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ORIGINAL RESEARCH

Indices Prediction of Bangladeshi Stock Based on Stacked and Bi-directional LSTM

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Abstract

Prediction is a very mythological job for traders who take part in the stock market business. While investors aim to secure profits but many become pauperized here due to the wrong prediction of the stock market price movement or for wrong analysis. Numerous algorithms have been developed for forecasting time series data, among which Long Short-Term Memory (LSTM), a variant of Recurrent Neural Networks (RNN), stands out for its widespread adoption in this domain. In this research, LSTM has been considered for price prediction over stock market data. Although LSTM is theoretically intended to provide an actual prediction but it shows that LSTM is quite below the line of proof of its theoretical correctness. Our study here gives a clear indication that LSTM is not enough to predict the market. We collected data from the Dhaka Stock Exchange (DSE) in Bangladesh with the aim of evaluating the performance of the model in forecasting daily stock price trends. Hyperparameter tuning was conducted, but these adjustments did not appear to significantly enhance the accuracy of our results. Ultimately, our findings suggest that relying solely on LSTM is not sufficient for accurately predicting the stock market.

Keywords

Stock Market Prediction, Dhaka Stock Exchange, Long Short-Term Memory

1 | INTRODUCTION

The stock market is a place where regular activities such as buying, selling, and issuing shares of publicly-held companies occur under specific regulatory frameworks [1]. It serves as a critical avenue for companies to raise capital by offering their shares to the market, while also providing investors with an opportunity to surpass the interest rates offered by banks [2]. The stock market plays an indispensable role in the rapid economic development of a nation. Economic growth is intricately linked to the performance of the stock market; a rise in the market typically correlates with higher economic growth, while a decline may indicate a slowdown. Investors invest in this profit-generating market, though it is bound to certain risks of ambiguity and uncertainty [3]. A key characteristic of the stock market is its fluctuating prices, which are challenging to forecast due to their high volatility. These prices are influenced by various economic and political factors, investor sentiment, leadership changes, and other variables [4]. However, to some extent, stock market behavior can be predicted. With the advancement of artificial intelligence and the availability of vast amounts of data, researchers can forecast stock market behavior more accurately and efficiently [5]. The prediction techniques in the stock market play a crucial role in bringing more people and existing investors to one place [6]. There are three popular types of stock analysis techniques like fundamental, technical and sentiment analysis. Various factors, including the firm's financial health, annual reports, balance sheets, return on equity, and political and environmental conditions, are considered in fundamental analysis to assess the value of stocks and securities [7]. Technical analysis involves forecasting future financial price movements primarily through the examination of historical data using charts and indicators [7][8]. While, sentiment prognosis involves analyzing people's feelings and opinions freely expressed on various platforms such as social media through posts, tweets, and photos [9].

While technical studies are primarily used for short-term trend prediction, typically spanning 1-3 months, they are inadequate for forecasting long-term trends, such as those spanning one year [10]. However, by integrating fundamental factors with technical data through correct preprocessing, it becomes feasible to predict stock values for longer periods, ranging from 6 months to 1 year, thereby enabling greater profitability in the market [11]. In recent times, researchers have utilized various machine learning techniques such as Regression Learning, Decision Trees, Random Forest, Artificial Neural Networks (ANN), Deep Learning, Naive Bayesian Statistics, and Support Vector Machine (SVM) to capitalize on stock market data for accurate price prediction.

In this study, we applied Stacked and Bi-directional LSTM models to analyze the daily price trends of five randomly selected stocks from the Dhaka Stock Exchange: ACI, BATA SHOE, ISLAMI BANK, GP, and RUPALILIFE. The primary objective was to assess the accuracy of these models for classification purposes, specifically in predicting daily price trends.

The paper is organized as follows: The next section reviews related works on price prediction through financial analysis. Following that, the third section introduces the basic terminologies used in this research. The fourth section outlines the research methodology and model. Experiential result analysis and discussion are provided in the fifth section. Finally, the conclusion and future works are presented in the last section.

2 | RELATED WORKS

Agrawal et al. [12] proposed a method for predicting stock market trends using Adaptive Straits Times Index (STI), aiding investors in making profitable investment decisions. This approach, employing correlation tensor to derive appropriate STIs from historical prices and volume data, achieves higher prediction accuracy and reduced Mean Squared Error, providing decision indicators (Price-rise: 1 and Price-fall: 0) to stockholders daily. The study investigates the selection of a minimal number of relevant TIs for forecasting stock price movement, revealing that choosing a large number (more than 30) of TIs may decrease prediction accuracy, increase misclassification cost, and reduce investment return.

In a study by Pang, X. et al. [13], an ensemble model of LSTM networks, incorporating Stock Technical Indicators (STIs), is utilized to predict stock market data for long and short-term decision-making. By combining an optimized Long Short-Term Memory (LSTM) model with highly correlated STIs, the research successfully demonstrates the application of adaptive TA on stock indices, presenting monthly trends accurately and indicating the nature of indices over the long term (Profit, Loss, and Neutral). The daily prediction model achieves up to 68.45% accuracy, with an average accuracy of 61.51%. Pang, Xiongwen et al. [14] proposed an LSTM neural network model with an embedded layer, achieving an average accuracy of 53.2% for selected stocks and 57% for the A-share composite index, higher than stochastic forecasts.

Many authors applied some machine learning based hybrid models. Z. D. Aksehir and E. Kilic [15] endeavored to predict the closing prices of the next day using decision tree and multiple regression methods. They observed that reducing the number of technical indicators positively affects the predictive performance of the models. Zhai, Y., Hsu, A., & Halgamuge, S. K. [16] presented a system based on the SVM algorithm to enhance the predictability of daily stock price trends, combining technical indicators and related news releases. The system achieves higher accuracy than using single-source data (news or technical indicators) alone. In [17], M. Hariadi, A. A. Muhammad, and S. M. S. Nugroho created a prediction model and Markov Chain Monte Carlo (MCMC) to generate predicted data, using parallel computing on Apache Spark to reduce computation time.

Some authors suggested to use hybrid LSTM model. J. Poddar, D. Trivedi, V. Parikh, and S. K. Bharti [18] proposed a model to hybridize Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) techniques, aiding decision-making in stock market investment. M. Mphahlele and J. A. Adisa [19] adopted a stacked Long Short-Term Memory network model to predict stock market behavior, achieving an accuracy of 53.6% in predicting future stock market behavior.

3 | METHODOLOGY

Dataset: In this study, we collected 10 years data from 2010 to 2020 of Dhaka Stock Exchange. We considered the historical price of BATA SHOE, ISLAMI BANK, ACI Ltd., RUPALILIFE, GP for the analysis. In figure 1 below we represent a plot diagram of Stock price and Stock volume. Here stock price consists of open price, high price, low price, and closing price for ISLAMI BANK stock.

Table 1 Historical price of ISLAMI BANK stock with Actual Price Trend

Data	Open	High	Low	Close	Volume	Trend
1/4/2010	22.64	22.95	22.53	22.83	1636417	Up
1/5/2010	22.65	22.97	22.64	22.85	2279360	Up
1/6/2010	22.83	22.91	22.68	22.85	1748221	Up
1/7/2010	22.94	22.95	22.72	22.75	1678115	Down

Data Preprocessing: Some data preprocessing techniques were applied to make the data ready for the processing. Such includes, (i) dropping the unnecessary columns i.e. Date and Volume, as we didn't take these into consideration while training the model, and (ii) Filling up missing values by using Linear Interpolation method. In this method, missing data is either replaced by its previous value or subsequent value. The formula of Linear Interpolation is:

$$y = y_0 + (x - x_0)\frac{y_1 - y_0}{x_1 - x_0} \quad (1)$$

(iii) Finally, applying the Min-Max scalar technique converts the entire dataset into 0 to 1.

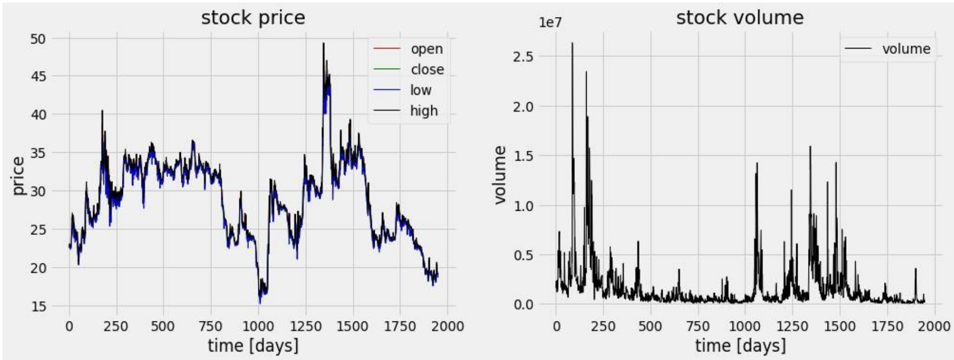

Figure 1 Plotting of open, high, low close price, and volume of ISLAMI BANK's stock data

$$X_{sc} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (2)$$

Dataset Splits: In this research, the dataset was divided into a training set and a validation set. 80% of the data has been allocated to the training set, with the remaining 20% reserved for the validation set. Before training, the dataset undergoes a data preparation step. During this step, we consider 60 consecutive data points for forecasting the price on the 61st day. This process is applied to the entire dataset.

Model Description: Two models named Stacked LSTM and Bid-irectional LSTM applied here for training the historical data. Here, the mode we used is Multi-layered and Multivariate in nature. Pseudo code of the model is:

Stacked LSTM model:

```
model = Sequential()
model.add(LSTM(256, activation='relu'))
model.add(Dropout(0.5))
model.add(LSTM(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(25))
model.add(Dropout(0.5))
model.add(Dense(1))
```

Bi-directional LSTM model:

```
model = Sequential()
model.add(Bidirectional(LSTM(256,activation='relu')))
model.add(Dropout(0.5))
model.add(Bidirectional(LSTM(128 activation='relu')))
model.add(Dropout(0.5))
model.add(Dense(25))
model.add(Dropout(0.5))
model.add(Dense(1))
```

Hyper-parameter Tuning: For several types of parameters, our models were trained separately. We tuned the models based on different set of parameters. These parameters include:

- Learning rate = 0.01/ 0.001/0.0001
- Batch Size = 16/32/64
- Number of Epochs = 50/100/200/500
- Features pair i.e. Open, Close, Open-Close, Open-High-Close, Open-Low-Close, Open-High-Low-Close (OHLC)

Model Fitness: After training the models by tuning different parameters, the training and validation losses were plotted to evaluate the model fitness. Figure 2 illustrates the plot between the training and validation loss. In figure, it is seen that the differences between the training loss and validation loss have been reduced as the number of epochs increased, indicating the improvement of the model.

Performance Matrices: Various error factors were considered to evaluate the performance of the model. These factors include: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Formulas are:

$$MAE = \frac{1}{n}\sum_{n=1}^{n}\left|y_i - y'_i\right| \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}\left|y_i - y'_i\right|} \qquad (4)$$

$$MAPE = \frac{1}{n}\sum_{n=1}^{n}\left|\frac{y_i - y'_i}{y_i}\right| \times 100\,\% \qquad (5)$$

Here, y_i is the actual value,
y'_i is the predicted value,
And n is the total number of samples.

4 | RESULT AND DISCUSSION

The Stacked and Bidirectional LSTM models appear to perform well for forecasting stock price data. Figure 3 illustrates the plot of actual and predicted data for ISLAMI BANK stock.

We assess the performance of our model by computing statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

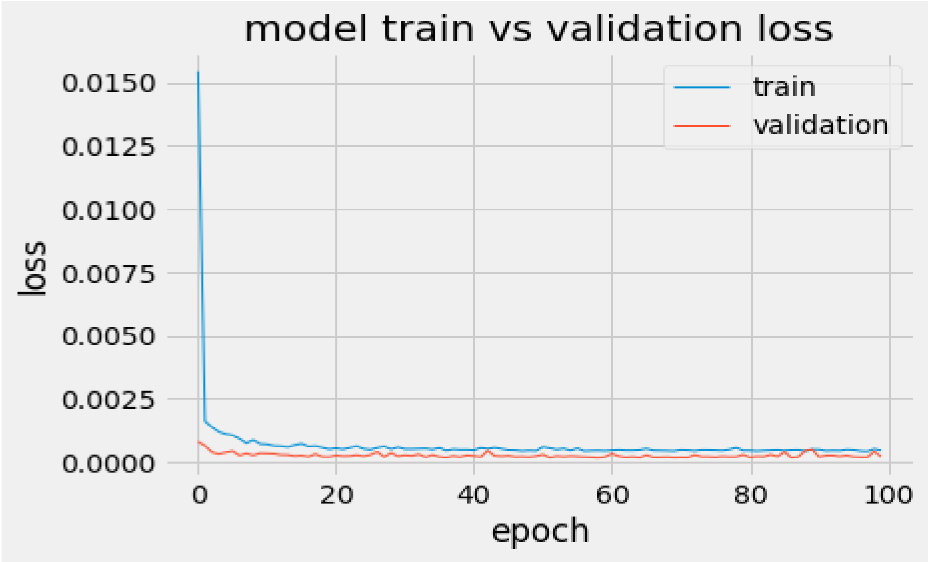

Figure 2 Plotting of training loss and validation losses for ISLAMI BANK Stock

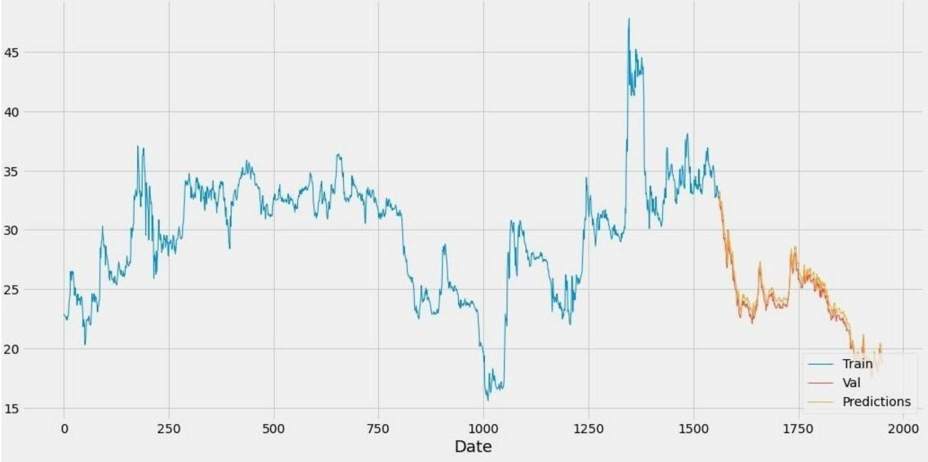

Figure 3 Plotting of the train set, validation set along with prediction price for ISLAMI BANK stock

However, the actual evaluation is derived from the accuracy of predicting the direction of price movements.

Table 2 presents the error metrics and accuracy values for ISLAMI BANK stock. Initially, only the daily closing price was considered as input. While the error metrics appeared promising for both models, but the accuracy was not satisfactory. To address this issue, additional features were incorporated into the input, including OPEN/CLOSE, OPEN/LOW/CLOSE, OPEN/HIGH/CLOSE, OPEN/HIGH/LOW, and CLOSE/HIGH/LOW. The model was then retrained with various parameter settings, but there was no significant improvement in the results. However, in some instances, the accuracy reached around 60%. Table 3 reflects the result for ISLAMIBANK stock.

This is not the unexceptional scenario of Stacked LSTM (SLSTM) and Bi-directional LSTM (BLSTM) models.

Table 2 Accuracy for SLSTM and BLSTM Algorithms

Algorithm	Input Parameters	Accuracy (%)
SLSTM	CLOSE	52.05
	OPEN/CLOSE	59.23
	OPEN/LOW/CLOSE	58.71
	OPEN/HIGH/CLOSE	59.23
	OPEN/HIGH/LOW	61.02
	CLOSE/HIGH/LOW	52.30
	OPEN/HIGH/LOW/CLOSE	58.20
BLSTM	CLOSE	51.79
	OPEN/CLOSE	50.25
	OPEN/HIGH/CLOSE	54.87
	OPEN/LOW/CLOSE	54.75
	OPEN/HIGH/LOW	52.04
	CLOSE/HIGH/LOW	52.32
	OPEN/HIGH/LOW/CLOSE	61.80

Table 3 Error factors and Accuracy for ISLAMI BANK stock [Batch Size=32, Learning Rate=0.001, Epochs=100, Parameter = CLose]

Model	RMSE	MAE	R-Squared	MAPE	Accuracy	Parameter
SLSTM	0.01	0.35	0.98	1.50	52.05%	CLOSE
BLSTM	0.02	0.40	0.98	1.76	51.79%	CLOSE

We choose five stocks randomly from Dhaka Stock Exchange (DSE), Bangladesh and apply the same model. Nothing has changed at all. Accuracy was still between 41% - 62%. The scenario represents at Table 4.

Table 4 Accuracy for five randomly chosen stock with SLSTM and BLSTM Model [Batch Size=32, Epochs=100, Input Parameter = OPEN/HIGH/LOW/CLOSE]

Model	Stock Name	Learning Rate	Accuracy (%)
SLSTM	ACI	0.001	49.10
	BATA SHOE	0.001	41.03
	ISLAMI BANK	0.001	58.20
	GP	0.001	45.54
	RUPALILIFE	0.001	55.01
BLSTM	ACI	0.001	60.35
	BATA SHOE	0.001	61.81
	ISLAMI BANK	0.001	61.79
	GP	0.001	52.35
	RUPALILIFE	0.001	58.09

After three unsuccessful attempts for improving accuracy, this time we considered the learning rate into action. Three different learning rates i.e. 0.01, 0.001, and 0.0001 were considered for the evaluation of the model.

Table 5 Accuracy for varying learning rates. [Batch Size=32, Epochs=100, Input Parameter = OPEN/HIGH/LOW/CLOSE]

Model	Stock Name	Learning Rate	Accuracy (%)
SLSTM	ACI	0.01	56.27
		0.001	49.10
		0.0001	50.38
	BATA SHOE	0.01	43.90
		0.001	51.43
		0.0001	41.04
	ISLAMI BANK	0.01	82.56
		0.001	58.21
		0.0001	51.79
BLSTM	ACI	0.01	58.4
		0.001	60.36
		0.0001	55.50
	BATA SHOE	0.01	61.1
		0.001	61.82
		0.0001	45.45
	ISLAMI BANK	0.01	60.4
		0.001	61.79
		0.0001	53.85

Table 5 shows the result of accuracy for three random stocks on the Dhaka Stock Exchange. We have seen some random results in table 5 for different learning rates. In this case, we got a tremendous accuracy of 82.56% for ISLAMI BANK stock. For some cases, accuracy was still below 50%.

Table 6 Accuracy for varying epochs. [Batch Size=32, Learning Rate = 0.001, Input Parameter = OPEN/HIGH/LOW/CLOSE]

Stock Name	Model	Epochs	Sign Accuracy (%)
GP	SLSTM	50	46.60
		100	57.33
		200	45.81
		500	52.09
	BLSTM	50	46.60
		100	41.10
		200	47.91
		500	58.64

After some unstable results of accuracy, this time we considered the number of epochs in action. For varying the number of epochs, we tried to find the accuracy but the results haven't changed. For GP stock of DSE, the result hovered around 50% which is still poor. Table 6 illustrates the scenario.

Finally, we tried with the batch size. For varying batch sizes, accuracy was calculated. Results are displayed in table 7. From the table, it is clear that we didn't see any significant change in the accuracy.

Table 7 Accuracy for varying batch sizes. [Learning Rate = 0.001, Epoch= 100, Input Parameter = OPEN/HIGH/LOW/CLOSE]

Stock Name	Model	Batch Size	Accuracy (%)
ISLAMI BANK	SLSTM	16	46.60
		32	58.21
		64	57.33
	BLSTM	16	45.81
		32	61.79
		64	46.60

5 | CONCLUSION

From the analysis of this work, we conclude that LSTM alone is not a reliable neural network for future use in stock market prediction. This conclusion was reached after applying two variants of the LSTM algorithm, Stacked LSTM (SLSTM) and Bidirectional LSTM (BLSTM), to the historical prices of five randomly selected stocks from the Dhaka Stock Exchange (DSE) in Bangladesh. Different parameters were tested to observe fluctuations in accuracy and assess whether trustworthy results could be extracted. Despite the various factors such as model type (SLSTM and BLSTM), batch size (16, 32, and 64), and epochs (50, 100, 200, and 500), the accuracy levels remained proportionally similar, indicating that neither model had a significant influence on the results—a concerning sign for market prediction.

Moreover, all accuracies were determined using a fixed Adam optimizer, yet the outcomes still showed nearly identical levels of accuracy across different configurations. This suggests that LSTM may produce incidental accuracy, making it an unreliable method for stock market prediction. However, LSTM-based hybrid models might offer more effective solutions for forecasting stock prices.

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Declaration of Interests

We, the authors of this research manuscript, declare that we have no financial interest. We have provided written comment to publish the paper in this journal.

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