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Optimizing Stock Market Prediction Using Long Short-Term Memory Networks

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Abstract

Deep learning plays a vital role in real-life applications, for example object identification, human face recognition, speech recognition, biometrics identification, and short and long-term forecasting of data. The main objective of our work is to predict the market performance of the Dhaka Stock Exchange (DSE) on day closing price using different Deep Learning techniques. In this study, we have used the LSTM (Long Short-Term Memory) network to forecast the data of DSE for the convenience of shareholders. We have enforced LSTM networks to train data as well as forecast the future time series that has differentiated with test data. We have computed the Root Mean Square Error (RMSE) value to scrutinize the error between the forecasted value and test data that diminished the error by updating the LSTM networks. As a consequence of the renovation of the network, the LSTM network provides tremendous performance which outperformed the existing works to predict stock market prices.

Keywords

Long Short-Term Memory (LSTM), Stock Market, Prediction, Time Series Analysis, Deep Learning

1. Introduction

Predicting the future is a very difficult and dauntless task. And when economics is involved in predicting, it should be precisely accurate and efficient. There is a lot of research work already done by many researchers and economists to forecast stock market prices using different data from various stock exchanges. Different stocks or shares are traded in the stock market. Stock market prices are remarkably erratic and fickle, so there are no coherent patterns in the data. Since all of the data are non-linear and fluctuating time series data, it's nearly impossible to predict stock market prices 100% accurately. But to increase the profits of investors, it is necessary to predict stock prices accurately as much as we can. So, the necessity of building automated models to predict stock prices using Neural Network models was felt by many statisticians and research-based companies. An appropriate prediction of future prices of a certain stock may lead to higher growth of profit for investors with stock investments.

T. Kinoto *et al.* introduced a prediction method for Tokyo Stock Exchange Prices Indexes (TOPIX) in [1]. Fujitsu and Nikko Securities companies worked together to develop the prediction model. They introduced a Modular Neural Networks model to forecast stock prices. By buying and selling using their prediction model, investors got higher profits than using the previous buying and holding approach. Later, traditional Machine Learning algorithms and statistical approaches were used to predict stock prices. B. Qian *et al.* analyzed the Dow Jones Industrial Average (DJIA) index data to forecast the stock market prices in [2]. They used multiple classifier algorithms namely Artificial Neural Networks (ANN), K-nearest neighbors (KNN), and Decision Tree algorithms to build their ensemble model. They illustrated a 34.64% error rate which was equivalent to almost 65% accuracy.

Gradually various types of modern Machine Learning and Deep Learning sequence models have been used to predict the stock market prices more accurately and more efficiently. Because of the stock data's enhancement and expectancy of meticulous prediction, deep learning models have been exploited to get more accurate results and agility of forecasting. In [3], M Hiransha *et al.* proposed four types of deep neural network models named Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), LSTM, and Convolutional Neural Networks (CNN) to forecast stock market prices. They used two stock markets' data: the National Stock Exchange (NSE) of India and the New York Stock Exchange (NYSE). The models were used to predict the stock prices of MARUTI, HCL, and AXIS BANK on the NSE stock market, as well as BANK OF AMERICA (BAC) and CHESAPEAK ENERGY (CHK) on the NYSE stock market. The obtained experimental results showed that CNN outperformed the other three networks, because it is capable of catching sudden changes in the system since a specific window is used to forecast the next instant. Though the CNN model outperformed other models for their datasets, LSTM networks are mostly convenient for classifying, processing, and generating predictions on time series data considering there can be slackening of unfamiliar continuation bounded by significant situations in a time series. In the LSTM, the memorization of earlier stages can be performed through gates with a long memory line incorporated. Many researchers developed their stock market prediction models by using LSTM networks and their model outperformed other models. Recently, M Nabipour *et al.* used Decision Tree, Bagging, Random Forest, Adaptive Boosting (AdaBoost), gradient boosting, Extreme Gradient Boosting (XGBoost), artificial neural networks (ANN), RNN, and LSTM models to make predictions on time series data [4]. They used emerging Iranian stock market data from November 2009 to November 2019 (10 years) of four stock market groups namely Diversified Financials, Petroleum, Non-metallic minerals, and Basic metals. Each of the prediction models was given ten technical indicators as inputs. With the lowest error and the best ability to fit, the experimental results showed that the LSTM model was the best model for predicting all stock market groups (by average values of MAPE: 0.60, 1.18, 1.52, and 0.54).

In this work, we are proposing a model using LSTM networks to forecast the closing price of the Dhaka Stock Exchange (DSE). We have collected data from the DSE data archive [5]. We have gathered the last two years' data on closing prices. Our contribution is given below:

- Proposing a sequence model to forecast the closing price of DSE where we have used 4 distinct datasets of the same duration of time.
- Our LSTM model achieved the lowest RMSE compared to existing models on different datasets and we have shown state-of-the-art solutions.
- Deploying our model in the stock market, investors would get more profits.

In the remaining paper, we have organized as follows: in section 2 a brief description of previous research works is illustrated, we have shown our proposed methodology in detail in section 3, section 4 demonstrates the experimental results and comparison table with existing works and finally, section 5 concludes the paper with mentioning future works.

2. Literature Review

Several Machine Learning algorithms and Deep Learning models were implemented with varied degrees of effectiveness to forecast stock prices. But unfortunately, stock forecasting is still limited because of its non-stationary, seasonal, and unpredictable nature. Due to a variety of challenges, the characteristics of this type of study are very complicated. We have gone over many recent related research articles to identify a research gap in the existing literature. In this context, this part aids us in providing a state-of-the-art solution. The details of our findings are summarized below.

In [6], Support Vector Machine (SVM) Regression was introduced by H Yang *et al.* for financial prediction to limit downside risk, which is crucial when dealing with volatile financial data. They offered two methods, one for fixed and asymmetrical margins (FAAM) and the other for non-fixed and symmetrical margins (NASM). SVM financial prediction with fixed margin was demonstrated in the first experiment, which included FASM and FAAM. The second experiment involved putting the SVM financial forecast to the test with NASM using shift windows. The use of standard deviation to calculate a variable margin produced a strong predictive outcome in the forecast of the Hang Seng Index, according to their findings. Their accuracy or error rate was below standard. A. Gupta *et al.* proposed a MAP (Mean Absolute Percentage) based on Hidden Markov Models (HMMs) for forecasting and predicting the stock value for the next day [7]. In this study, four different stocks—TATA Steel, Apple Inc., IBM Corporation, and Dell Inc. had been used. The input parameters were Open, Close, High, and Low. For each stock, a separate HMM was trained and thus their model for one particular stock was independent of the other stocks. The MAPE was used to estimate the performance accuracy and they achieved the lowest MAPE of 0.611 for IBM Corporation stock. The obtained experimental results showed that the MAP-HMM model outperformed the HMM-fuzzy model, ARIMA, and ANN for Apple Inc. and IBM Corporation. RP Schumaker *et al.* [8] also applied SVM for stock market prediction. They used a variety of linguistic textual representations in this research collecting data from different online breaking news articles:

1) Company generated sources, 2) Independently generated sources. They created Bag of Words, Noun Phrases, and Named Entities methods and applied SVM regression. Their results showed that directional accuracy of 50.8% where noun phrases performed better. Their result was not good enough and used a comparatively small dataset.

The deep convolutional LSTM model was utilized as a predictor by A. Kelotra *et al.* [9] to efficiently assess stock market movements. The MSE and RMSE of the model were 7.2487 and 2.6923, respectively, after it was trained using a Rider-based monarch butterfly optimization technique. M Usmani *et al.* compared different machine learning techniques in [10]. In this research work, a total of 9 parameters are used as input for the prediction model. From September 2015 to January 2016, data for this study was gathered from News and Twitter throughout three months. The MLP model outperformed other models with an accuracy of 77% according to the trial data. Biswas *et al.* proposed different deep learning algorithms such as LSTM, XGBoost, Linear Regression, Moving Average, and Last Value models in [11] [12]. The measurement of Mean Absolute Percentage Error (MAPE) is used to compare the models, and it is shown that the LSTM technique outperforms all other methods with a MAPE of 0.635.

The authors proposed a hybrid deep learning model integrating LSTM, GRU, linear regression (LR), and Light Gradient Boosting Machine (LightGBM). This model was tested on multiple public and private datasets, achieving an enhanced stock prediction RMSE value of 0.351 [13].

In [14] the author applied various methods, including Single Layer Long Short Term Memory (LSTM), 3-Layer LSTM, 3-Layer Bidirectional Long Short Term Memory (BiLSTM), and Hybrid Convolutional Neural Network-Long Short Term Memory (CNN-LSTM). This model aimed not only to find realistic price estimates but also to reduce the features that influence stock price estimates through technical indicators.

From the above studies, we can see that Deep Learning models can give higher accuracy to forecast time series data. So, we have worked to forecast the closing price of Dhaka Stock Exchanges' two years' data of the four different banks using the LSTM networks. We have measured the RMSE to find the accuracy of our model.

3. Methodology

In this segment, we describe the methodology we followed sequentially to build our forecasting model. Our methodology is divided into three parts: 1) Data collection and preprocessing, 2) LSTM Networks and 3) Proposed methodology.

3.1. Data Collection and Preprocessing

The dataset used in our study was obtained from the Dhaka Stock Exchange data archive and we have collected 407 observations for each of four banks: Bank Asia, Brac Bank, Dhaka Bank, and Islami Bank, which contains the same types of data. The data is obtained from the period 15-07-2018 to 25-03-2020. We used these data to develop the recommended model for forecasting closing prices. After presenting the data to the system, we divided the data into training and testing sets with a partition ratio of 80-20. For each partition, we applied a common data preprocessing pipeline which was constituted by normalizing the time-series input data using zero mean and unit variance.

3.2. LSTM Networks

LSTM Network is an advanced RNN that was introduced by Hochreiter Schmidhuber (1997), allows information to persist and helps to determine structure dependence in progression prediction. LSTM is designed to avoid long-term dependency problems hence a good fit for time-series models. LSTM uses a technique for knowledge-flowing named cell state, which helps to remove or add information carefully with the help of regulating structure named gates. The LSTM cell consists of three different gates: a forget gate, an input gate, and an output gate. Figure 1 shows a pictorial representation of LSTM. The main part of LSTM is a cell state: (C_{t-1}, C_t) which is represented by a horizontal line in our figure, cell states regulate the information flow over the cell f_t indicates the forget

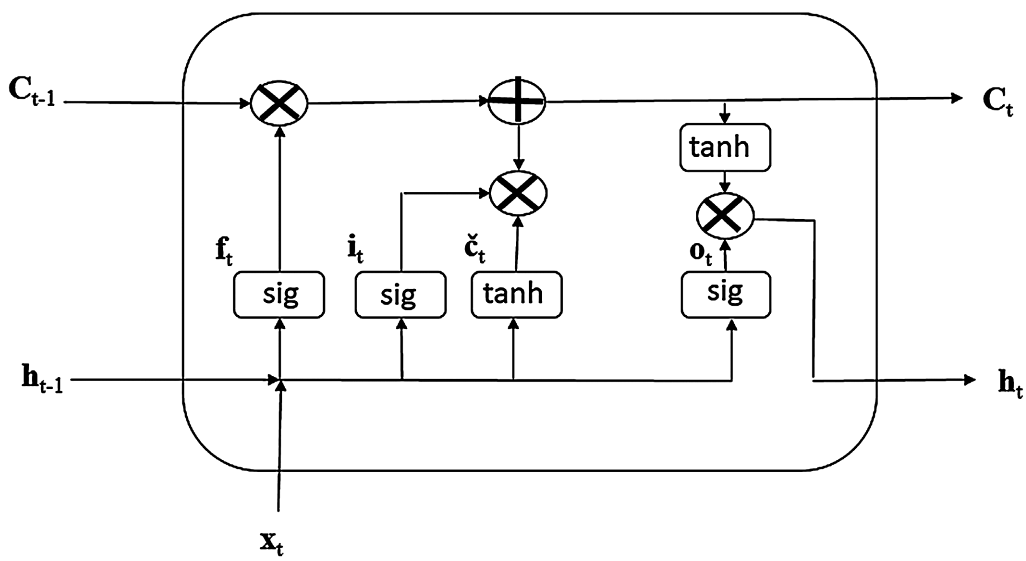

Figure 1. Pictorial representation of LSTM Networks [15].

gate: helps to decide which information needs to be pruned by passing the information from the current input X(t)and hidden state h(t − 1) through the sigmoid function, the value of f(t) will later be used by the cell for point-by-point multiplication.it indicates input gate: which update the cell status by passing the current state X(t) and previously hidden state h(t − 1) through the second sigmoid function, output values ready for point-to-point multiplication. It indicates the output gate: passing the values of the current state and previous hidden state through the third sigmoid function, then the function generates the new cell state from the cell state and both outputs are multiplied point-by-point.

3.3. Proposed Methodology

This section describes our proposed method to forecast the closing price using the LSTM network. Figure 2 illustrates the overview of our proposed methodology. At first, we take the stock dataset of four banks and then divide the dataset into training and testing data. The first 80% of the data have been exploited for training the network and the last 20% for testing the forecasted data. For both training and testing data, we have done the standardization process for all of our datasets of 4 banks. Then we passed the data to the LSTM architecture. After we have trained our LSTM network to forecast future time steps, then we have compared forecasting and observed data. We have also calculated the RMSE (How about MAPE, Directional Accuracy?) values of 4 banks. Lastly, we have updated our network state with observed values. Then we trained our model again to get better accuracy.

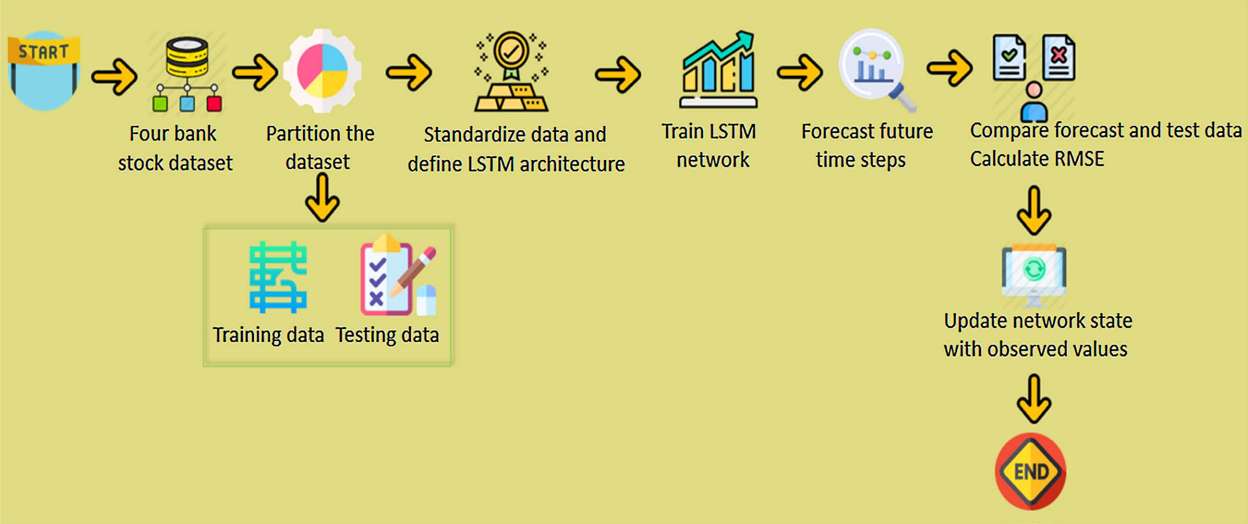

Figure 2. Overview of our proposed methodology.

3.4. Training Strategy

We trained our model for 250 epochs with a batch size of 32. Our model uses the Adam optimizer with a 'piecewise' learning rate scheduler. Initially, the learning rate was 0.005 with a drop period of 125 epochs and a drop factor of 0.2. In each batch, we randomly shuffled the batch in the training step to improve generalization.

We also employed different hyper-parameter configurations for training the model, the above-described configuration provided the best performance.

4. Experimental Result

To analyze the experimental result, we have calculated RMSE (Root Mean Square Error) for all of the datasets. RMSE is the most commonly used for measuring the differences between sample or population values expected by an estimator and the observed numeric values. The value of RMSE is always positive and 0 indicates that the data is perfectly suited. A lower RMSE is often preferable to a greater one to get higher accuracy. To avoid the training from diverging and for perfectly fitting, we standardized the training data to get zero mean and unit variance. Using the same parameters as the training data, we standardized the test data. RMSE is calculated by the following formula (Equation (1) to Equation (7)).

$$\mu = mean\left(X_{Train}\right) \tag{1}$$

$$\sigma = std\left(X_{Train}\right) \tag{2}$$

$$X_{Train} = \left(X_{Train} - \mu\right)/\sigma \tag{3}$$

$$Y_{Train} = \left(Y_{Train} - \mu\right)/\sigma \tag{4}$$

$$X_{Test} = \left(X_{Test} - \mu\right)/\sigma \tag{5}$$

$$Y_{Pred} = \sigma * Y_{Pred} + \mu \tag{6}$$

RMSE is generated from the standardized data on the training progress graph. Then we have calculated the RMSE based on the unstandardized forecasts.

$$rmse = sqrt\left(mean\left(\left(Y_{Pred} - Y_{Test}\right)^2\right)\right) \tag{7}$$

To forecast the values of future time steps of a sequence, where the responses are the training sequences with values shifted by one-time step. The LSTM networks learn to forecast the value of the next time step. **Figure 3** illustrates the forecasted closing prices for 4 banks with training data.

Then we compared forecasted values with the remaining 20% of test data for each of the banks. While comparing, we have measured the RMSE values for each bank. **Figure 4** depicts the comparison for Brac Bank which has a RMSE value of 35.9808. **Figure 5** represents the comparison for Bank Asia where we have obtained an RMSE value of 1.3293. A comparison for Islami Bank is illustrated in **Figure 6** where we have got an RMSE value of 5.9538. The comparison for Dhaka Bank is shown in **Figure 7** that has a RMSE value of 3.6859.

As we have access to the real values of time steps between forecasts, we can update the network state with the actual values rather than the forecasted values. Initially, we have set up the network state. Resetting the network state using reset state on new data, we have prevented previous forecasts from influencing the forecasts on the new data. **Figure 8** illustrates the comparison of updated forecasted values with test data for BRAC Bank and we have achieved an RMSE value of 4.5124. The comparison of updated forecasted values with observed data from

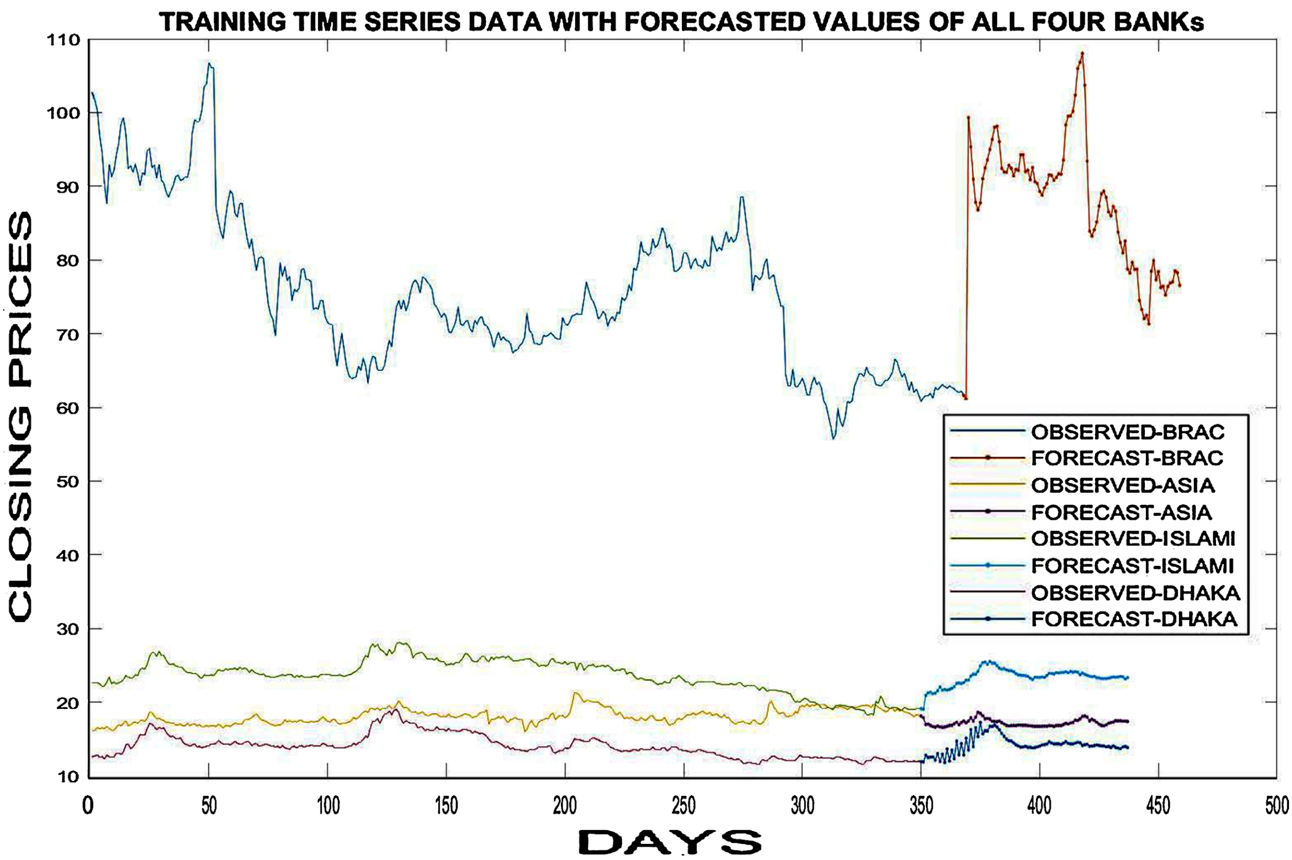

Figure 3. Forecasted closing prices for 4 banks with training data.

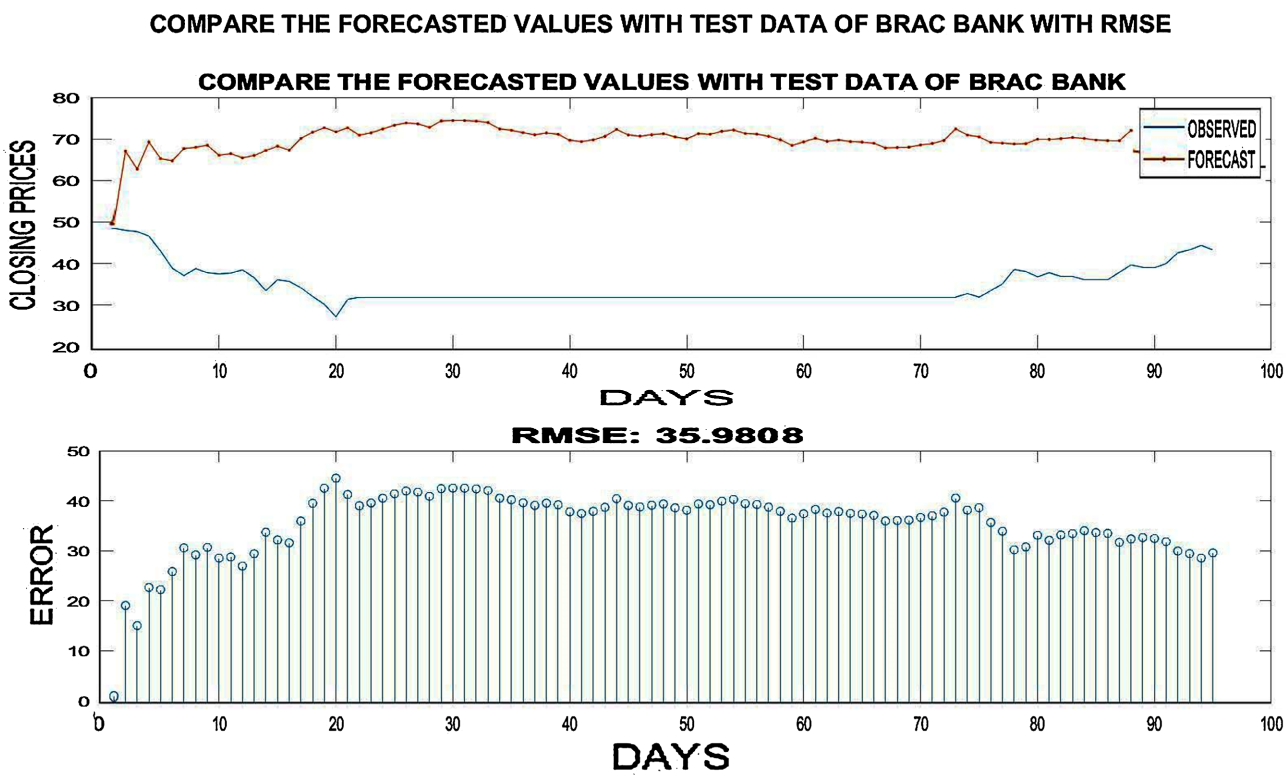

Figure 4. Comparison of forecasted values with observed data of BRAC Bank.

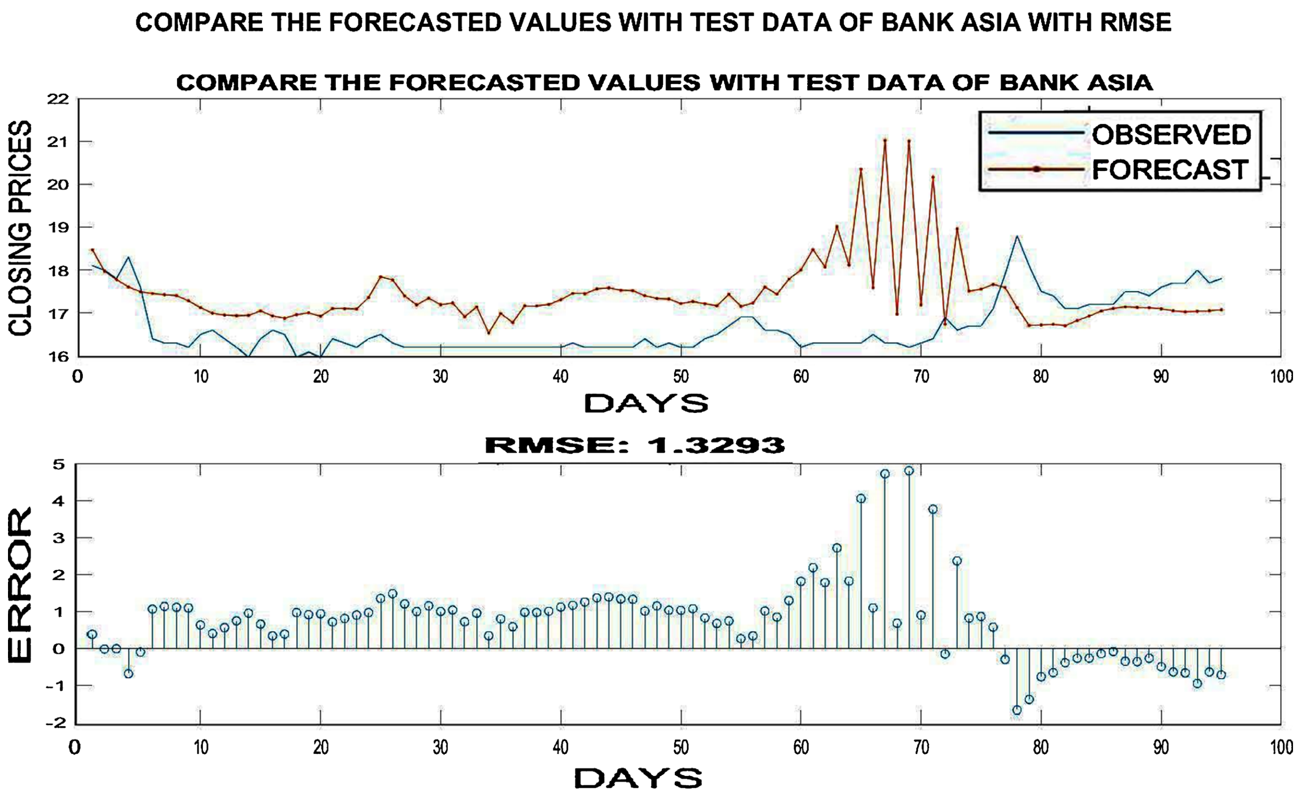

Figure 5. Comparison of forecasted values with observed data of Bank Asia.

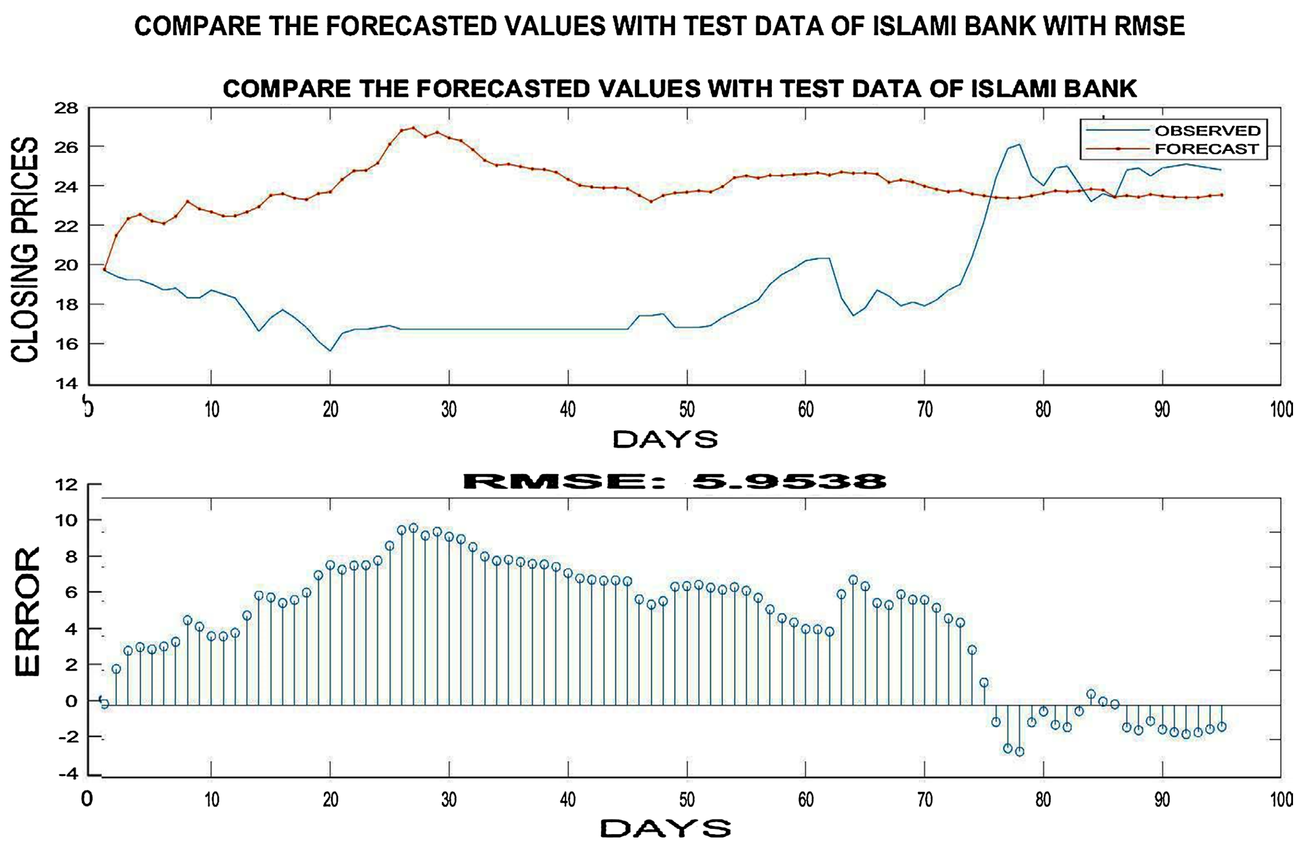

Figure 6. Comparison of forecasted values with observed data of Islami Bank.

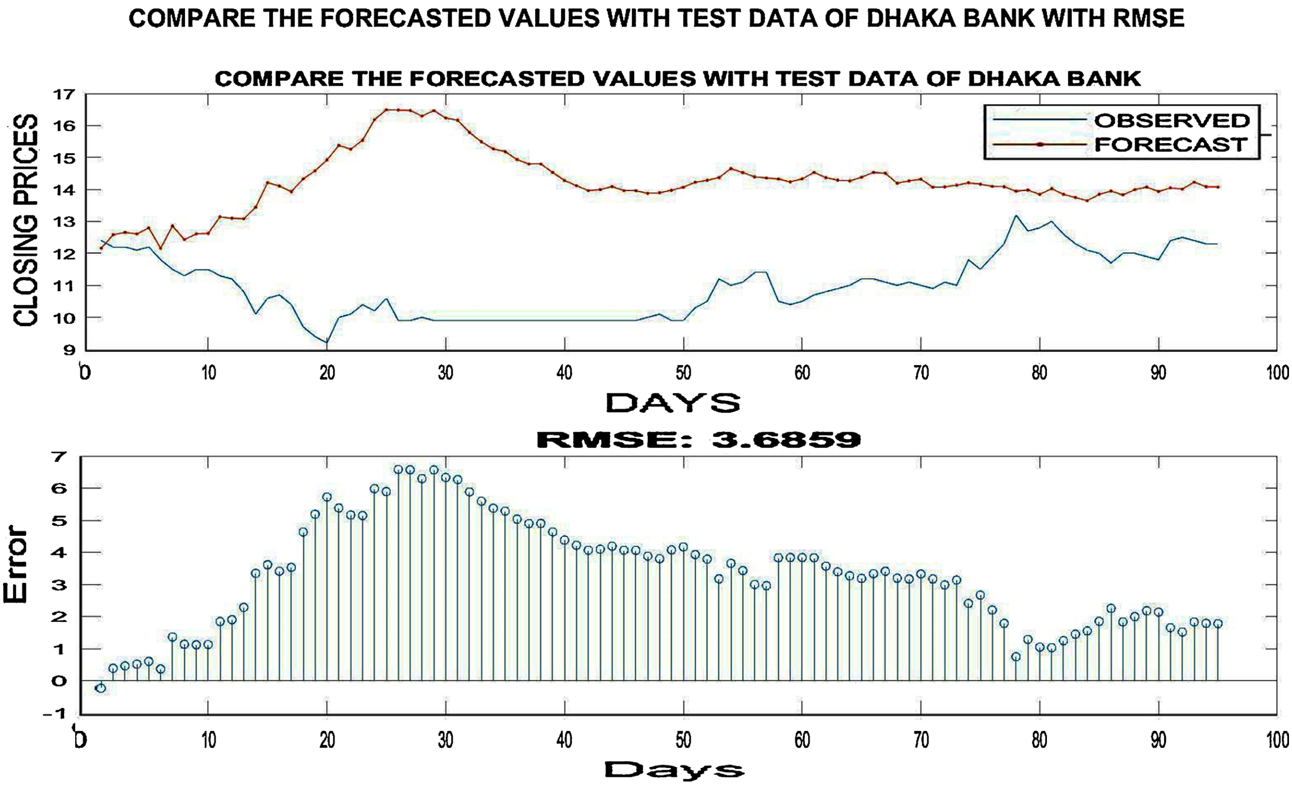

Figure 7. Comparison of forecasted values with observed data of Dhaka Bank.

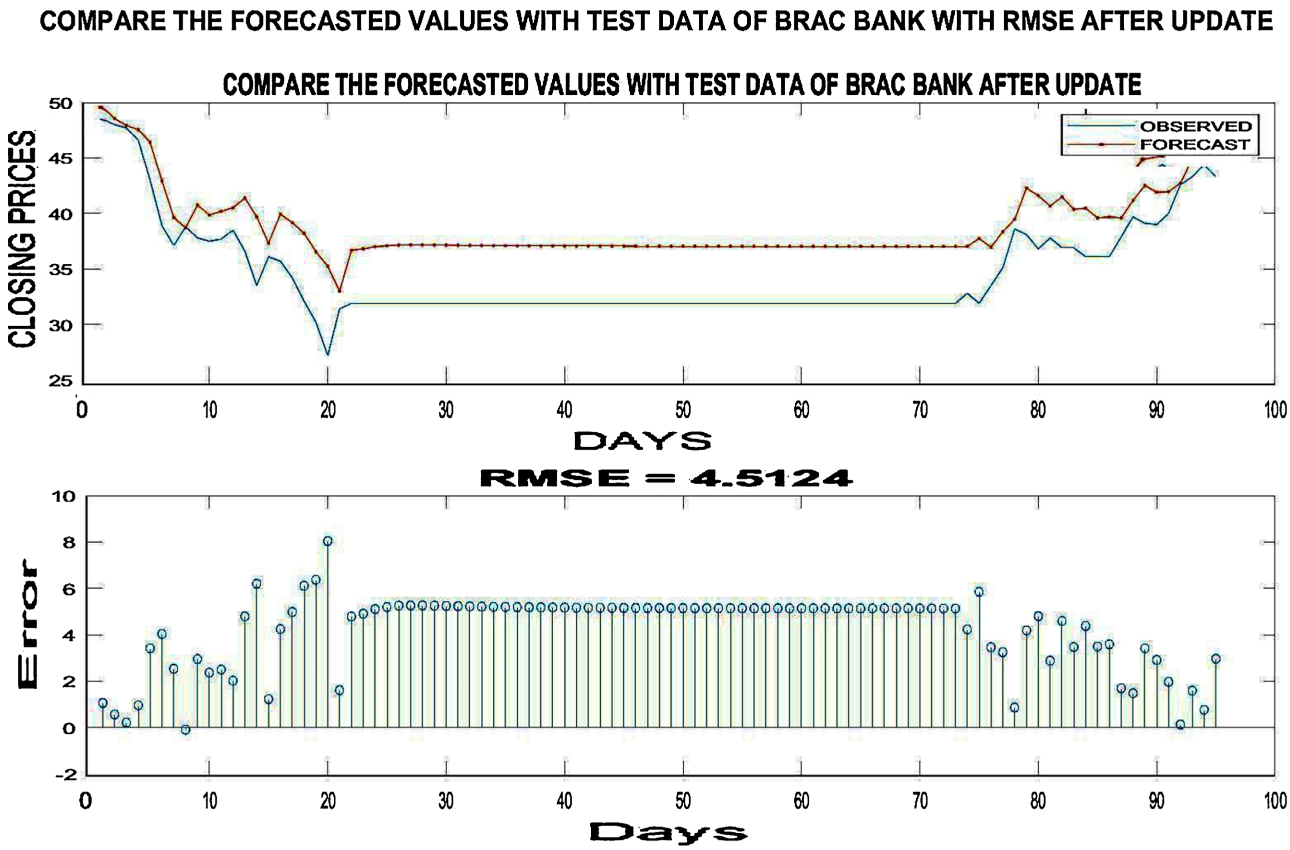

Figure 8. Comparison of forecasted values with observed data of BRAC Bank after update.

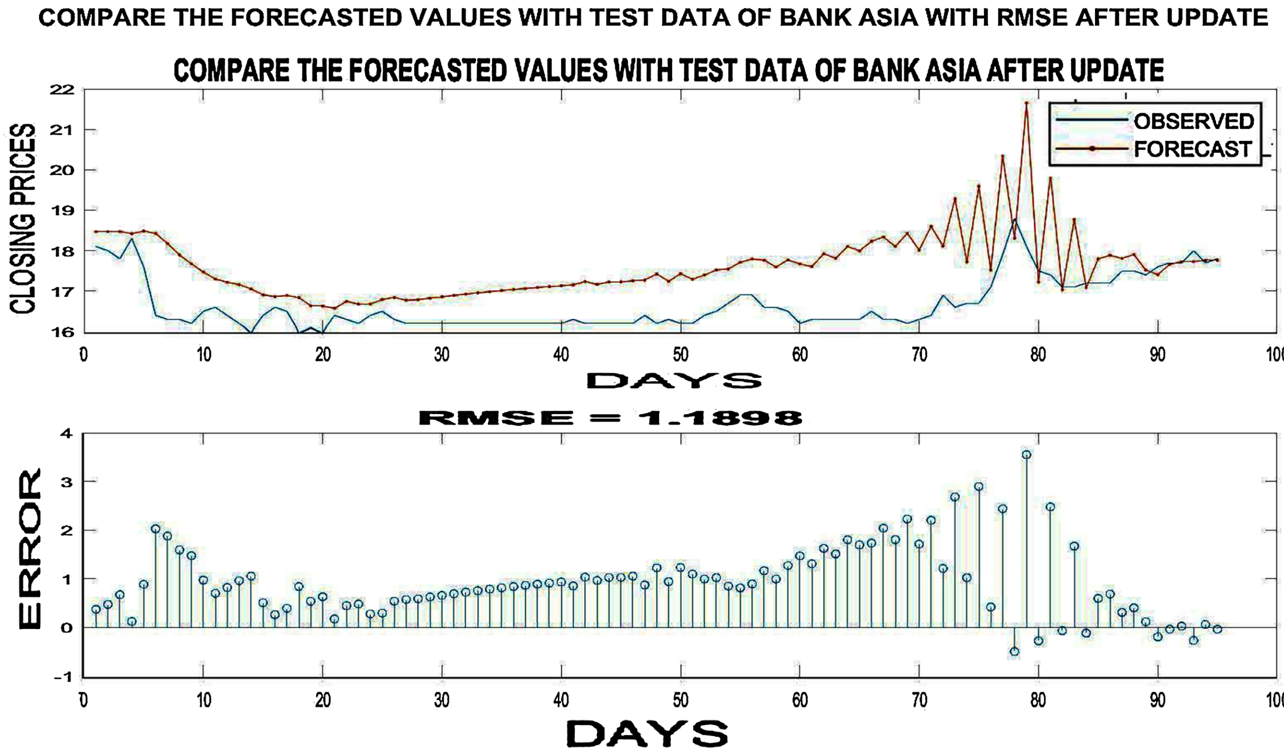

Figure 9. Comparison of forecasted values with observed data of Bank Asia after update.

Bank Asia is shown in **Figure 9** where the RMSE value is 1.1898. **Figure 10** depicts the comparison of updated forecasted values with observed data for Islami Bank and we have got RMSE value of 0.84084. The comparison of updated forecasted values with observed data of Dhaka Bank is shown in **Figure 11** where the RMSE value is 0.33193.

The predictions are more accurate while updating the network state with actual values rather than expected values. **Table 1** demonstrates the overall comparison of RMSE values of testing with initial training and after testing with updated training. From the above table we can see that, for Brac Bank RMSE is updated from 35.9808 to 4.5124, for Bank Asia RMSE is updated from 1.3293 to 1.1898, for Islami Bank RMSE is updated from 5.9538 to 0.84084, and for Dhaka Bank RMSE value is updated from 3.6859 to 0.33193. We have achieved the lowest RMSE of 0.33193 for Dhaka Bank which is the most accurate result of our study. We have shown a comparison of our work with some existing works related to stock market prediction in **Table 2**.

5. Comparison with the Existing Methods

In this section, we evaluate the performance of the proposed LSTM network against recent deep learning-based methods cited in [18], [19], and [20] (see **Table 3**). Important parameters including prediction accuracy, mean squared error (MSE), and computational efficiency are the main emphasis of the comparison. Because of its capacity to accurately describe sequential patterns, the results demonstrate that the suggested LSTM performs better than conventional approaches in

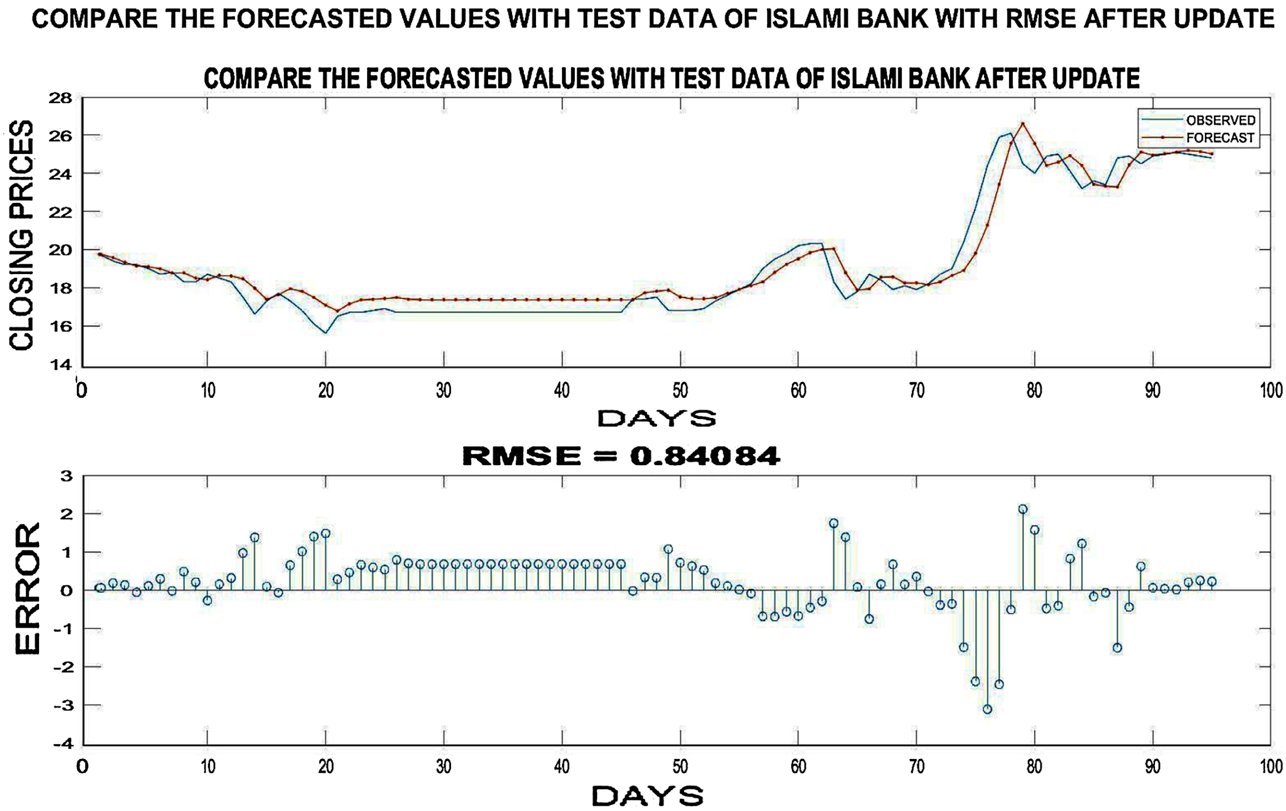

Figure 10. Comparison of forecasted values with observed data of Islami Bank after update.

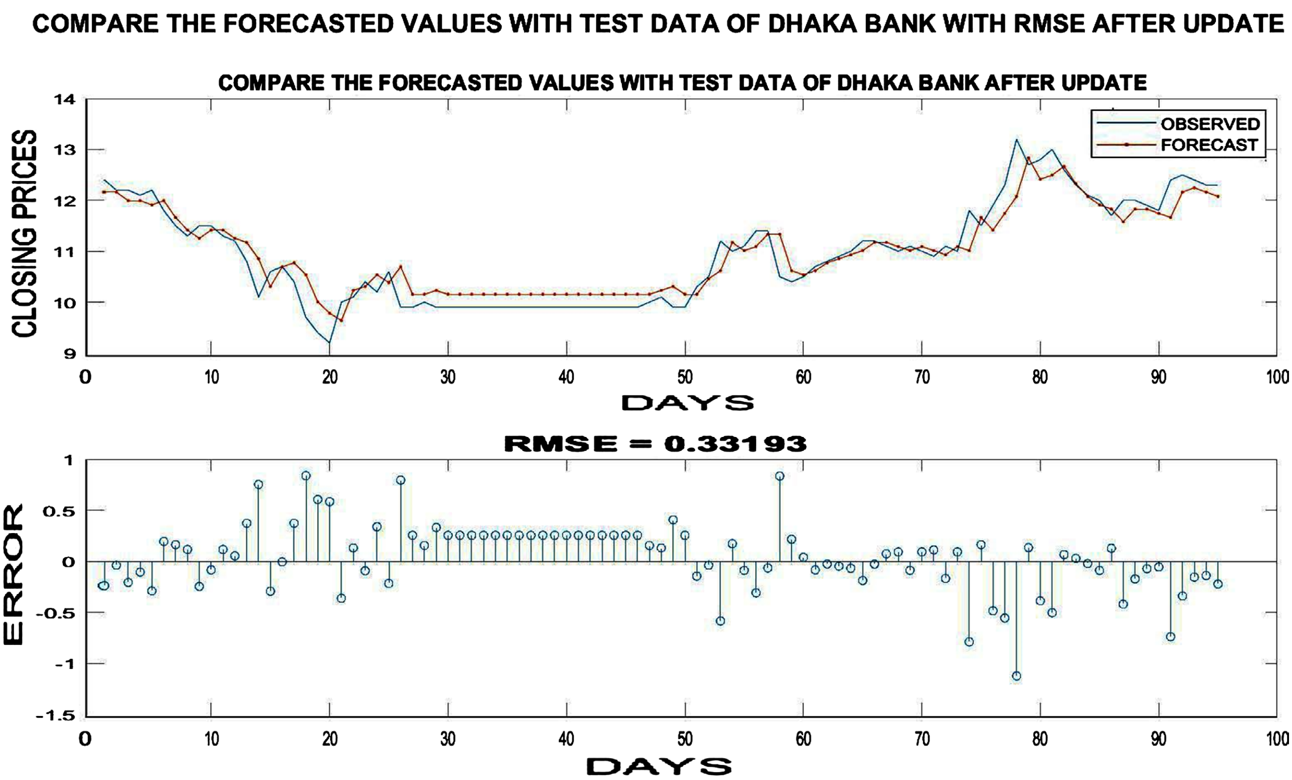

Figure 11. Comparison of forecasted values with observed data of Dhaka Bank after update.

Table 1. Comparison of the RMSE values of four banks.

Bank	Initial RMSE	Updated RMSE
Brac Bank	35.9808	4.5124
Bank Asia	1.3293	1.1898
Islami Bank	5.9538	0.84084
Dhaka Bank	3.6859	0.33193

Table 2. Recent studies on stock market prediction.

Reference	Datasets	Methods	Best Methods	Result	Limitations
[1]	Tokyo Stock Exchange Prices Indexes (TOPIX)	Modular Neural Networks model	Modular Neural Networks Model	Buying and selling using the prediction system made more profit than the previous buying and holding approach	needed much time for simulation to calculate moving average
[2]	Dow Jones Industrial Average (DJIA) index data	ANN, KNN, Decision Tree	ANN	65% accuracy	prediction accuracy can be improved
[8]	textual financial data from online breaking news articles	Created a bag of words, noun phrases, named entities. Applied SVM regression	Noun phrases	directional accuracy of 50.8%	accuracy was not that good, using a comparatively small dataset
[7]	four different stock indices TATA Steel, Apple Inc., IBM Corporation and Dell Inc.	HMM (Hidden Markov Model-based MAPE	MAP-HMM	MAP-HMM model outperforms HMM-fuzzy model, ARIMA, and ANN for Apple Inc. and IBM Corporation	authors did not show a correlation
[16]	Shanghai A-share composite index and Sinopec	LSTM neural network with embedded layer and automatic encoder	Deep LSTM with embedded layer	The deep LSTM with embedded layer have better predictive performance for the Shanghai A-share composite index	There are still some deficiencies in the input of historical
[4]	Iranian stock market and employ data of 4 stock market groups	decision tree, bagging, random forest, Adaboost, gradient boosting, XGBoost, ANN, RNN and LSTM	LSTM	MAPE: 0.60, 1.18, 1.52 and 0.54 for 4 groups	problem was the great runtime (80.902 ms per sample)
[17]	yfinance library	traditional strategies and LSTM	LSTM	It shown with a cumulative return of 33.03%	authors did not add Deep Reinforcement Learning
Ours	Dhaka Stock Exchange data for 4 Banks	LSTM	LSTM	lowest RMSE 0.33193 for Dhaka Bank	Outperforms existing models

Table 3. Comparison of the RMSE for recent methods in stock price prediction on our dataset.

Reference	Model	RMS
[18]	Deep Neural Nets	2.551
[19]	Multi-model	1.179
[20]	FineBERT-LSTM	0.341
Ours	LSTM	0.331

identifying long-term dependencies included in stock price data. Additionally, our model shows better generalization on test data, proving that it is resilient to over-fitting, a typical problem in deep learning models. The suggested approach offers a more workable solution for real-world applications by striking a good balance between training time and forecast accuracy in terms of computational complexity. These assertions are supported by thorough experimental findings and visualizations that demonstrate the benefits of the suggested strategy for managing the intricacies of stock price prediction.

6. Conclusion

Time Series Forecasting is very effective in predicting the upcoming days' stock prices. We have built an LSTM model to predict stock prices with the lowest RMSE. This prediction model can be very helpful to all stockholders to invest their money in it if they can understand previously that there can be more profit. We have achieved the lowest RMSE of 0.33193 for Dhaka bank data of the Dhaka Stock Exchange. In this work, we have only used four banks' data for two years, but in the future, we will try to collect more data and apply other Deep Learning models so that we can find more authentic results for forecasting the stock market closing prices and show the state-of-the-art solution.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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