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Stock Trend Prediction Using LSTM with MA, EMA, MACD and RSI Indicators

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Abstract

The stock market that has been known volatile is always an attractive target for the researchers to perform research and experiment on. Stock trend prediction is one of the most famous topics that is done as the movement of a stock is full of uncertainty and is affected by many different factors. In this research, the technical indicator of a stocks has been utilized (MA, EMA, RSI and MACD) to get the signal of the upcoming trend of a stock in order to achieve stock trend prediction. Machine learning techniques is also applied to process those stock data and stock indicator. The technique that is proposed to develop the stock prediction model is the Long Short Term Memory Neural Network, also known as LSTM. After the model is developed, it will be used to carry out prediction on stock and compare the actual stock movement with the predicted stock movement to find out its accuracy in making stock trend prediction. Three stocks will be used to validate the performance of the model which are Public Bank, Tenaga, and Apex Healthcare. The results show that the trend of the inspected stocks are successfully predicted using the LSTM model.

Keywords

Stock trend prediction, MA, EMA, MACD, LSTM

Introduction

Stock trend prediction is a challenging task due to the high-noise, dynamic, non-linear, non-parametric, and chaotic properties of stock data (Su et al., 2024). Over the past decade, it has garnered significant attention from researchers in various fields, particularly in Finance and Data Science. Despite its challenges, stock trend prediction is crucial for investors to make informed decisions, reduce risks, and increase profits (Chaudhari and Thakkar, 2023). Even though stock prices may not precisely reach targeted predictions due to their random movement, predicting trends remains valuable. There are three primary types of stock movement trends: uptrend, downtrend, and sideways (Chakole et al., 2021; He et al., 2022). Uptrend signifies upward movement with higher peaks and troughs, downtrend involves a downward price movement, and sideways indicates horizontal movement with balanced supply and demand forces. Predicting these trends assists investors in avoiding downtrends and recognizing uptrends in advance, facilitating informed decision-making about stock investments or trades (Simanjuntak et al., 2023; Voss & Mohan, 2016; Lai et al.,2022).

Two types of analyses for stock trend prediction are highlighted: technical analysis and fundamental analysis. Fundamental analysis is suitable for a predicting time horizon of one year

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or longer, whereas technical analysis is favored for shorter time horizons. Numerous studies have employed methods such as image processing on stock chart patterns, combining classification models with technical indicators, and utilizing turning points for segmentation based on piecewise linear regression . (Zhai et al., 2007; Teixeira and Oliveira, 2010; Oh and Kyoung-Kim, 2002; Luo and Chen, 2013). Neural Networks have also been employed for prediction. Technical indicators play a crucial role in stock trend prediction, summarizing different behaviors and trends based on price, volume, and value of a share. Examples include Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Exponential Moving Average (EMA), and Moving Average (MA). These indicators offer insights into whether a stock is likely to go bearish or bullish, helping investors make more informed decisions.

Moving on to stock trend prediction algorithms, researchers have explored various approaches such as decision trees, clustering, and machine learning methods. The Random Forest technique has been proposed for stock trend prediction, achieving high accuracy for short-term forecasts. Long Short-Term Memory Neural Network (LSTM), a variation of Recurrent Neural Network (RNN), has gained popularity due to its ability to handle time series data and overcome the gradient disappearance problem faced by RNN (Gao et al.,2018). LSTM utilizes a special gate mechanism neural unit structure, incorporating input, output, and forget gates, along with a memory neuron, to enhance memory capacity and improve prediction accuracy (Chen & Zhou, 2021). Many researchers have explored the stock trend prediction using various technical indicators, however, there is lack of research on applying LSTM with the combination of MA, EMA, RSI and MACD to predict the stock market.

Methodology

The daily stock data and information are sourced from Kaggle, a prominent online platform providing diverse datasets, APIs, and knowledge. Kaggle offers accessible datasets, and the stock datasets acquired include information from four major stock markets: Forbes 2000, Nasdaq, NYSE, and S&P500. Each stock's data encompasses details such as opening/closing prices, volume, daily low/high prices, and adjusted closing prices spanning over a decade until the present, available in both CSV and JSON formats. To enhance data quality, essential preprocessing techniques, including data reduction and transformation, are implemented. Given the substantial volume of daily stock information, data reduction involves analyzing all stocks to identify historical uptrend and downtrend periods. The resulting dataset is then divided into 20% and 80%, with the latter serving as training data for the prediction model.

For the prediction model's input variables, a crucial data transformation is applied to convert daily opening and closing prices into stock indicators, namely MACD, RSI, EMA, and MA. These indicators, derived from algorithmic analyses of stock information, provide more nuanced input for the prediction model. The chosen prediction algorithm is the Long Short-Term Memory Neural Network (LSTM). Before developing the model, hyperparameters, including the number of LSTM layers, nodes per layer, and fully connected layers, are configured. Leveraging insights from previous research with optimal performance, the model is set to include 32, 64, or 128 nodes per layer, normalized between 1 and 0, with 25 epochs and a batch size of 15. The final architecture consists of 3 LSTM layers and 2 fully connected layers.

The training process of the stock prediction model commences with loading the dataset, followed by preprocessing techniques and the crucial step of splitting the data into an 80-20 ratio for training and testing, respectively. The training dataset is utilized to train the prediction model, while the testing dataset evaluates its performance. The results of the model are then displayed, providing insights into the predictive accuracy and effectiveness of the implemented LSTM-based stock trend prediction system. Following the training of the model, stock prediction is initiated through the invocation of the prediction function. This function requires parameters such as the stock name, processed dataset, look-back duration, and the duration for prediction. Within this function, the prediction unfolds iteratively, forecasting day by day for the specified prediction duration. The process begins with loading the trained prediction model for the respective stock, and subsequently, the pre-processed data is fed into the loaded model to generate predictions.

During each prediction iteration, the outcomes undergo an inverse transform to restore the data to its original range. The close, open, high, and low prices are then extracted and appended as a new row into the stock dataset. This updated dataset is employed in subsequent predictions, effectively creating a dynamic feedback loop for refining predictions over time. This iterative process continues for the specified prediction duration. Upon completion, the stock dataset is returned, and it undergoes extraction into two distinct sets: the original data and the predicted data. This separation ensures clarity and readability when visualizing the stock trends on a graph. The extracted datasets are then passed to another function named 'plot_graph,' responsible for visually representing the future predicted stock trends. Post-prediction, the graph displays two distinct lines representing the original close prices and the predicted close prices. These lines are appropriately labeled to distinguish between the actual historical data and the forecasted values, enhancing the interpretability of the plotted graph. This visualization serves as a valuable tool for assessing the model's predictive performance and gaining insights into the projected future trends of the selected stock.

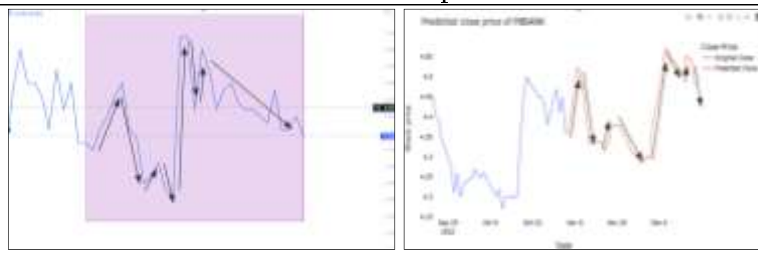
Results and Discussion

In this section, we delve into the evaluation methods employed for assessing the effectiveness of the Stock Trend Prediction model. The precision and accuracy of the model are gauged through a meticulous comparison between the actual stock prices and trends and their corresponding predicted results. This dual assessment provides valuable insights into the model's performance. The comparison of trends allows us to ascertain the model's capability to generate stock trend predictions that closely mirror the actual stock movements. Simultaneously, the comparison of prices enables us to quantify the variance between the predicted close prices and the actual close prices. To execute these evaluations, a subset of stocks from the Bursa stock market is strategically chosen. The dataset for each selected stock is retrieved, encompassing historical data until the past 30 days. This temporal scope ensures that the predicted results encapsulate the forthcoming 30 days from the dataset's last recorded day, providing a robust evaluation period.

The stocks subjected to experimentation and evaluation are meticulously enumerated in Table 1, offering transparency about the specific assets under scrutiny. This systematic approach to model evaluation ensures a comprehensive understanding of its predictive capabilities across various stocks, contributing to a nuanced assessment of its overall performance.

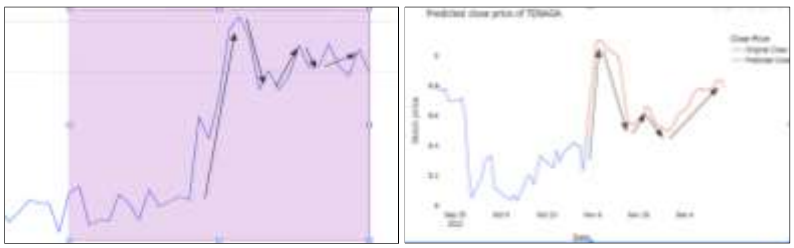
Table 1. 3 stocks used to access the model’s performance

Test case	Stocks
1	Public Bank
2	Tenaga
3	Apex Healthcare



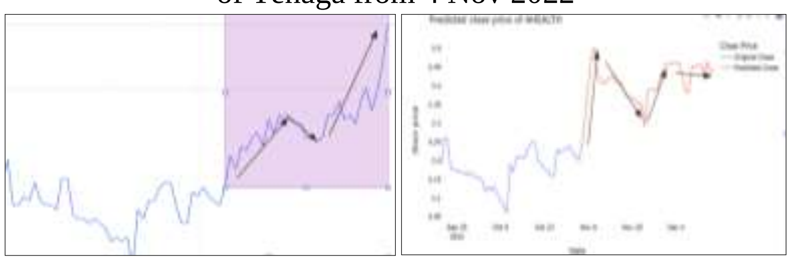
(a) (b)

Figure 1. (a) Actual Stock Movement of Public Bank from 4 Nov 2022 (b) Predicted Stock Movement of Public Bank from 4 Nov 2022



(a) (b)

Figure 2. (a) Actual Stock Movement of Tenaga from 4 Nov 2022 (b) Predicted Stock Movement of Tenaga from 4 Nov 2022



(a) (b)

Figure 3. (a) Actual Stock Movement of Apex Healthcare from 4 Nov 2022 (b) Predicted Stock Movement of Apex Healthcare from 4 Nov 2022

From Figure 1(a) and Figure 1(b), it is able to be seen that the actual and predicted stock movement of Public Bank is mostly similar. It is able to predict that the stock will be going uptrend in the beginning and follow by a W shape movement which may seem to be a bullish signal but despite that it is still able to predict that the stock will be going downtrend afterwards.

In Figure 4(a), it is shown that there are 15 predictions that has more than 0.10 difference and 1 prediction that more than 0.20 difference, however the rest of the predictions are able to stay within a 0.10 difference with some of the results being lower than 0.05 of difference. The small difference in price may be due to the speed of the predicted stock movement is quite similar to the actual one.

	original_close	predicted_close	difference
0	4.35	4.524979	-0.174979
1	4.38	4.502325	-0.122325
2	4.40	4.457290	-0.057290
3	4.43	4.393383	0.036617
4	4.45	4.333364	0.116636
5	4.38	4.338786	0.041214
6	4.37	4.334188	0.035812
7	4.30	4.314153	-0.014153
8	4.31	4.333070	-0.023070
9	4.33	4.378667	-0.048667
10	4.29	4.378321	-0.088321
11	4.28	4.359492	-0.079492
12	4.52	4.349551	0.170449
13	4.52	4.325126	0.194874
14	4.41	4.314511	0.095489
15	4.50	4.284986	0.215014
16	4.47	4.289587	0.180413
17	4.41	4.302096	0.107904
18	4.44	4.297512	0.142488
19	4.45	4.381942	0.068058
20	4.42	4.501461	-0.081461
21	4.41	4.571963	-0.161963
22	4.41	4.564372	-0.154372
23	4.40	4.544161	-0.144161
24	4.39	4.540736	-0.150736
25	4.44	4.501510	-0.061510
26	4.38	4.553532	-0.173532
27	4.38	4.543972	-0.163972
28	4.40	4.538288	-0.138288
29	4.37	4.475478	-0.105478

(a)

	original_close	predicted_close	difference
0	8.500000	9.092076	-0.592076
1	8.270001	9.105536	-0.835535
2	8.300000	9.098343	-0.798343
3	8.300000	9.063188	-0.763188
4	8.450000	9.048776	-0.598776
5	8.400000	8.998824	-0.598824
6	8.300000	8.838321	-0.538321
7	8.480000	8.648914	-0.168914
8	8.380000	8.546101	-0.166101
9	8.410000	8.538049	-0.128049
10	8.440000	8.594343	-0.154343
11	8.420000	8.652987	-0.232987
12	8.910000	8.656808	0.253192
13	8.780000	8.606260	0.173740
14	9.020001	8.547447	0.472554
15	9.420000	8.509644	0.910356
16	9.500000	8.495287	1.004713
17	9.380000	8.517767	0.862233
18	9.070000	8.563438	0.506562
19	9.180000	8.605803	0.574197
20	9.070000	8.653247	0.416753
21	9.150000	8.714567	0.435433
22	9.330000	8.755290	0.574710
23	9.200000	8.773809	0.426191
24	9.210000	8.775574	0.434426
25	9.340000	8.773750	0.566250
26	9.210000	8.801991	0.408009
27	9.150000	8.836345	0.313655
28	9.310000	8.840542	0.469458
29	9.180000	8.789412	0.390588

(b)

	original_close	predicted_close	difference
0	3.31	3.482759	-0.172759
1	3.28	3.503898	-0.223898
2	3.33	3.431978	-0.101978
3	3.32	3.409263	-0.089263
4	3.35	3.406888	-0.056888
5	3.36	3.429184	-0.069184
6	3.33	3.408456	-0.078456
7	3.39	3.411620	-0.021620
8	3.36	3.397572	-0.037572
9	3.40	3.374346	0.025654
10	3.39	3.363446	0.026554
11	3.39	3.351539	0.038461
12	3.38	3.352141	0.027859
13	3.38	3.289456	0.090544
14	3.35	3.389105	-0.039105
15	3.35	3.380859	-0.030859
16	3.34	3.423543	-0.083543
17	3.35	3.443265	-0.093265
18	3.40	3.458835	-0.058835
19	3.40	3.458756	-0.058756
20	3.43	3.460751	-0.030751
21	3.39	3.422750	-0.032750
22	3.40	3.385716	0.014284
23	3.38	3.381290	-0.001290
24	3.43	3.449003	-0.019003
25	3.46	3.455846	0.004154
26	3.41	3.425840	-0.015840
27	3.45	3.465880	-0.015880
28	3.51	3.433893	0.076107
29	3.60	3.443578	0.156422

(c)

Figure 4. Difference in actual and predicted close price of (a) Public Bank (b) Tenaga and (c) Apex Healthcare from 4 Nov 2022

In test case 2, a close examination of the predicted stock movement in Figure 2(b) compared to the actual stock movement in Figure 2(a) reveals an interesting pattern. While on the surface, the two movements may seem similar in terms of direction, it becomes apparent that the difference in magnitude between them is substantial. This discrepancy is particularly evident in the initial downtrend observed in the actual movement, which is notably smaller than the corresponding downtrend in the predicted movement. This initial difference in magnitude sets the stage for subsequent price variations. Upon closer analysis of Figure 4(b), it becomes apparent that the substantial difference in price can be attributed to two primary factors. First, as mentioned earlier, the difference in magnitude plays a significant role. The predicted movement exhibits more pronounced fluctuations, leading to larger price variations compared to the actual movement. This disparity in the intensity of price changes is a key contributor to the observed differences.

Second, another noteworthy factor contributing to the price difference is the speed at which the predicted stock movement unfolds in comparison to the actual movement. The predicted movement appears to accelerate more rapidly, reaching its peak earlier than the actual movement does. This accelerated pace in the predicted movement leads to an earlier onset of the subsequent downtrend. Consequently, the entire price difference between the predicted and actual movements is influenced by this temporal discrepancy. Moving on to test case 3, the stock movements depicted in Figure 3(a) and Figure 3(b) exhibit substantial disparities in their trend patterns. While the actual stock movement in Figure 3(a) gradually ascends in an uptrend fashion, the predicted stock movement in Figure 3(b) presents a distinct pattern. In the predicted movement, there is an initial sharp upward spike, followed by a subsequent downtrend, and eventually a period of sideways movement towards the end of the observed period. Despite the pronounced differences in the trend of the stock movements, a surprising observation emerges when examining the close prices in Figure 4(c). It becomes evident that the predicted close prices and actual close prices generally exhibit a remarkable degree of proximity. From the 4th day of the observed period until the 29th day, the predicted close prices manage to maintain a difference of less than 0.1 compared to the actual close prices. This observation is particularly intriguing as it suggests that, although the predicted trend of the stock may not be entirely accurate, the predicted prices have the potential to eventually converge closely to the actual prices.

In summary, these test cases highlight the complexities involved in predicting stock movements accurately. While there may be discrepancies in the trends observed in predicted and actual movements, factors like the magnitude of fluctuations and the speed of movement can significantly impact the resulting price differences. Additionally, the observed phenomenon in test case 3 underscores the potential for predicted prices to align closely with actual prices despite differing trend patterns. This suggests that, in some instances, predictive models may still offer valuable insights into price levels even when trend predictions are less accurate.

Conclusion

In conclusion, this research advances stock trend prediction by integrating LSTM with crucial technical indicators, including MA, EMA, MACD, and RSI. Utilizing Kaggle datasets from major stock markets, the study demonstrates the model's effectiveness in capturing trends and predicting stock prices. While some variations exist, particularly in timing and magnitude, the LSTM-based model showcases notable accuracy in predicting close prices. The research emphasizes the dual evaluation of trend and price differentials, providing a comprehensive understanding of the model's performance. Overall, the study contributes valuable insights to the field, offering a promising approach for investors seeking precise stock predictions, albeit with areas for further refinement. The integration of LSTM with technical indicators holds potential for enhancing decision-making in stock trading and investment strategies.

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