Stock Market Prediction with RNN-LSTM and GA-LSTM

Xinyue Liang

School of Mathematics and Science, Xi'an Jiaotong-Liverpool University, Suzhou, China, 215123

Abstract: The stock price reflects various factors such as the rate of economic growth, inflation, overall economy, trade balance, and monetary system, all of which impact the stock market as a whole. Investors often find the principle of stock price trends unclear because of the many important variables involved. When creating an investment strategy or determining the timing for buying or selling stocks, forecasting stock market trends plays a critical role. It is difficult to estimate the value of the stock market due to the non-linear and dynamic nature of the stock index. Numerous studies using deep learning techniques have been successful in making such predictions. The Long Short Term Memory (LSTM) has become popular for predicting stock market prices. This paper thoroughly examines methods for predicting stock market performance using RNN-LSTM and GA-LSTM, provides explanations of these methods, and performs a comparative analysis. We will discuss future directions and outline the significance of using RNN-LSTM and GA-LSTM for forecasting stock market trends, based on the papers we have reviewed.

1. Introduction

As the social economy rapidly develops, the increasing number of listed companies has made stocks a hot topic in the financial field. The stock market is a platform where individuals can purchase and sell shares of publicly traded companies, aiming to generate profits. It is a crucial measure of a nation's economic well-being as it indicates how well business are performing and the overall state of the business environment. The stock market functions through a system of exchanges, such as the Dow Jones (DJIA), which is a prominent stock market in the United States [1]. These exchanges are where buyers and sellers come together to trade stocks.

Scholars have conducted extensive research on stock prediction methods due to the non-linear, high noise, complexity, and timing-related characteristics of stock market data [2]. Various factors can impact stock prices, including the economy, political stability, and individual company performance [3]. Stock prices are influenced by the principle of supply and demand, with buyers willing to pay higher prices for stocks they believe will increase in value, and sellers willing to accept lower prices for stocks they think will decrease in value [4][5][6]. The fluctuating pattern of stocks frequently influences various economic activities to some degree [7], which has led to increasing scholarly interest in predicting stock prices. Investors can use a variety of tools and strategies to predict and analyze stock prices, such as fundamental analysis, which assesses a company's financial situation and industry conditions, and technical analysis, which examines trends and patterns in stock prices and trading volume [8][9].

In the past few years, artificial intelligence (AI) has increasingly been used in the financial sector, particularly in the stock market. AI algorithms can analyze large amounts of data and use that analysis to make predictions or decisions. This can be helpful in forecasting stock prices, recognizing patterns, and making investment choices. AI algorithms can examine historical stock prices, company financial statements, and market trends in the stock market to forecast future performance. AI is capable of monitoring real-time market conditions and recognizing opportunities to buy or sell stocks. Overall, AI has the potential to greatly enhance the efficiency and precision of stock market analysis and decision-making, ultimately resulting in improved investment outcomes for investors [10][11]. Long Short-Term Memory (LSTM) is a type of computer program specifically created to analyze and comprehend data containing long-term dependencies. It is commonly employed when analyzing time series data, such as the prices of stock market. Time series data is a sequence of previous stock prices and financial information, which LSTM can analyze to recognize patterns and trends, helping to forecast future stock prices. LSTM is especially beneficial for analyzing stock market data due to its ability to process data with multiple input and output time steps. For instance, the value of a company's stock can be affected by a range of factors, including economic indicators, market trends, and new specific to the company. The LSTM model can take into account both direct and indirect factors that can influence stock prices, enabling more accurate predictions based on these relationships. Investing in the stock market carries risks, as stock values can fluctuate significantly.

*Corresponding author: Xinyue.Liang23@xjtlu.edu.cn

However, over the long term, investing in the stock market can result in significant profits.

2. The basic fundamental of rnn-lstm, ga-lstm

2.1. The review of the RNN-LSTM, GA-LSTM

The RNN-LSTM is a very vital model in today's society and can be applied in many fields. The stock market, also known as the equality market, has a significant impact on the modern economy. The increase or decrease in the stock price significantly impacts the investor's profit. However, the existing forecasting methods concentrate on forecasting the movement of stock indices or predicting the future price of a single company based on its daily closing price. Hence, many researchers propose the RNN-LSTM and use it to predict the price of NSE listed companies and make a comparison of their performance [12]. The method is an approach that does not rely on a specific model. Instead of fitting the data to a particular model, they are using deep learning architectures to uncover the underlying dynamics present in the data. What's more, researchers find that the RNN-LSTM can maintain the weights for each data variable with stochastic gradient descent. This feature can help people improve the efficiency and accuracy of stock price prediction systems currently in use. People have examined future stock prices by using a data set of closing prices, developed and trained the LSTM model, and have taken a sample of the data set to produce stock predictions. They also calculated additional RMSE to evaluate the accuracy and performance of the forecasts [13]. In addition, predicting stock prices is crucial for attracting investors and driving growth in a company's stock value. This can help increase speculator interest and ultimately benefit shareholders. Therefore, many researchers have conducted numerous studies. Based on the simulation results, it is evident that by utilizing RNN models with appropriate hyper-parameter adjustments, our proposed method can accurately predict future stock trends [14]. Furthermore, analyzing finances has become a complex undertaking in today's world of valuable and improved investments. Some researchers study the application of RNN incorporating LSTM to predict stock market trends for Portfolio Management. The model utilizes historical time series data of stocks within the portfolio. The model has been compared with traditional Machine Learning Algorithms including Regression, Support Vector Machine, Random Forest, Feed Forward Neural Network, and Backpropagation [15].

The GA-LSTM is a deep learning technique and it has excellent learning ability from enormous dataset. With recent advancements in computing technology, vast quantities of data and information are being continually amassed. In finance, there are significant opportunities to generate valuable insights through the analysis of real-time data, given the vast amount of information generated by the financial market. Hence, some researchers explore the time-related characteristics of stock market data by proposing a systematic approach to decide the optimal time window size and topology for the LSTM network using GA [16]. To assess the suggested hybrid method, they selected daily data for the Korea Stock Price Index (KOSPI). The experiment results show that the combination of LSTM network and GA in the hybrid model performs better than the benchmark model. What's more, as smart grids continue to advance, precise forecasting of electric load has become more crucial. This can assist power companies in optimizing load schedules and minimizing unnecessary electricity generation. Therefore, researchers use a machine learning approach to build predictive models for short to medium-term aggregate load forecasting. This method involves the LSTM based neural network, which is configured in various ways to create accurate forecasting models. The results from the study using electricity consumption data from France's metropolitan area indicate that the LSTM-based model achieved greater accuracy compared to the machine learning model, even after it was optimized using hyperparameter tuning [17]. In addition, a real-world building can be considered a complex energy engineering system, and its actual energy consumption is influenced by various factors. Accurately predicting energy consumption and efficiently managing energy systems are crucial for enhancing building energy efficiency. The suggested system for forecasting building energy consumption comprises three layers: data acquisition and storage layer, data pre-processing layer and data analytics layer. The central component of the data analytics layer is a combined GA and LSTM neural network model designed to accurately and reliably predict energy usage. Two actual educational buildings were selected by researchers to assess the effectiveness of the proposed system for forecasting energy consumption in buildings. Experiments have shown that the adaptive LSTM neural network outperforms both the existing feedforward neural network and LSTM-based prediction models in terms of accuracy and robustness. It performs better than LSTM networks whose hyper-parameters are determined through grid search, Bayesian optimization, and PSO [18]. Furthermore, an effective stock price forecasting algorithm, which combines GA and LSTM network optimization, has been developed by some researchers to capture trends in the big data era. The test results indicate that the time series algorithm, which has been optimized using GA and LSTM network, demonstrates accurate prediction of stock prices. It shows a strong alignment with actual price trends and values, and exhibits a high level of generalization ability. This research outcome not only introduces a new approach for predicting stock prices but also offers a valuable resource for leveraging computer technology and big data in financial market analysis [19].

Based on these literature, we can find that RNN-LSTM and GA-LSTM are commonly used in finance and proved more accurate than other models. Hence, we use the RNN-LSTM and GA-LSTM as our models to conduct the experiment.

2.2. The structure of RNN, LSTM and GA

RNN is a type of neural network in which connections between the computational units create a directed cycle, introduced in 1986 [20]. Unlike feed forward networks, RNN have the ability to process various sequences of inputs due to their internal memory. Each computing part of a RNN has an activation that changes with time and a weight that can be adjusted. RNNs are built by repetitively using the same set of weights across a structure that resembles a graph. Unlike the MLP that only takes the current input, the RNN receives inputs from both the present and the past. Data from two sources is utilized to determine the response to a new data set. This process involves a feedback loop, where the output at any given moment becomes the input for the following moment. We can summarize that the recurrent neural network possesses memory. Every input sequence contains a wealth of information, which is saved in the hidden state of recurrent networks. The network continually reuses this concealed information as it moves forward to handle a new example. The equation for input to the hidden layer is provided:

$$h_t = g_n(W_{xh}X_t + W_{hh}h_{t-1} + b_h) \quad (1)$$

where as h_t: hidden layer at t th instant, : function, g_n: function, W_{xh}: input to hidden layer weight matrix, X_t: input at t th instant, h_{t-1}: hidden layer at $t-1$ th instant, b_h: bias or threshold value hidden to output layer equation is given as

$$Z_t = g_n(W_{hz}h_t + b_z) \quad (2)$$

where as Z_t: output vector, W_{hz}: hidden to output layer weight matrix, b_z: bias or threshold.

LSTM is a special kind of RNN, introduced in 1997 by Hochreiter and Schmidhuber [21]. These networks are skilled at understanding long-term relationships. These networks are specifically created to avoid the issue of long-term dependency, but it is within their normal function to retain information for extended periods. LSTMs have a unique architecture in comparison to other types of neural networks. A conventional RNN is a basic neural network with a feedback loop, while LSTM is a more complex architecture that incorporates memory cells or blocks instead of a single neural network layer. The cells contain a variety of gates that can regulate the influx of input. An LSTM cell consists of input gate, cell state, forget gate, and output gate. It also includes a sigmoid layer, a tanh layer and a point wise multiplication operation. The different gates and what they do are listed below:

Input gate: Input gate consists of the input.

Cell State: Runs through the entire network and has the ability to add or remove information with the help of gates.

Forget gate layer: Decides the fraction of the information to be allowed.

Output gate: It consists of the output generated by the LSTM.

Sigmoid layer generates numbers between zero and one, describing how much of each component should be let through.

Tanh layer generates a new vector, which will be added to the state.

The cell state is changed according to the outputs from the gates. We can express this mathematically using the following equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

$$c_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (5)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t * \tanh(c_t) \quad (7)$$

where x_t: input vector, h_t: output vector, c_t: cell state vector, f_t: forget gate vector, i_t: input gate vector, o_t: output gate vector and W, b are the parameter matrix and vector.

GA is a type of metaheuristic and stochastic optimization algorithm that draws inspiration from the natural process of evolution, introduced in 1975 by Holland, J. H. [22]. They are commonly employed to discover nearly optimal solutions for optimization problems with extensive spaces. The GA process involves using operators that replicate natural genetic and evolutionary principles, like crossover and mutation. The key characteristic of GA is the population of "chromosomes". Every chromosome represents a possible solution to a specific problem and is typically presented as a series of binary digits. The process of GA can be categorized into six stages: initialization, fitness calculation, termination condition check, selection, crossover, and mutation, as shown in Figure 1. During the initialization stage, a chromosome is randomly chosen from the search space, and its fitness is evaluated using a predetermined fitness function. The fitness function is a method for quantifying the performance of a chromosome with a numerical value. During the fitness function calculation, only solutions displaying outstanding performance are retained for subsequent reproductive processes. Superior chromosomes that have been selected produce offspring by exchanging corresponding parts of their genetic code and altering gene combinations. The process of crossover generates fresh solutions by combining existing ones. During the process of mutation, a single chromosome is chosen to have one randomly selected bit altered. The purpose of this process is to bring diversity and innovation into the solution pool through the arbitrary swapping or deactivation of solution bits.

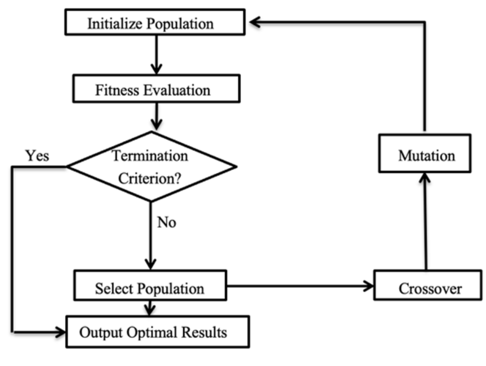

Figure 1. The flow chart of GA

The chromosome that is created through selection, crossover, and mutation processes is then evaluated for its fitness to the model and checked against termination criteria. The standard procedure for GA ends when the termination criteria are met. If certain termination conditions are not met, the selection, crossover, and mutation processes will be repeated in order to produce a better-performing chromosome.

2.3. The model evaluation

MSE:

$$\mathrm{MSE}[X] = E\left[\left(X - \tilde{X}\right)^2\right] \tag{8}$$

MSE is the mean squared error, which is considered to provide a quantitative description of both random error and systematic error, and can be used to measure the "precision" in metrology.

MAE:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n} \tag{9}$$

MAE is the mean absolute error, which is a measure of the error between paired observations that express the same phenomenon.

MAPE:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100\% \tag{10}$$

MAPE is the mean absolute percentage error which is a commonly used index for measuring the difference between predicted values and actual values, especially in regression model evaluation.

3. Results

3.1. Analysis of experimental results

By collecting five years (2019~2024) of stock data for Coca Cola, Chow Tai Fook (CTF), and Nike on Yahoo Finance, we can see that the actual values generally match the predictions, but there are also some errors present, as shown in Table.1.

Table.1. Comparison of stock data for three companies

Models	LSTM			RNN-LSTM			GA-LSTM		
Company	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
NIKE	7.488	2.112	0.021	11.044	2.660	0.025	24.485	4.246	0.042
CTF	0.152	0.298	0.027	0.161	0.310	0.028	0.230	0.377	0.034
Coca Cola	0.449	0.512	0.009	1.377	1.019	0.017	0.481	0.535	0.009

From Table 1, we can see that the data for NIKE generated higher values when using the three models, but comparatively, the LSTM (7.488, 2.112, 0.021) and RNN-LSTM (11.044, 2.660, 0.025) models produced lower errors. On the other hand, the data for Chow Tai Fook (CTF) and Coca Cola generated lower values when using these three models, with the LSTM (0.027, 0.009) model performing the best, and RNN-LSTM (0.028, 0.017), a hybrid model, also showing minimal errors. After applying the three models, and comparing the predicted data with the actual data, we have concluded that LSTM has better predictive performance and relatively smaller errors. The RNN-LSTM model performs better too, among the hybrid models. It can not only produce results similar to LSTM, but also combine the advantages of both RNN and LSTM models, making the final results more valuable.

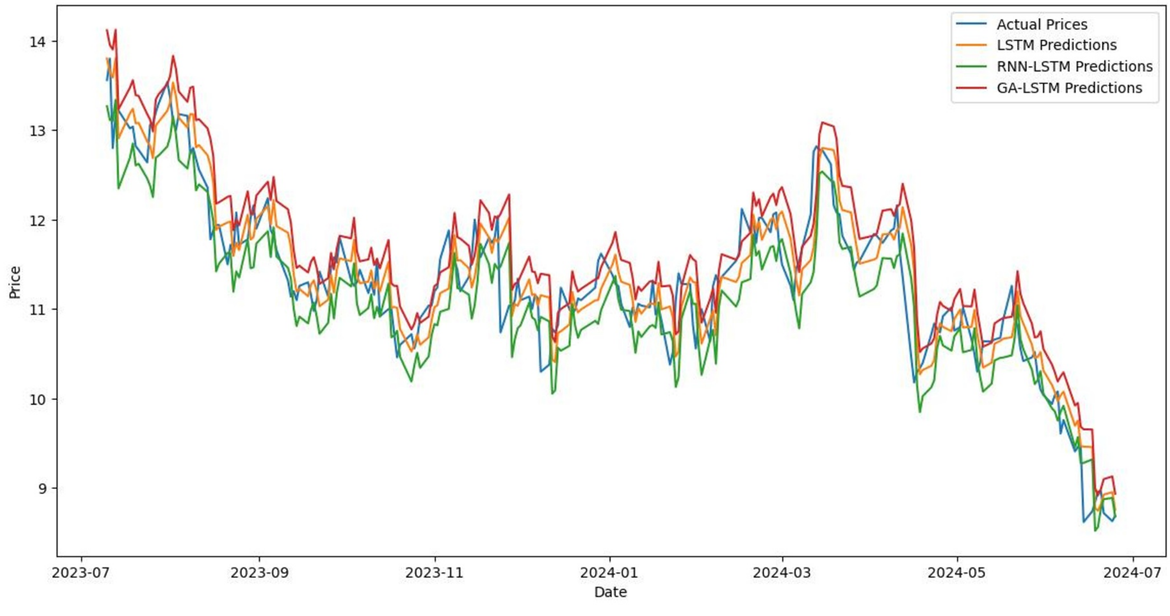

Figure 2. The comparison of three models

For example, Figure 2 presents the data of Chow Tai Fook (CTF) over five years, showing the comparison of errors after using three models: LSTM, RNN-LSTM, and GA-LSTM. From this figure, we can clearly see that the error of LSTM is the smallest, while the errors of the remaining two hybrid models are larger, but they still have some predictive value.

4. Conclusions

The article uses data from Chow Tai Fook (CTF), Coca Cola and Nike over a period of five years, and applies three different models LSTM, RNN-LSTM, and GA-LSTM to predict future stock trends. The experimental results show that, regardless of the company, the LSTM model performs the best, producing significantly lower errors compared to the other two hybrid models. Among the hybrid models, the RNN-LSTM model performs better, generating smaller errors.

In the current AI-driven era, researching these models is aimed at relatively accurate stock market prediction, assisting participants in making better decisions when purchasing stocks to meet people's needs. Experimental results demonstrate that these models can contribute to stock prediction, enabling people to use these models to assist in their judgments and obtain greater profits. Moreover, after conducting experiments in the field of stock prediction, I believe researchers should carry out more similar studies to develop more accurate models for predicting stock market trends. Present models still have some limitations and have not completely eliminated the influence of certain factors, resulting in errors. Therefore, we need broader research to address these shortcomings. In the future, we can use nearly error-free models to accurately predict stock trends, leading to a better development of the stock market.

References

1. S. Gürbüz, A. Şahbaz, Investigating the volatility spillover effect between derivative markets and spot markets via the wavelets: The case of Borsa İstanbul, Borsa Istanbul Review, 22 (2) (2022), pp. 321-331
2. P. Ding, Quantitative Investment: Strategy and Technology, Beijing, China:Electronics Industry Press, pp. 122-127, 2012.
3. Gülmez, B. (2023). Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm. Expert Systems with Applications, 227, 120346.
4. B. Bosworth, S. Hymans, F. Modigliani, The stock market and the economy, Brookings Papers on Economic Activity, 1975 (2) (1975), pp. 257-300
5. D. Shah, H. Isah, F. Zulkernine, Stock market analysis: A review and taxonomy of prediction techniques, International Journal of Financial Studies, 7 (2) (2019), p. 26
6. R.J. Teweles, E.S. Bradley, The stock market, Vol. 64, John Wiley & Sons (1998)
7. E. F. Fama and K. R. French, "Common risk factors in the returns on stocks and bonds", J. Financial Econ., vol. 33, no. 1, pp. 3-56, Feb. 1993.
8. H. Lim, R. Rokhim, Factors affecting profitability of pharmaceutical company: An Indonesian evidence, Journal of Economic Studies, 48 (5) (2020), pp. 981-995, 10.1108/JES-01-2020-0021
9. T.N.L. Nguyen, V.C. Nguyen, The determinants of profitability in listed enterprises: A study from Vietnamese stock exchange, The Journal of Asian Finance, Economics and Business, 7 (1) (2020), pp. 47-58
10. A. Ashta, H. Herrmann, Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance, Strategic Change, 30 (3) (2021), pp. 211-222
11. C. Milana, A. Ashta, Artificial intelligence techniques in finance and financial markets: A survey of the literature, Strategic Change, 30 (3) (2021), pp. 189-209
12. Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2017, September). Stock price prediction using LSTM, RNN and CNN-sliding window model. In 2017 international conference on advances in computing, communications and informatics (icacci) (pp. 1643-1647). IEEE.
13. Srivastava, P., & Mishra, P. K. (2021, October). Stock market prediction using RNN LSTM. In 2021 2nd Global Conference for Advancement in Technology (GCAT) (pp. 1-5). IEEE.
14. Sunny, M. A. I., Maswood, M. M. S., & Alharbi, A. G. (2020, October). Deep learning-based stock price prediction using LSTM and bi-directional LSTM model. In 2020 2nd novel intelligent and leading emerging sciences conference (NILES) (pp. 87-92). IEEE.
15. Pawar, K., Jalem, R. S., & Tiwari, V. (2019). Stock market price prediction using LSTM RNN. In Emerging Trends in Expert Applications and Security: Proceedings of ICETEAS 2018 (pp. 493-503). Springer Singapore.
16. Chung, H., & Shin, K. S. (2018). Genetic algorithm-optimized long short-term memory network for stock market prediction. Sustainability, 10(10), 3765.
17. Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (2018). Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. Energies, 11(7), 1636.
18. Luo, X. J., & Oyedele, L. O. (2021). Forecasting building energy consumption: Adaptive long-short term memory neural networks driven by genetic algorithm. Advanced Engineering Informatics, 50, 101357.
19. Sha, X. (2024). Time Series Stock Price Forecasting Based on Genetic Algorithm (GA)-Long Short-Term Memory Network (LSTM) Optimization. arXiv preprint arXiv:2405.03151.
20. Williams, Ronald J.; Hinton, Geoffrey E.; Rumelhart, David E. Learning representations by back-

propagating errors. Nature. October 1986, 323 (6088): 533–536.

21. S. Hochreiter and J. Schmidhuber, "Long short-term memory", Neural computation, vol. 9, no. 8, pp. 1735-1780, 1997.
22. Holland, J.H. Adaptation in Natural and Artificial Systems; University of Michigan Press: Ann Arbor, MI, USA, 1975; p. 183.