 4 CONCLUSIONS

In order to make more accurate stock price predictions, this thesis offers a novel model named LSTM-GBM, which combines LSTM's ability to forecast time series and GBM's skill to capture and simulate possibility in the stock market. To assess the capability of this model, this thesis compared LSTM-GBM with LSTM model and GBM model. Besides, this thesis proposed a possible lifting scheme which is adding a LSTM system after the LSTM-GBM model. This model is named LSTM-GBM-LSTM. The performance of LSTM-GBM is also compared with the performance of LSTM-GBM-LSTM in the experiment. The results clearly state that LSTM-GBM is most capable of making predictions among the four models because LSTM-GBM has made the most accurate forecast. The MSE of LSTM-GBM is the lowest while the MAE and the  $r^2$  score of LSTM-GBM is closely similar to the result of LSTM. Those data shows that LSTM-GBM model is able to make compelling predictions. Therefore, this model might assist traders and investors to predict stock prices in stock market. In terms of future works, both LSTM-GBM and LSTM-GBM-LSTM have the potential to perform better. For LSTM-GBM, more parameters are able to be adjusted and more standards of selecting the target paths are able to be adopted. Besides, the GBM system might learn more historical data through some possible improvement. In addition, the model tends to make predictions of low expectations due to the design of TPFM and it is able to make the forecast prices' expectation close to the real data. For LSTM-GBM-GBM, the high MSE and negative  $r^2$  score both imply that this model has a large space for improvement. For example, potential methods of combining LSTM and GBM are able to be applied. Those improvements may promote the ability of the models. Besides, the data may state that LSTM-GBM-LSTM model has the problem of overfitting. Therefore, adopting regularization method or other methods for solving the overfitting problem may increase the performance of LSTM-GBM-LSTM model. The problem may be solved by reducing the complexity of the model as well. A number of methods are feasible to increase the performance of LSTM-GBM-LSTM so that the improvement of this model may be an optional topic for further studies. In conclusion, LSTM-GBM model performs the best and it is recommended to adopt this framework to forecast the share prices in reality. Meanwhile, greater effort in the future is needed for reducing the MSE and solving the possible overfitting problem of LSTM-GBM-LSTM model.

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