Stock Price Prediction Based on CNN, LSTM and CNN- LSTM Model

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Abstract: Stock investments are perennially recognized for their high potential returns and commensurate risk levels. While CNN and LSTM models individually demonstrate proficiency in data prediction, each has its inherent limitations. In pursuit of overcoming these limitations, this research proposes a composite CNN-LSTM model. Initially, this paper selects two disparate stocks for evaluation, employing the individual CNN and LSTM models to predict their prices. Subsequently, the construction of the hybrid model involves utilizing the CNN layers to extract spatial features, which are then transformed into a one-dimensional vector. This vector is subsequently fed into the LSTM layer to capitalize on its sequence data handling capabilities, culminating in the model's predictive execution. The final phase of this study entails a comparative analysis of the predictive performance. The results show that the CNN-LSTM model inherits the advantages of the two individual models and is both highly stable and extremely efficient in making predictions on big stock data. This enhancement is particularly notable when compared to the single CNN and LSTM models, underscoring the efficacy of integrating these two distinct computational approaches into a unified predictive framework.

1 INTRODUCTION

With high risk and high returns, stocks have always been popular and have become a favorite form of investment. The stock market is a significant and volatile component of the financial market, which is a very complicated and uncertain field. However, the high volatility of stocks in the stock exchange market poses a challenge to traditional quantitative trading strategies (Kong et al., 2024). When forecasting stocks, investors should not only build models to forecast stock data, but also pay attention to macroeconomic factors, company fundamentals, market sentiment and other multi-dimensional information to comprehensively analyze the dynamics of the stock market. With the advent of the era of big data analytics, machine learning and deep learning have shown great potential to surpass traditional machine learning in data prediction (Hu et al., 2019) When dealing with enormous amounts of stock data, some academics have used different ways. Nowadays, neural network model, random forest model, deep learning model and time series model are widely used by academics. These approaches have produced stock trend forecasting models that have a higher forecasting accuracy than individual forecasts (Zhang 2023). However, scholars have found that many times models do not predict stock prices. Therefore, it is particularly important to construct a model that can be used scientifically with high accuracy and stability. In the following, this paper will introduce two widely used models, the CNN model and the LSTM model. In this paper, these two models will be fused to obtain the CNN-LSTM model and compare the performance of them.

Convolutional Neural Networks (CNNs) have a great advantage in extracting features because CNNs have a convolution layer and the convolution layer can extract features very well. Since CNNs can share the convolution Kernel, CNNs can also handle high dimensional data very well. In addition, the CNN model has an efficient operating speed, which is a great advantage when dealing with large datasets. However, the disadvantages of CNN are also obvious. For example, the correlation between the local and the overall could be ignored by the Pooling layer, which could lose a lot of important data. In conclusion, when predicting stocks, CNN models have the advantages of strong feature extraction capability, the ability to handle time series data, and higher prediction accuracy in some cases. However, it also suffers from high requirements on the size and diversity of the

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dataset, model complexity needs to be balanced, and there may be overfitting and other shortcomings.

Long Short Term Memory (LSTM) model is a variant of RNN. LSTM has forgetting gate and memory gate so that he can remember and use past information. This is different from the traditional RNN model where the original information fades away over time. Therefore, LSTM is very suitable for processing long sequential data and has high practical value for predicting the results of stock data. Although LSTM is well received by many scholars, in fact, it still has some defects. First of all, the LSTM model is complex and takes a long time to run. Its four main parts-memory cells, input gates, forgetting gates, and memory gates-have complex calculations. Secondly, LSTM is also likely to end up with overfitting results when processing data, as it over-memorizes and uses past information. In conclusion, when predicting stocks, the LSTM model has the advantages of the ability to handle long-term dependencies, flexibility, and high prediction accuracy. However, it also suffers from long computation time and high model complexity.

This paper believes that CNN model and LSTM model each has its own advantages and disadvantages in stock prediction. CNN are usually computationally more efficient, which gives CNNs an advantage when dealing with large-scale datasets. However, the convolutional kernel of CNNs usually has a fixed size, which limits the scope of its observations. As a result, CNNs may not be as effective as LSTMs in capturing long-term dependencies. LSTM are able to capture and model long-term dependencies in data through their unique gating mechanism. This makes LSTM perform well in handling sequential data with long-term dependencies. However, LSTM needs to maintain internal state at each time step, which causes it to be computationally more complex and time-consuming than CNN.

The motivation behind this paper is to address the limitations and performance differences between CNNs and LSTMs in stock prediction by exploring and comparing their capabilities. Both models have their own shortcomings when it comes to predicting stocks, necessitating a deeper comparative analysis to uncover their nuanced performance characteristics. Additionally, this paper not only compares the traditional CNN and LSTM models individually but also examines the CNN-LSTM fusion model to better understand the performance differences among these methods. Through rigorous comparative analysis, the paper seeks to provide valuable insights into the potential of hybrid approaches for enhancing the accuracy and efficiency of stock prediction models.

In conclusion, both CNN and LSTM models have their own shortcomings when it comes to predicting stocks. Their performance differences need to be further explored from the comparative analysis, in addition, this paper adds CNN-LSTM fusion model to increase the comparative relationship to compare the performance differences of these methods.

2 METHOD

First, this paper will construct CNN model, LSTM model and CNN-LSTM model and predict two different stock data of different sizes and visualize the prediction results. Second, this paper will introduce several evaluation metrics to evaluate each model. Finally, we will compare the models, analyze the reasons for the different results, and give appropriate advice to investors.

2.1 Model Construction

- **CNN Model**

In the fields of text classification, natural language processing, and imagine recognition, CNN is recognized as a well-developed technology with strong feature extraction capabilities in both data space and time series (Lecun et al., 1989). The structure of CNN usually consists of Input layer, Convolution layer, ReLU, Pooling layer, Rasterization, Fully Connected layer, ReLU and Output layer (Figure 1). Moreover, Convolution layer, ReLU and Pooling layer are stackable and reusable, which is the core structure of CNN. The CNN network receives multi-dimensional data as input from the input layer, and to extract features from the data, convolution operations are performed on the input data by a convolution layer made up of several convolution kernels. After the convolution process, the pooling layer is used to minimize the feature dimension. Furthermore, because of its local invariance, the pooling layer improves network stability and lessens model overfitting (Qi, 2024). The pooling layer also helps the model capture key features in the stock data and ignore unimportant details. The fully connected layer located at the end of the CNN can integrate the features extracted from the previous layers very well. It spreads the feature maps output from the convolutional and pooling layers and performs a linear transformation through the weight matrix and bias terms. Finally, the activation function generates the final forecast (Auntie and Chen, 2023).

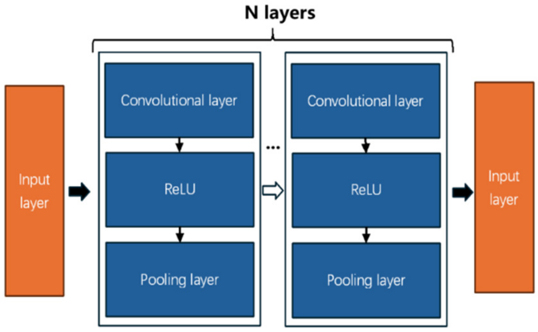

Figure 1: CNN model structure (Picture credit: Original).

- **LSTM**

Due to the gradient explosion and gradient vanishing problems of traditional recurrent neural networks, LSTM was created to solve this problem (Luo et al., 2024). LSTM is a Long Short-Term Memory network, a special kind of RNN (Recurrent Neural Network). Compared with traditional RNNs, LSTM is able to solve long sequence problems effectively by introducing the concepts of memory cells, input gates, output gates and forgetting gates. As a result, LSTM is more appropriate for processing and forecasting significant events with long intervals in a time series (Liu et al., 2024).

Forget gates and memory gates are structures unique to the LSTM and also its strengths. Some "information" about the previous state of the LSTM may become "outdated" with the passage of time. The "Forge gate" is responsible for selectively forgetting specific elements of the previous cell state in order to prevent excessive memory from impairing the neural network's processing of the current input. The following equation can be used to describe the computation of the forgetting gate and is f_t the output vector of the sigmoid neural layer.

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

Whenever a new input value is fed, the LSTM will first decide which memories to forget based on the new input value and the output of the previous moment. The Memory Gate can judge itself and decide whether or not to incorporate the current data into the control unit of the unit state. The memory gate also performs two more crucial functions. The first is to retrieve the valid information from the current input, which is determined by the formula:

$$C_t' = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{2}$$

The other important operation is to filter and rate the extracted valid information, which is calculated as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

In practical calculations, the LSTM model has some drawbacks. First, the computational complexity of the LSTM model is high. Because LSTM uses a gating mechanism and a long-term memory mechanism compared to traditional RNN, the computation of the LSTM model is greatly increased, so it takes a lot of time when running large data. Secondly, when using the LSTM model to predict the data, this is a time series prediction, so the results obtained will have a certain lag.

- **CNN-LSTM**

CNN, as a network feature extractor, has excellent feature extraction capability, in this model, CNN model will be used for feature extraction. The idea of extraction of Hua's research (2021) is to first input the data from the input layer (Hua , 2021); then use multiple convolutional layers to extract the spatial features of the input data; add pooling layers (e.g., max-pooling) between the convolutional layers to reduce the spatial dimensions of the data while retaining the important features; and finally use an activation function (ReLU) after each convolutional layer to increase the nonlinearity of the model. At this point, the obtained reshape the output of the CNN layer into a shape suitable for the LSTM input before passing it to the LSTM layer for processing (Zhou 2022). The LSTM, in turn, introduces gating units to preserve and forget the time series features, thus realizing improved prediction accuracy (Figure 2). Finally, a fully connected layer is added after the LSTM layer as an output layer to output the prediction results. The CNN-LSTM model, which combines the advantages of CNN and LSTM networks, is able to extract the time domain features while taking into account the effects of multiple influencing factors on the network, so that the prediction results are accurate and at the same time fast and efficient (Liu et al., 2024 & Hua, 2021).

Table 1: Stock data.

Date	Open	High	Low	Close	Adj Close	Volume
2010/2/1	6.870357	7	6.832143	6.954643	5.887797	7.5E+08
2010/2/2	6.996786	7.01	6.906429	6.995	5.921964	6.98E+08
2010/2/3	6.970357	7.15	6.943571	7.115357	6.023856	6.15E+08
2010/2/4	7.026071	7.084643	6.841786	6.858929	5.806765	7.58E+08

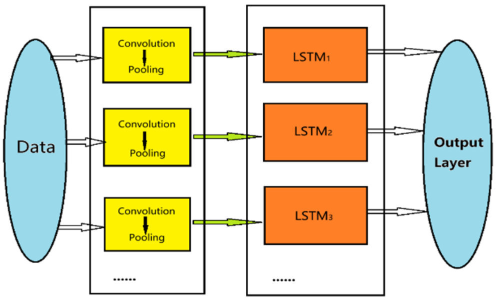

Figure 2: CNN-LSTM model structure (Picture credit: Original).

3 RESULTS

3.1 Data Choosing

Accurate data is essential before research beginning. In this paper, two datasets are used. Apple's stock price from January 8, 2010 to April 5, 2024 and Nike's price from January 8, 2022 to April 5, 2024, respectively. They both from Yahoo platform, in addition, it contains not only the closing price, but also the opening price, sales volume, the highest price of the day, and the lowest price of the day. The table 1 shows part of Apple's data.

3.2 Evaluation Indicators

In this section, four indicators, Root Mean Squared Error, Mean Relative Error, symmetric Mean Absolute Percentage Error and R-Square are chosen to evaluate the prediction accuracy of the stock price prediction model. The following are their formulas:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n}|O_i - P_i|}{n} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(\widehat{y_i} - y_i)}{y_i}\right| \tag{7}$$

Both RMSE and MAE represent the degree of deviation between the predicted and true values, so the smaller the RMSE and MAE, the better the model. Generally, R^2 ranges from 0 to 1. The better the variables in the equation explain y and the more closely the model fits the data, the closer R2 is to 1; conversely, the closer it is to 0, the less well the model fits the data. MAPE is expressed as a percentage. It can be used to indicate the magnitude of the model error, so the closer the MAPE is to 0 the more accurate the model is done by Zhang in 2021 (Zhang, 2021).

In addition to these four metrics, this paper will also calculate the running time of each model for both datasets. (The time here is measured in seconds).

3.3 Apple's Stock Data

Apple's stock data contains 3584 sets of data, which is a larger dataset. When building models, there is need to set look_back=n. It means to predict tomorrow's closing price using data from the previous n days at the current point in time. In making predictions on Apple Inc.'s corporate data, all of three models set look_bask=60. (When debugging the model, after changing the value of look_back several times, it was finally found that the model could fit the data well when look_back=60).

3.3.1 CNN

CNN demonstrates its strength in handling long time series (Figure 3). As can be seen from the prediction curve, the true and predicted values are very close to each other. There is only a small error at the local extreme points.

3.3.2 LSTM

According to the prediction curve in the figure 4, it is LSTM demonstrates its strength in handling long time series. But LSTM model still has a lag (i.e., the true value lags behind the predicted value).

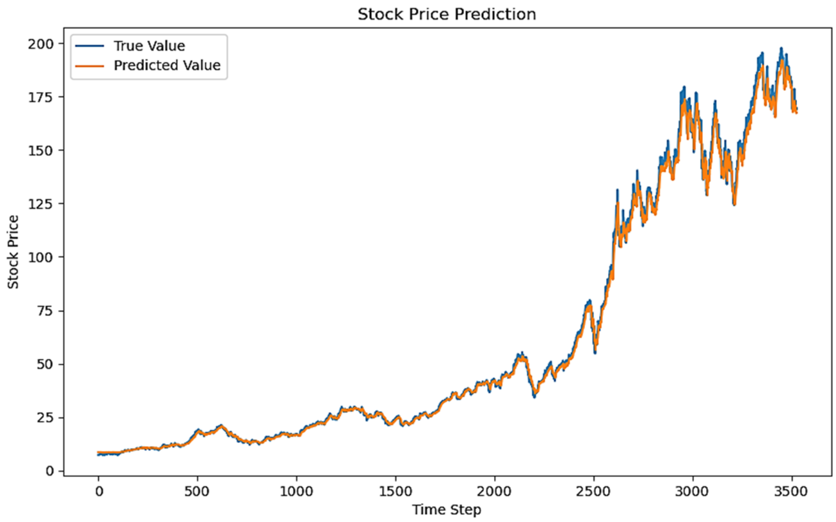

Figure 3: CNN predict result of APPLE's (Picture credit: Original).

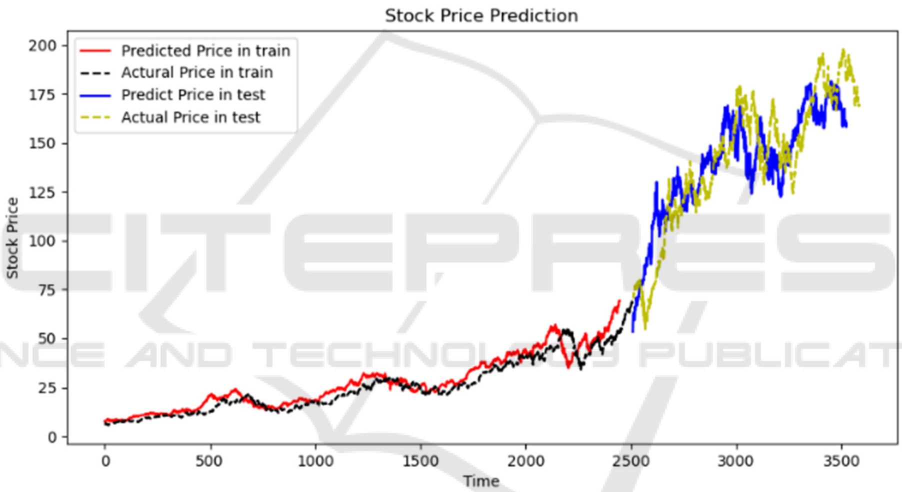

Figure 4: LSTM predict result of APPLE's (Picture credit: Original).

3.3.3 CNN-LSTM

The figure 5 shows the prediction results of the CNN-LSTM model. From the prediction curve, it can be seen that the CNN-LSTM composite model can demonstrate better results than both the CNN model and the LSTM model alone in predicting larger time series. This paper argues that the CNN model effectively reduces noise when extracting features. Compared to the LSTM model which will extract all the data when processing the data, the CNN-LSTM model takes advantage of the CNN in extracting the features and greatly reduces the error of the results and it solves the problem of lagging prediction results.

3.4 Nike's Stock Data

Compared to Apple's stock data, Nike's stock data is a smaller data set with only 562 data sets. In making predictions on Nike's stock data, all of three models set look_bask=10. (When debugging the model, after changing the value of look_back several times, it was finally found that the model could fit the data well when look_back=10.)

3.4.1 CNN

As can be seen from the figure 6, the CNN model performs equally well when dealing with small datasets. Although it is not as good as when dealing with APPLE's dataset, the true and predicted values are very close to each other and fit well.

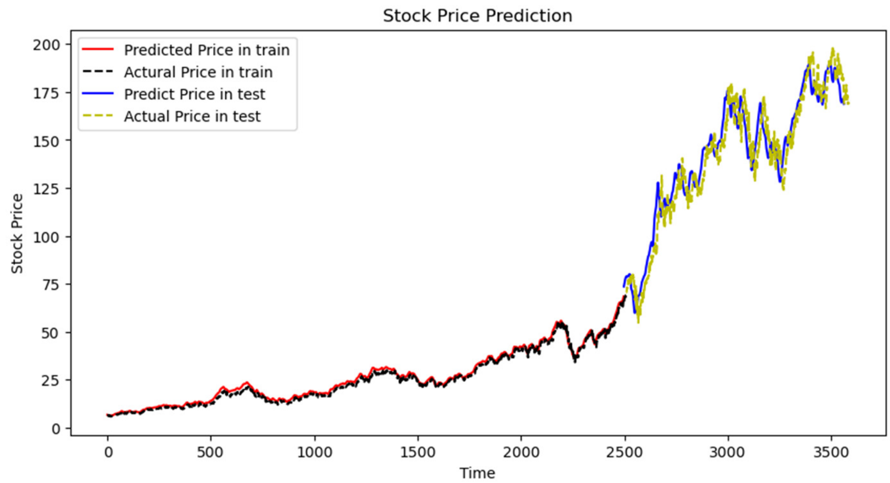

Figure 5: CNN-LSTM predict result of APPLE's (Picture credit: Original).

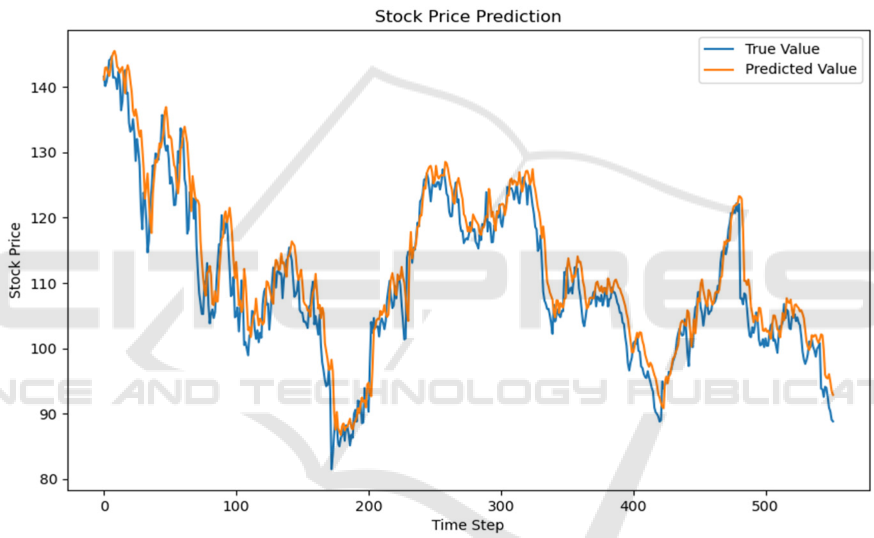

Figure 6: CNN predict result of NIKE's (Picture credit: Original).

Table 2: Summary of evaluation indicators.

Apple's stock data	Method	RMSE	MAE	R^2	SMAPE	Time
	CNN	6.6710	1.7869	0.9979	4.3039%	7.97s
	LSTM	43.4755	34.3995	0.7315	11.1565%	92.87s
	CNN-LSTM	45.4162	35.7618	0.7174	11.5060%	7.91s
Nike's stock data	Method	RMSE	MAE	R^2	SMAPE	Time
	CNN	11.6657	2.5883	0.9244	2.3619%	2.44s
	LSTM	9.5071	7.3367	0.2957	5.0222%	6.35s
	CNN-LSTM	9.0999	7.0301	0.6696	2.8232%	1.72s

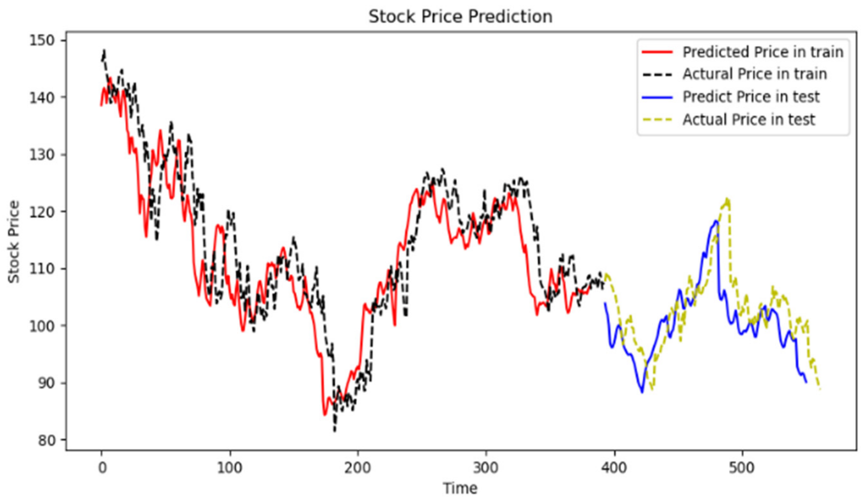

Figure 7: LSTM predict result of NIKE's (Picture credit: Original).

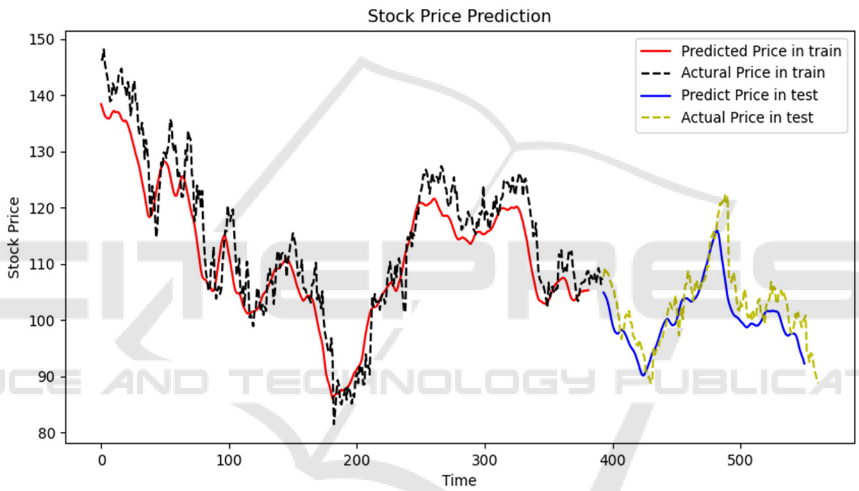

Figure 8: CNN-LSTM predict result of NIKE's (Picture credit: Original).

3.4.2 LSTM

The figure 7 shows the prediction results of the LSTM model. From the prediction curves, it can be found that the LSTM model is still stable in its prediction for small datasets. But the shortcoming is that the lag of LSTM model is still obvious.

3.4.3 CNN-LSTM

From the prediction results (Figure 8), it can be seen that the CNN-LSTM model is not very effective in handling small datasets. the CNN model extracts the features and then puts the features into the LSTM layer for processing, which solves the problem of lagging prediction results of the LSTM model. However, at the same time, the CNN model extracts too few features, which leads to insufficient training of the LSTM model, and obvious errors can be seen in the final prediction results.

3.5 Summary of Evaluation Indicators

By comparing the evaluation metrics of these three models (Table 2), this paper draws the following conclusions:

(1) In overall, the CNN model outperforms the LSTM model in stock prediction. First of all, the CNN model fits better in terms of prediction results, both when predicting large stock data and small stock data, and there is no lag in the prediction results, as is the case with the LSTM model. Secondly, CNN model takes very less time in predicting stocks. Especially when predicting large stock data, the CNN model shows great efficiency and accuracy. As can be

seen in previous experiments, when predicting APPLES' stock data, the CNN model took only 7.97 seconds, but the LSTM model took 92.87 seconds.

(2) The CNN-LSTM model has an excellent fit. It not only solves the defect of lagging prediction results of LSTM model, but also obtains extremely high efficiency. As can be seen from the runtime result data in the chart, the CNN-LSTM model took only 7.91 seconds to process APPLE's stock data. The CNN-LSTM model does not perform very well when predicting small stock data. From the prediction curve, the curve fitting is not very good and there is a significant error. Although the CNN-LSTM model can still achieve short time consumption and no lag when predicting small stock data, the prediction error is relatively large and the curve is not fitted very well. Through the analysis, this paper finds that since the CNN-LSTM model extracts features from the convolutional layer in the CNN model and then uses the features as inputs to the LSTM layer, this can easily lead to the output of the CNN that may lose some important information of the original data that is important for the LSTM, and this can lead to a degradation of the fusion model's performance.

(3) From the results, CNN model has better accuracy, stability and short time consuming when predicting stock prices. CNN-LSTM model performs well when dealing with large stock data, not only efficient but also accurate. However, when dealing with small stock data, it can lead to poor fitting due to too little feature data. Thus, in this paper, CNN-LSTM model is considered to be poor in stability. LSTM model will show deviation between the predicted curve and the real curve when predicting the stock price, and high time consuming is also its defect. Nevertheless, this paper does not consider the LSTM model and CNN-LSTM model as unsuitable for predicting stock prices compared to the CNN model because in machine learning and financial forecasting, simply performing well on a training set is not enough to show that the model works just as well in real-world applications. When predict the stock data, both LSTM and CNN-LSTM models consider the effect of feature values on the target value (stock closing price) and are accompanied by long term memory, so the predict results of them have more real-world applications value, while CNN models do not have these properties. Therefore, in this paper, we believe that the prediction results of LSTM and CNN-LSTM models have the higher reference value for investors.

4 CONCLUSION

Stock price prediction is a multifaceted and intricate endeavor influenced by a myriad of factors. While both CNN and LSTM models have demonstrated efficacy in this domain, each exhibits inherent limitations. To address this challenge, this study introduces a novel stock price prediction methodology leveraging a hybrid CNN-LSTM model. By amalgamating the feature extraction prowess of CNN with LSTM's adeptness in sequence data processing, the resultant model achieves heightened accuracy and enhanced stability. In the experimental setup, we initially curate two distinct stock datasets varying significantly in size, accompanied by four evaluation metrics. Subsequently, standalone CNN and LSTM models are trained and evaluated on these datasets individually. Prediction outcomes are obtained and corresponding evaluation indices computed. Thereafter, the hybrid CNN-LSTM model is formulated, trained on the same datasets, and evaluated using the established metrics. Comparative analysis of the prediction outcomes across the three models and the four evaluation metrics ensues.

The analysis shows that the CNN model exhibits short time-consumption, stability, and accuracy when dealing with both large and small stock data. The LSTM model, on the other hand, possesses the drawbacks of long time-consumption and the generation of deviations between the prediction curves and the true-value curves. The CNN-LSTM model solves the two problems existing in the LSTM model, however, since the features extracted by the CNN model lose some important information about the original data, this makes the data processed by the LSTM layer incomplete, and this can lead to a degradation in the performance of the fusion model. Although both the LSTM model and CNN-LSTM model are not as suitable as the CNN model for stock price prediction in terms of the results, their prediction results have higher practical application value because they put the feature values into the model to join the training and introduce the memory gate and forgetting gate.

Finally, this paper argues that the CNN-LSTM fusion model is suitable for predicting large stock data because this model is characterized by high efficiency, accuracy, and realistic applications. For investors, this paper holds that both CNN model and

LSTM model are good prediction models when predicting stocks, but CNN-LSTM fusion model is a better choice when predicting stock data of long time series

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