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Comparison between autoregressive integrated moving average and long short term memory models for stock price prediction

Pi Rey Low[1], Eric Sakk[2]
Department of Statistics and Data Science, Dietrich College of Humanities and Social Sciences, Carnegie Mellon University, Pittsburgh, Pennsylvania[1]
Department of Computer Science, Morgan State University, Baltimore, United States of America[2]

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ABSTRACT

This study compares the forecasting accuracy in stock price prediction of two widely established models - a more traditional autoregressive integrated moving average (ARIMA) model and a deep learning network, the long short-term memory (LSTM) model. They perform exceptionally well in time series data analysis and are applied to ten different stock tickers, comprising exchange-traded funds (ETFs) from different market sectors for the purpose of this study. The parameters in both models were optimised and this process revealed several differences from existing literature with regards to the optimal combination of parameters in both models. Upon comparing their performances, despite being more accurate when making point predictions, the ARIMA was outperformed significantly by LSTMs in terms of long-term predictions. Point predictions made by ARIMA were found to have similar accuracies as the long-run predictions made by LSTMs.

Corresponding Author:

Pi Rey Low
Department of Statistics and Data Science, Dietrich College of Humanities and Social Sciences,
Carnegie Mellon University
Pittsburgh, Pennsylvania
Email: pirey.low@gmail.com

1. INTRODUCTION

Today's financial climate has seen stock prices become more volatile and unprecedented, resulting in the prediction of stock prices becoming increasingly challenging due to their reliance on historical price data and patterns which might not reflect recent trends. Time series forecasting can be performed via several methods but they fall into two broad categories, traditional methods and deep learning networks. Traditionally, there have been several techniques, such as the autoregressive (AR), Autoregressive moving average (ARMA), simple exponential smoothing (SES) and most notably the ARIMA model [1]. The ARIMA model has been designed to predict future data points in a non-stationary time series with accuracy.

With the advent of computational powers and the proliferation of new machine learning techniques, many deep learning methods have been developed, such as artificial neural networks (ANN), multilevel perceptrons (MLP), recurrent neural networks (RNN), and long short term memorys (LSTMs). LSTMs are capable of learning long-term dependencies and remembering information for long periods of time and thus is one of the best models to analyse and predict stock price time series data [2].Therefore, it is a vital question of whether traditional forecasting models or deep learning networks are more accurate in making forecasts. This study describes the structures and operations within two models, ARIMA and LSTM. In determining the optimal combination of parameters used in the ARIMA, combinations commonly used in past research were tested. It was found that despite their high performances in other experiments from existing literature, such as the partial autocorrelation function (PACF) test or Augmented Dickey-Fuller (ADF) test, there are numerous other combinations of parameters that have similarly high accuracies. This work builds upon those studies to point out the fact that the predictive capabilities using different sets of parameters cannot be judged solely on the PACF or ADF tests and that performances vary depending on the stock ticker as well as the time period. Optimal combinations of parameters for both the ARIMA and LSTM were then used to build the models. The forecasting accuracies of the ARIMA and LSTM models were then compared by calculating their error rates.

2. LITERATURE REVIEW

2.1. ARIMA model

ARIMA is a generalised ARMA model, which was introduced by Box, Jenkins, and Reinsel in 1970. It combines both autoregressive and moving average processes. ARIMA (*p*, *d*, *q*) comprises 3 parts as described,

– Autoregressive (AR): Observations from previous time steps are input to a regression equation to predict the value at the next time step. This is determined by the parameter 'p', representing the order or number of time lags of the autoregressive model.
– Integrated (I): This process differentiates the data to make the series stationary. This is determined by the parameter '*d*', representing the degree of differencing. Generally, in most financial time series, a single differentiation is enough to make the series stationary and for the ARIMA model to be applied [3].
– Moving average (MA): The model takes into consideration the relationship between an observation and a residual error from a moving average model applied to past observations. This is determined by the parameter 'q', representing the order of the moving average.

After differentiating the series, the ARMA model, with a time series X_t, where t represents the time index, can be represented by the following equation,

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q} + \epsilon_t$$

where α and θ are estimated coefficients and ϵ are white noise errors.

Following that, the autoregressive process predicts the variable using a linear combination of past values. The moving average process then gives a prediction of the variable from a moving average model on past prediction errors [3]. Several studies have analysed the accuracy of ARIMA models in stock price forecasting.

Results from analysing stock data from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) using ARIMA revealed that ARIMA has a strong potential for short-term prediction and can compete favourably with existing techniques [4]. Similarly, the accuracy in predicting stock prices on 56 Indian stocks was above 85% for all market sectors [5]. ARIMA has been established to be relatively more robust and efficient than complex structural models for short-run forecasting. However, its performance in forecasting essentially relies on past values as well as previous error terms and does not assume knowledge of any underlying relationships unlike deep learning models [6].

2.2. LSTM model

LSTMs are a variation of RNNs and have gained much recognition in time series forecasting as they overcome the vanishing gradient problem in RNNs and are able to remember information for a longer time. In a typical LSTM, a cell state runs through the entire network and each LSTM layer comprises memory cells which consist of gates, serving to add or remove information. Figure 1 depicts an individual LSTM cell with functions that have been numbered corresponding to the equations. The 3 gates are,

– ***The Forget Gate***: determines information from previous cells to be remembered;
– ***The Input Gate***: determines input information to be retained; and
– ***The Output Gate***: determines the information leaving the memory cell to both the next memory cell and the next neural network layer.

The following are the equations within a memory cell of the LSTM,

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

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\beta_t = \tanh\left(W_\beta \cdot [h_{t-1}, x_t] + b_\beta\right) \tag{3}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{4}$$

$$h_t = o_t * \tanh c_t \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \beta_t \tag{6}$$

where x_t is the input vector, h_t is the output vector, C_t is the cell state vector, f_t is the forget gate vector, i_t is the input gate vector, β_t is a vector used to update the cell state subsequently, o_t is the output gate vector, W and b are the weight vectors and bias vectors respectively.

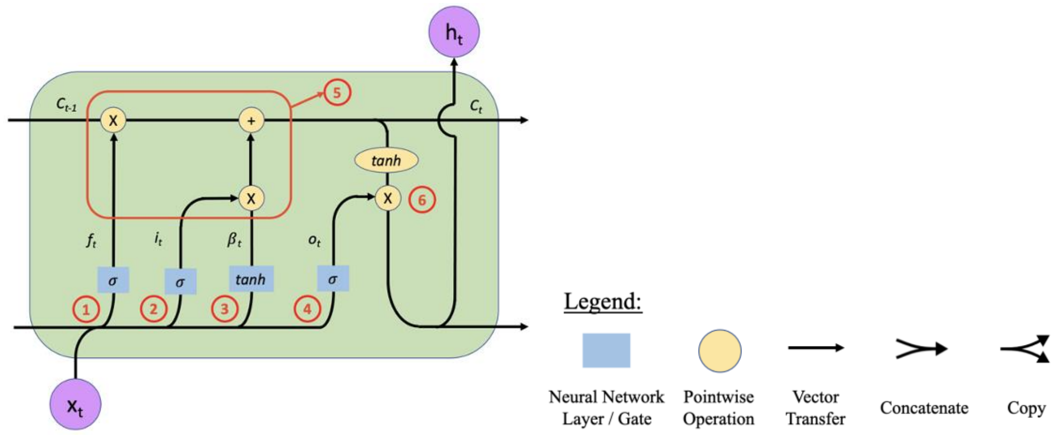


Figure 1. Structure of a LSTM Cell

LSTMs are designed to remember information and forecast time series data and thus much research has been done to analyse its effectiveness on stock price forecasting. When used to predict returns of the Chinese stock market, results confirmed significant forecasting accuracy and the promising predictive power of LSTM [7]. LSTMs trained with various sizes of input data were still found to predict share prices with a very low loss and error rate [8]. Another study emphasised the remarkably high accuracy of 94.8% and efficiency of the LSTM when tested on the stock price of a private sector bank in India [9].

2.3. Existing literature on comparisons between ARIMA and LSTM related models

In recent times, more research has delved into the widely acclaimed LSTM, which have been found to outperform many models, be it conventional methods or newer deep learning networks. As such, comparisons between LSTM and ARIMA in stock price prediction has become a widespread topic of interest. Despite the success of ARIMA models in time series analysis and forecasting, LSTMs and deep learning models often provide greater accuracy [10], [11]. A study reflected how the average error rate obtained by LSTM was between 84% to 87% less than ARIMA, indicating the superiority of LSTM [1]. When applied to 284 stocks from the S&P 500 stock market index, the results confirmed a significant reduction in prediction errors when LSTM is used as compared to ARIMA [3]. Further research found that LSTM is able to learn non-linear relationships from data, thus resulting in lower error than ARIMA [1], [12], [13].

Although the forecast accuracies in long term prediction of both models decrease, LSTM outperforms ARIMA significantly. Despite making rather accurate predictions at the beginning, the error of forecasts increased for ARIMA as time passed, while LSTM performed better in the long term [14]. Another study also found that despite ARIMA having a better accuracy in short-term prediction, LSTM is better than ARIMA in prediction accuracy and stability for the closing price of the SSE 50 Index in the long run [15].

Upon analysing the principles and prediction results of both models, LSTM had a better predictive ability, but was greatly affected by the data processing [16]. However, another study found that when increasing the amount of data, the models were trained with, from 1 year to 3 or 5 years, neither yielded an improved result. Despite that, LSTM forecasted with 94% peak accuracy, while ARIMA reached 56% and LSTM constantly outperformed ARIMA [17]. In another form of time series data, results showed that LSTM can reduce training error by as much as 95% as compared to ARIMA when used for spot price prediction [18]. In predicting Bitcoin prices, LSTM gives significantly better predictions than ARIMA as well [19], [20].

3. METHODOLOGY

With the large amount of data being processed for stock price forecasting, computational approaches are used to build models, be it traditional ones or deep learning networks. Python modules were used to perform various mathematical and data-handling functions as well as extract packages. The Yahoo finance package (yfinance) was used in this study to retrieve our stock price data. The popular Pandas package was used to convert financial time series data into suitable data structures for analysis and visualisation while Numpy was utilised to perform numerical and array calculations. Matplotlib was also used for the 2D and 3D plotting of data for further analysis. To organise and split our data into training and test sets, the Sci-kit Learn package was employed.

The ARIMA was designed using the statsmodel package while the Keras package was used to build LSTMs, comprising LSTM and dense layers. The LSTM in this study was optimised using the loss function of the mean squared error and the 'adam' optimiser. Their various architectures will be discussed. Comparisons of forecasting accuracy were based on the mean squared error (MSE) of each model.

3.1. Development of ARIMA model

As the performance of ARIMA depends greatly on the p, d, q parameters, various combinations of these parameters, including those used in past literature, were tested. The funds used for this were the S&P500 fund (SPY), Financial Select Sector SPDR Fund (XLF), Technology Select Sector SPDR Fund (XLK), Industrial Select Sector SPDR Fund (XLI), Materials Select Sector SPDR Fund (XLB), Energy Select Sector SPDR Fund (XLE), Consumer Staples Select Sector SPDR Fund (XLP), Health Care Select Sector SPDR Fund (XLV), Utilities Select Sector SPDR Fund (XLU) and Consumer Discretionary Select Sector SPDR Fund (XLY). The combinations used in past studies have been referenced accordingly within Tables 1 and 2. The dataset used spanned from 1 January 2014 to 31 December 2021 and the first 1,915 data points were used to train the models. The last 100 data points were used as the test set for point predictions to be made.

Table 1. MSE for different p, d, q combinations for ARIMA on SPY, XLF, XLK, XLI and XLB funds

Fund / *p, d, q*	SPY	XLF	XLK	XLI	XLB
0, 1, 0 [1]	14.262	0.19185	3.7461	0.94633	0.66610
1, 1, 0	14.626	0.19082	3.7778	0.95990	0.67884
2, 1, 0 [21]	14.708	0.19186	3.7994	0.96037	0.67823
3, 1, 0	14.787	0.19257	3.8161	0.96057	0.67877
4, 1, 0	14.490	0.18846	3.7354	0.94479	0.67793
5, 1, 0 [1], [12]	14.588	0.19130	3.7443	0.96296	0.68739
0, 1, 2 [22]	14.734	0.19234	3.8117	0.95852	0.67777
1, 0, 0 [4], [16]	14.388	0.19222	3.7685	0.94808	0.67131
1, 0, 2 [5]	-	0.19271	-	0.96011	-
1, 1, 1 [15]	14.664	0.19073	3.7932	0.96154	0.67431
1, 1, 2 [13]	15.339	0.19208	3.7941	0.99764	0.69479
1, 2, 1 [14]	14.606	0.19127	3.7603	0.96298	0.67877

Table 2. MSE for different *p*, *d*, *q* combinations for ARIMA on XLE, XLP, XLV, XLU and XLY funds

Fund / *p, d, q*	XLE	XLP	XLV	XLU	XLY
0, 1, 0 [1]	0.85086	0.27609	1.0423	0.36149	5.0210
1, 1, 0	0.85115	0.28897	1.0776	0.36217	5.0615
2, 1, 0 [21]	0.85572	0.28733	1.0777	0.36786	4.9916
3, 1, 0	0.85314	0.28585	1.0781	0.37011	5.0031
4, 1, 0	0.85629	0.28458	1.1067	0.38237	4.9132
5, 1, 0 [1], [12]	0.85989	0.28744	1.0982	0.38525	4.9243
0, 1, 2 [22]	0.85607	0.28688	1.0824	0.36779	4.9718
1, 0, 0 [4], [16]	0.84455	0.28005	1.0499	0.36597	5.0486
1, 0, 2 [5]	0.85003	0.29047	-	0.37251	-
1, 1, 1 [15]	-	0.28777	1.0770	0.36515	5.0468
1, 1, 2 [13]	-	0.28958	1.1140	0.36451	4.9888
1, 2, 1 [14]	0.85052	0.28855	1.0775	0.36268	5.0465

As stock price data is often non-stationary in nature, some combinations of parameters were unable to induce stationarity and lead to the convergence of forecasts, thus returning an error (as indicated by a blank cell in Tables 1 and 2). While studies have conducted various experiments, such as the ADF and PACF tests, and each found an optimal combination of *p, d, q* parameters, the results in Tables 1 and 2 illustrate how different combinations have very similar accuracies. How the combinations fare against one another also vary depending on the ticker as a combination that is optimal for one ticker might not have the greatest predictive capability for another ticker.

When comparing their performances across these 10 stock tickers, it was found a single finite difference without AR or MA modelling, which is the ARIMA (0, 1, 0), performs slightly better than other *p, d, q* combinations for the datasets in this work, similar to a past study [1]. This implies that the time series data can be modelled as the fractional integral of a white noise process (i.e. a Wiener process). This conclusion is consistent with the literature dealing with financial data series analysis [23]. Thus, this combination of parameters will be used in the ARIMA models for this study.

3.2. Development of LSTM model

Another study [24] conducted prior to this investigated the optimisation of parameters in LSTMs with respect to the SPY fund when making long run predictions. The dataset used spanned from 1 January 2012 to 31 December 2021 and the first 1200 data points were used to train the models. It was found that the architecture that produced the most accurate forecasts was 1 LSTM layer and 2 dense layers. The optimal range for the number of time steps was 30 and that for the number of units was 130. 4 features were found to be the most favourable, where the past 4 days of closing prices were input into a single LSTM cell. Thus, the LSTM used in this study comprised 1 LSTM layer, 2 dense layers, 30-time steps, 130 units and 4 features.

4. RESULTS AND DISCUSSION

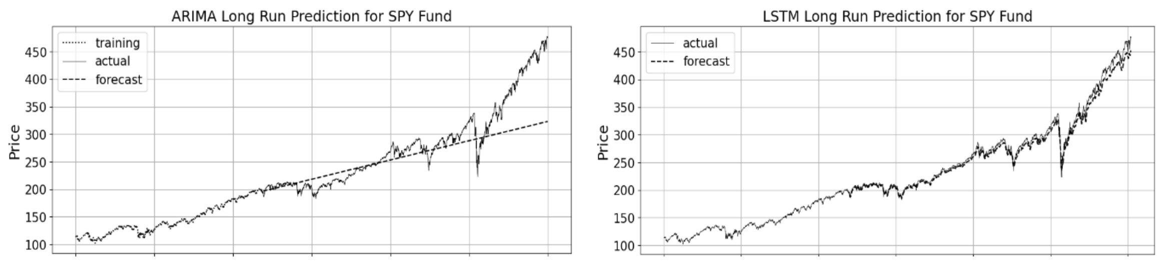
4.1. Long run predictions

This study investigated the performances of both models to make long term price predictions. The dataset used spanned from 1 January 2012 to 31 December 2021 and the first 1200 data points were used to train the models. Table 3 illustrates the superiority of LSTMs to ARIMA when making predictions in the long run, given the significantly lower MSE that they produce. This is reflective of the results found in several studies where LSTMs were found to outperform ARIMA [1], [3].

Figure 2 illustrates the long run forecasts using ARIMA and LSTM. ARIMA is only able to make a linear long-term prediction, as illustrated in Figure 2(a), if it is not retrained upon each daily forecast. This is further corroborated by numerous studies where it was found that LSTMs outperform ARIMA as they were able to learn non-linear relationships from data, as illustrated in Figure 2(b), unlike ARIMA which made directional predictions and were better in forecasting linear time series [1], [21], [25]. As shown in Figure 2(a), although forecasts made by ARIMA are rather similar to the actual closing prices initially, they are highly inaccurate in the long run [14].

Table 3. MSE for long run predictions

STOCK TICKER	MSE FOR LSTM	MSE FOR ARIMA
SPY	30.35	2,145.76
XLF	0.28	15.09
XLK	4.82	1,458.26
XLI	4.20	59.29
XLB	0.51	60.89
XLE	1.40	2,884.28
XLP	0.81	26.92
XLV	6.36	62.22
XLU	0.41	14.10
XLY	4.24	717.25



(a) (b)

Figure 2. Long run prediction for SPY fund for (a) ARIMA and (b) LSTM

4.2. Point predictions

The performances of both models in making point predictions were also studied. This was done by adding the actual closing price of the next day to the training set and fitting it to the model on each iteration after forecasting the closing price for that day. The dataset used spanned from 1 January 2014 to 31 December 2021 and the first 1,990 data points were used to train the models. The last 25 data points were used as the test set for point predictions to be made.

Table 4 illustrates how the ARIMA outperforms LSTMs in making point predictions, highlighting the accuracy of short-term forecasts ARIMA produce [4]. ARIMA performed better when retrained upon each iteration and made forecasts only for the following day's closing price as compared to its long-term prediction. However, this was contrary to LSTMs where retraining the model repeatedly resulted in poorer performances.

Table 4. MSE for point predictions

STOCK TICKER	MSE FOR LSTM	MSE FOR ARIMA
SPY	106.21	30.76
XLF	1.00	0.33
XLK	36.89	8.43
XLI	4.12	1.92
XLB	3.77	1.03
XLE	1.49	0.92
XLP	1.51	0.57
XLV	8.12	1.25
XLU	1.99	0.53
XLY	33.30	10.03

4.3. Summary

Despite ARIMA having a better accuracy in short-term prediction, LSTMs are more accurate and stable in the long run [15]. The point predictions made by ARIMA and the long-run predictions made by LSTMs have similar accuracies. However, LSTMs have greater potential in improving forecasting accuracy.

First, the use of LSTM requires the setting of several parameters in its architecture to obtain optimal performance. Choosing the right parameters to find the right model architecture can cause the performance to vary significantly [1]. This is due to the higher complexity of deep learning models which require adjustments to its architecture, such as the number of neurons in the input layer and hidden layer, and the tuning of other hyperparameters [13]. Although the parameters chosen were proven to be optimal in a study prior to this, it is possible that this combination is not unique and its performance might vary when the stock ticker or time period changes.

Additionally, LSTMs are greatly affected by data processing and the dynamic nature of the stock market cannot be analysed using only historic data, but current conditions as well, including trending news in politics and economics that impact the behaviour of investors and consequently, stock markets [16]. Other studies claim that LSTMs, unlike ARIMA, require designed features as patterns cannot be automatically detected within data. These features include technical indicators, such as trading volume, momentum and volatility. This helps LSTMs distinguish between temporary price movements and long-term trends, reducing its vulnerability to false signals [16], [26], [27].

4.4. Future work

Despite both models showing strong performances when forecasting stock prices, LSTM does have more potential for improvement and adjustments compared to ARIMA. This is a promising area for future research where LSTM models can be optimised by increasing the variety of input variables. Other forms of data, such as technical indicators as well as sentiment analysis could be incorporated into the LSTM model for a more holistic approach instead of solely analysing price data. In this regard, a few studies have integrated technical indicators in LSTMs [27]–[29] while others have examined the use of sentiment analysis with LSTMs [30]–[32]. Hence, future research could attempt combining both technical indicators and sentiment analysis into the model as well as other input variables such as the prices of related stocks, so that newfound revelations can be made.

5. CONCLUSION

This study has investigated the forecasting accuracies of ARIMA and LSTM when forecasting stock prices for all 10 different stock tickers, comprising the ETFs for various market sectors. LSTMs were found to perform better in long-term predictions while ARIMA was superior in point predictions. The point predictions made by ARIMA have similar accuracies as the long-run predictions made by LSTMs. All in all, both the ARIMA and LSTM are well-established models for stock price prediction and show remarkable forecasting accuracy. While the ARIMA model and LSTM model had similar accuracies in our study, the LSTM model has a larger capacity for improvement and is a captivating area to be researched upon. This study has shed light on the efficacy of ARIMA and LSTM models and hopes to spark further investigations and curiosity in the field of time series analysis and stock price forecasting.

REFERENCES

[1] M. Rhanoui, S. Yousfi, M. Mikram, and H. Merizak, "Forecasting financial budget time series: Arima random walk vs lstm neural network," *IAES International Journal of Artificial Intelligence*, vol. 8, no. 4, pp. 317–327, 2019, doi: 10.11591/ijai.v8.i4.pp317-327.

[2] S. Mehtab, J. Sen, and A. Dutta, "Stock price prediction using machine learning and lstm-based deep learning models," 2021, pp. 88–106.

[3] J. Oliver Muncharaz, "Comparing classic time series models and the LSTM recurrent neural network: An application to S&P 500 stocks," *Finance, Markets and Valuation*, vol. 6, no. 2, pp. 137–148, 2020, doi: 10.46503/zvbs2781.

[4] A. A. Adebiyi, A. O. Adewumi, and C. K. Ayo, "Stock price prediction using the ARIMA model," *Proceedings-UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, UKSim 2014*, pp. 106–112, 2014, doi: 10.1109/UKSim.2014.67.

[5] P. Mondal, L. Shit, and S. Goswami, "Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices," *International Journal of Computer Science, Engineering and Applications*, vol. 4, no. 2, pp. 13–29, 2014, doi: 10.5121/ijcsea.2014.4202.

[6] A. Meyler, G. Kenny, and T. Quinn, "Forecasting Irish inflation using ARIMA models," *Central Bank and Financial Services Authority of Ireland Technical Paper Series*, vol. 3, no. July, pp. 1–48, 1998.

[7] K. Chen, Y. Zhou, and F. Dai, "A LSTM-based method for stock returns prediction: A case study of China stock market," *Proceedings - 2015 IEEE International Conference on Big Data, IEEE Big Data 2015*, pp. 2823–2824, 2015, doi: 10.1109/BigData.2015.7364089.

[8] P. and M. S. Pm, "Stock Price Prediction Using LSTM," *Test Engineering and Management*, vol. 83, 2020.

[9] R. Pradhan, K. Bharadwaj, A. Saxena, and V. Rajpoot, "Stock trend prediction and analysis using LSTM neural network and dual moving average crossover algorithm," *IOP Conference Series: Materials Science and Engineering*, vol. 1131, no. 1, p. 012005, 2021, doi: 10.1088/1757-899x/1131/1/012005.

[10] S. O. Ojo, J. Adeola Adisa, P. A. Owolawi, C. T. Du, and M. Mphahlele, "Stock market behaviour prediction using long short-term memory network and gated recurrent unit∗," *Proceedings - 2020 International Conference on Computational Science and Computational Intelligence, CSCI 2020*, pp. 615–621, 2020, doi: 10.1109/CSCI51800.2020.00109.

[11] S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," *2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2017*, vol. 2017-January, pp. 1643–1647, 2017, doi: 10.1109/ICACCI.2017.8126078.

[12] A. V. Alzheev and R. A. Kochkarov, "Comparative analysis of ARIMA and LSTM predictive models: Evidence from Russian stocks," *Finance: Theory and Practice*, vol. 24, no. 1, pp. 14–23, 2020, doi: 10.26794/2587-5671-2020-24-1-14-23.

[13] K. Zhou, W. Y. Wang, T. Hu, and C. H. Wu, "Comparison of time series forecasting based on statistical ARIMA model and LSTM with attention mechanism," *Journal of Physics: Conference Series*, vol. 1631, no. 1, 2020, doi: 10.1088/1742-6596/1631/1/012141.

[14] G. Abdoli, "Comparing the prediction accuracy of LSTM and ARIMA models for time-series with permanent fluctuation," *SSRN Electronic Journal*, 2020, doi: 10.2139/ssrn.3612487.

[15] J. Hao, X. Li, Y. Lv, and N. Xiao, "A comparative study on SSE 50 index prediction based on ARIMA model and LSTM neural network," *Proceedings - 2021 3rd International Conference on Machine Learning, Big Data and Business Intelligence, MLBDBI 2021*, pp. 216–219, 2021, doi: 10.1109/MLBDBI54094.2021.00049.

[16] Q. Ma, "Comparison of ARIMA, ANN and LSTM for stock price prediction," *E3S Web of Conferences*, vol. 218, 2020, doi: 10.1051/e3sconf/202021801026.

[17] A. H. Manurung, W. Budiharto, and H. Prabowo, "Algorithm and modeling of stock prices forecasting based on long short-term memory (LSTM)," *ICIC Express Letters*, vol. 12, no. 12, pp. 1277–1283, 2018, [Online]. Available: https://accounting.binus.ac.id/publication/C129A09C-1844-465E-8F31-1807DB73ED77/algorithm-and-modeling-of-stock-prices-forecasting-based-on-long-sort-term-memory-lstm/.

[18] M. Baughman, C. Haas, R. Wolski, I. Foster, and K. Chard, "Predicting amazon spot prices with LSTM networks," *Proceedings of the 9th Workshop on Scientific Cloud Computing, ScienceCloud 2018 - Co-located with HPDC 2018*, 2018, doi: 10.1145/3217880.3217881.

[19] A. O. Çıbıkdiken and E. Ş. Karakoyun, "Comparison of ARIMA time series model and LSTM deep learning algorithm for bitcoin price forecasting," *Multidisciplinary Academic Conference 2018*, 2018.

[20] S. McNally, J. Roche, and S. Caton, "Predicting the price of Bitcoin using machine learning," *Proceedings - 26th Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, PDP 2018*, pp. 339–343, 2018, doi: 10.1109/PDP2018.2018.00060.

[21] A. A. Adebiyi, A. O. Adewumi, and C. K. Ayo, "Comparison of ARIMA and artificial neural networks models for stock price prediction," *Journal of Applied Mathematics*, vol. 2014, 2014, doi: 10.1155/2014/614342.

[22] Y. B. Wijaya, S. Kom, and T. A. Napitupulu, "Stock price prediction: Comparison of Arima and artificial neural network methods - An Indonesia stock's case," *Proceedings - 2010 2nd International Conference on Advances in Computing, Control and Telecommunication Technologies, ACT 2010*, pp. 176–179, 2010, doi: 10.1109/ACT.2010.45.

[23] E. Panas, "Estimating fractal dimension using stable distributions and exploring long memory through ARFIMA models in Athens stock exchange," *Applied Financial Economics*, vol. 11, no. 4, pp. 395–402, 2001, doi: 10.1080/096031001300313956.

[24] P. R. Low and E. Sakk, "Parameter optimisation of LSTM Models in stock price prediction," *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, vol. 2022-Novem, 2022, doi: 10.1109/TENCON55691.2022.9978045.

[25] J. Sterba and K. Hilvska, "The implementation of hybrid ARIMA-neural network prediction model for agregate water consumtion prediction," *Journal of Apploed Mathematics*, vol. 3, no. 3, pp. 123–130, 2010.

[26] S. O. Ojo, P. A. Owolawi, M. Mphahlele, and J. A. Adisa, "Stock market behaviour Prediction using Stacked LSTM Networks∗," *Proceedings - 2019 International Multidisciplinary Information Technology and Engineering Conference, IMITEC 2019*, 2019, doi: 10.1109/IMITEC45504.2019.9015840.

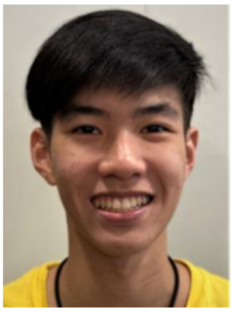
[27] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-based model to forecast stock prices," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/6622927.

[28] T. Kim and H. Y. Kim, "Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data," *PLoS ONE*, vol. 14, no. 2, 2019, doi: 10.1371/journal.pone.0212320.

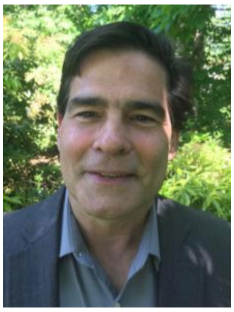
[29] A. Altan and S. Karasu, "Crude oil time series prediction model based on LSTM network with chaotic Henry gas solubility optimization," *Energy*, vol. 242, 2022, doi: 10.1016/j.energy.2021.122964.

[30] J. Li, H. Bu, and J. Wu, "Sentiment-aware stock market prediction: A deep learning method," *14th International Conference on Services Systems and Services Management, ICSSSM 2017 - Proceedings*, 2017, doi: 10.1109/ICSSSM.2017.7996306.
[31] R. Akita, A. Yoshihara, T. Matsubara, and K. Uehara, "Deep learning for stock prediction using numerical and textual information," *2016 IEEE/ACIS 15th International Conference on Computer and Information Science, ICIS 2016 - Proceedings*, 2016, doi: 10.1109/ICIS.2016.7550882.
[32] Q. Zhuge, L. Xu, and G. Zhang, "LSTM neural network with emotional analysis for prediction of stock price," *Engineering Letters*, vol. 25, no. 2, pp. 167–175, 2017.

BIOGRAPHIES OF AUTHORS



Pi Rey Low is a high school graduate from Raffles Institution in Singapore. He has completed A Levels, achieving the highest grades for all subjects and is incoming student at Carnegie Mellon University. Having a keen interest in artificial intelligence and computer science, he has been working on numerous research papers on deep learning, machine learning, stock price prediction and analysis, as well as the optimization of AI models. He can be contacted at email: pirey.low@gmail.com.



Dr Eric Sakk is currently an Associate Professor of Computer Science at Morgan State University. He received his Ph.D. in Electrical and Computer Engineering with a minor in applied mathematics from Cornell University. He performs research in the field of machine learning, quantum computation, system theory and bioinformatics. He can be contacted at email: eric.sakk@gmail.com or eric.sakk@morgan.edu.