Stock market prediction using the LSTM algorithm in association with the Relative Strength Index (RSI) and Exponential Moving Average (EMA) indicators.

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Research Article

Keywords: Long Short-Term Memory (LSTM), Relative Strength Index (RSI), Exponential Moving Average (EMA), Machine Learning (ML), Stock Prediction

Posted Date: October 4th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3377026/v1

Abstract

Because of the unpredictable nature of the financial market, stock prediction is very difficult. To invest investors' hard-earned money in the financial market, we require additional information. Traditional models like linear regression and Support Vector Regression (SVR) are used to predict stock prices, but they do not have much accuracy. Recurrent Neural Network (RNN) is having "vanishing gradient" issues. In this study, we explain the technique of combining the Long Short-Term Memory (LSTM) machine learning algorithm with leading indicators like the Relative Strength Index (RSI) and the Exponential Moving Average (EMA), i.e., the slow EMA, medium EMA, and fast EMA. For this study, we have selected seven different stocks from the National Stock Exchange (NSE), and the dataset period is from January 1, 2012, to December 31, 2022. When we add extra features like RSI, 50-day EMA, 100-day EMA, and 150-day EMA to traditional ones like open, high, low, close, and volume, we get better results than when we only use traditional ones like open, high, low, close, and volume. When the indicators are added along with the traditional features, the Mean Absolute Percentage Error (MAPE) goes down, the R2 score (coefficient of determination) goes up, and the model does better than the conventional model. This study and analysis helps to improve intraday trading by predicting the value and trend of certain stocks.

1. Introduction:

The stock market is one of the parameters used to analyze the economic growth of a country. Different sentiments, such as positive or negative news, also had an impact on stock prices [1]. In stock market prediction research, previous researchers used linear regression and Support Vector Regression (SVR) models, but they had less accuracy [2]. In the stock market, there are two types of analysis. First is fundamental analysis, in which a stock's potential growth is carefully observed. In another type, a technical analysis of the stock is done. For this type of analysis, different technical indicators are taken into account, like the RSI, EMA, MACD and Bollinger Bands, etc. By using this indicator, trading can be improved [3]. In the current situation, time series forecasting has become very popular and has more scope in research like stock price forecasting, weather forecasting etc. The LSTM machine learning algorithm is very effective in time series analysis. It discards unnecessary information and carries only important information for future states [4]. The RNN algorithm stores the current state, and the output of the current state is again provided as input to the model as feedback for betterment and more refinement. The LSTM is a type of RNN, but the RNN has a problem called the "vanishing gradient problem" that makes it hard to train. So to implement an effective study, LSTM is a better choice. In many studies, the Autoregressive Integrated Moving Average (ARIMA) is used for time series forecasting; it has good flexibility. Time-series analysis, which mostly uses the SVM model, is another area where AI is used [5]. The input features also play a big role in making the model better, so to build prediction models, you need to be able to extract features well. In this study, we are focusing on the LSTM algorithm and using technical analysis indicators as features.

2. Literature Survey:

G. Bathla et al. published a study in 2020 in which deep learning and LSTM were used to predict S&P 500 stock prices. Experimental analysis proved that, compared to the SVM model, LSTM performed better [1]. Another group of researchers, Y. Zeng et al., came up with a model in 2018 that used LSTM to extract the abilities of stocks. Using these extracted characteristics leads to better results [6]. S. Yao et al. (2018) applied LSTM to detect price movement for short-term trends. The model performs better in terms of precision and recall rate [7]. Wenjie Yang et al. in 2020 presented a study in which the LSTM is used to detect anomalies in the Chinese Stock Exchange; the experimental result shows that MAE is less than 4.0 consistently [8]. L. Troiano et al. give a model that shows how to decide whether to keep the stocks you already own or sell them. He made his decision about the stock by using the LSTM algorithm and the MACD indicator [9]. D. Wei et al. implemented the model for the Shenzhen stock index over the course of a year in 2019. To improve the accuracy of the model, he used LSTM along with a batch gradient descent algorithm that acts as an attention layer that can help to predict the stock price [10]. J. Wang et al. used a hybrid model to predict the stock price in 2022. This model had multifactor analysis, secondary decomposition, and an attention-based LSTM. The accuracy of the proposed module is 30%, and the MAPE is also lower than in other models [11]. Many researchers compared the LSTM algorithm with traditional machine learning algorithms like linear regression SVM, but the accuracy of the LSTM algorithm is better as compared to other algorithms, so in this analysis we are focusing on the features that are provided to the LSTM model because effective feature selection produced better output, so in this study we have provided technical indicators like RSI and different combinations of EMA like slow EMA, medium EMA, and fast EMA to improve the accuracy of the LSTM model.

3. Long-Short-Term Memory (LSTM):

The structure of the LSTM cell is as shown in Fig. 1. In this figure, there is input h_{t-1}^{l-1} and states that contain both h_{t-1}^{l} and C_{t-1}^{l} form a tuple. In the beginning, the inputs are preprocessed with a kernel labelled "⊗", and the output is divided into four parts $i, f, cando$ that correspond to the same letters in the figure. h_t^l is the output and also states the next step. This makes use of the Sigmoid and Tanh activation functions [12].

The equation to calculate the forget gate is as follows:

$$f_t^l = \sigma(W_f \bullet [h_{t-1}^l, h_{t-1}^{l-1}] + b_f)$$

$W_f and b_f$ are the weight and offset metrics of the neural network layer, and the input gate is made up of some old information being left behind and some new information being saved. These two parts meet the cell's needs. [13].

4. Methodology:

For this study and analysis, we looked at data of SBI, RELIANCE, HDFC BANK, INFOSYS, TCS, ASIAN PAINTS, and HINDUSTAN UNILEVER, which are all blue-chip stocks on the NSE of India. The stock-related data is collected from Yahoo Finance [14]. The period of the dataset is from January 1, 2012, to December 31, 2022. At first, we only gave the model the most basic functions, such as open, close, high, low, and volume. Figure 2 represents the architecture of the proposed model.

We have divided the data into 75% for training and 25% for testing. After data preprocessing, the model is trained using the LSTM algorithm, and the testing and training validation losses are shown in Fig. 3. From the figure, it is clear that our model is trained properly and losses are reduced.

After that, along with the primary features, we have applied the other technical indicators as features, like the RSI, 20-day EMA, 100-day EMA, and 150-day EMA. The training and testing validation loss after applying the technical indicator is shown in Fig. 4. It will show that the model is trained properly and the losses are reduced. The model can figure out a stock's trend, like whether it's going up or down, and it can predict how much the stock will be worth on the next trading day. This model is helpful for intraday trading-related decisions.

Table 1 shows the summary of our LSTM model. It has three columns: Layers, Output Shape and Parameters. The total number of epochs for training the model is 30. The model is trained with nine features and 30 days of historical data.

Table 1
the LSTM model summary

Layer (type)	Output Shape	Parameters
lstm_input_shape (InputLayer)	[(None, 30, 9)]	NA
first_layer (LSTM)	(None, 150)	96000
dense_layer (Dense)	(None, 1)	151
activation_layer (Activation)	(None, 1)	NA
Total parameters: 96,151		
Trainable parameters: 96,151		
Non-trainable parameters: 0		

There are 96,151 total trainable parameters and 0 non-trainable parameters, so there is no waste of data for model training.

5. Result and Discussion:

The period of the dataset is from January 1, 2012, to December 31, 2022. The LSTM algorithm is used to train the model. To measure how well it works, we chose two parameters: MAPE and R2 Score.

5.1 MAPE: It is the measure of the model's accuracy, which is known as the mean absolute percentage error. The formula for MAPE is as shown below.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{At - Ft}{At} \right|$$

where, the actual value is denoted as A_t and the predicted value is denoted as F_t. Actual value and predicted values difference is taken and divided by the actual value of A_t. For each predicted point in time, this ratio's absolute value is calculated, summed, and divided by the n fitted points.

5.2 R2 Score (coefficient of determination): An indicator of how much of the variation in the dependent variable can be explained by the independent variable is called the R2 Score in a regression model. As it is a percentage, it will take values between 0 and 1.

$$R^2 = 1 - \frac{sumsquaredregression\,(SSR)}{totalsumofsquares\,(SST)}$$

5.3 Comparison of the model with primary features and with technical indicators (RSI and EMA): The values of MAPE and R2 for training and testing data are shown in Table 2. When we applied the basic features to the model, after applying the technical indicators RSI, 50-day EMA, 100-day EMA, and 150-day EMA, the reading of the model was taken and entered into Table 3.

Table 2
R2 Score for Training and Testing of Data with Open, Close, High, Low, and Volume Features

NAME of Stock	R2 for Training	R2 for Testing	MAPE for Training	MAPE for Testing
SBIN	0.9774679372	0.9661528141	1.122198179	2.880187759
RELIANCE	0.9961593907	0.8747344292	0.6716667949	3.066481391
HDFC BANK	0.9952192568	0.658695855	1.090111729	2.839836654
TCS	0.9947298147	0.9242239748	0.7357223106	1.893796089
HINDUNILIVER	0.9973803221	0.8319295256	0.7620302908	2.772791345
ASIAN PAINT	0.9926290354	0.9323522255	0.9399561788	2.127373511
INFOSYS	0.9899493297	0.9075629272	0.7126099922	2.585034382

Table 3
R2 Score for Training and Testing of Data with Open, Close, High, Low, Volume, RSI, and EMA Features

NAME of Stock	R2 for Training	R2 for Testing	MAPE for Training	MAPE for Testing
SBIN	0.973706101	0.9569879873	1.232717925	2.783599898
RELIANCE	0.9941692109	0.8773018997	0.8495975047	2.951976094
HDFC BANK	0.9961039126	0.7980685757	0.7859606998	2.04185219
TCS	0.9949565187	0.9171948323	0.7271116996	1.7141307
HINDUNILIVER	0.9969823256	0.8969267333	0.8443033445	1.99559005
ASIAN PAINT	0.9963166318	0.9273372883	0.5783251469	1.865475871
INFOSYS	0.9931093192	0.9339953521	0.5736429443	2.436657014

We look at the readings from the testing dataset because the model was trained with the training dataset, so it doesn't know anything about the testing data. The testing data is new to the model. Figure 5 shows that the MAPE goes down when technical indicators like the RSI and different versions of the EMA are used. When we figure out the R2 score, we look at the readings from the testing dataset. From Fig. 6, it is clear that the R2 score goes up in HDFC Bank and Hindustan Unilever stocks.

From the outcomes of the model, it is clear that when we applied the technical indicators like RSI and the 50-day EMA, the 100-day EMA, and the 150-day EMA along with the basic features, the result of the model improved, and it can now predict the next trading day's closing price and the trend of a stock more accurately.

6. Conclusion:

Since the stock market is very unpredictable in nature, it is hard to make accurate predictions, but our model's preferred outcomes are pretty close. In this study, we tested the model using the LSTM algorithm on seven large-cap stocks from the NSE, India. At first, we used simple features like open, close, high, low, and volume. Then, we used more advanced features like RSI and different variants of EMA. It's clear that when we employ extra features like RSI, 50-day EMA, 100-day EMA, and 150-day EMA, the MAPE goes down, and in some cases, like HDFC Bank and Hindustan Unilever stocks, the R2 score is improved. So, we can say that the model's performance can be improved by combining the features used for technical analysis of the stock with the LSTM machine learning algorithm, and we can predict the stocks effectively. The trend obtained as an outcome may attract new investors to invest with faith and hope in the financial market.

Declarations

Conflicts of Interest:

The authors have no conflicts of interest to declare

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Figures

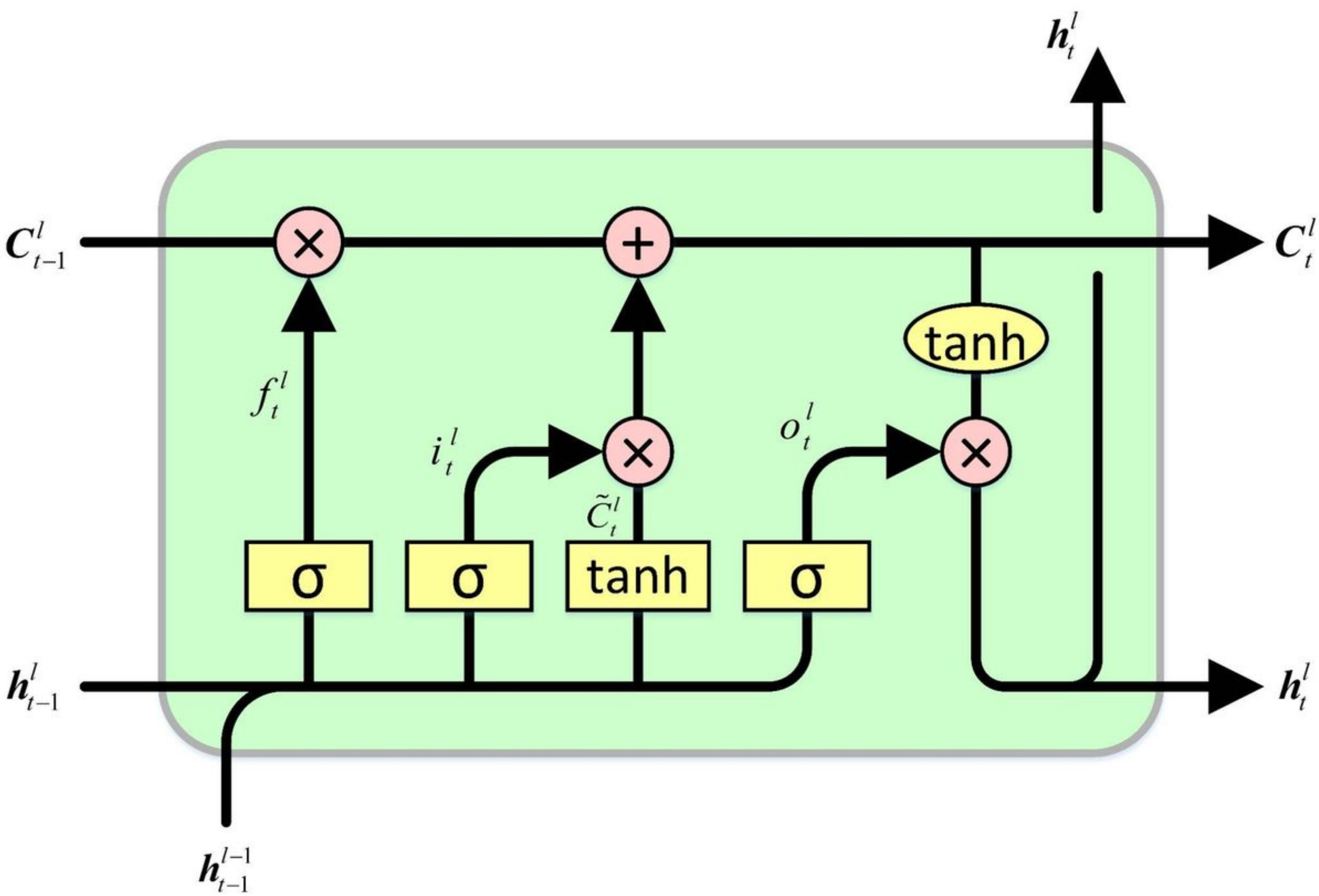

Figure 1

LSTM Cell Structure [15]

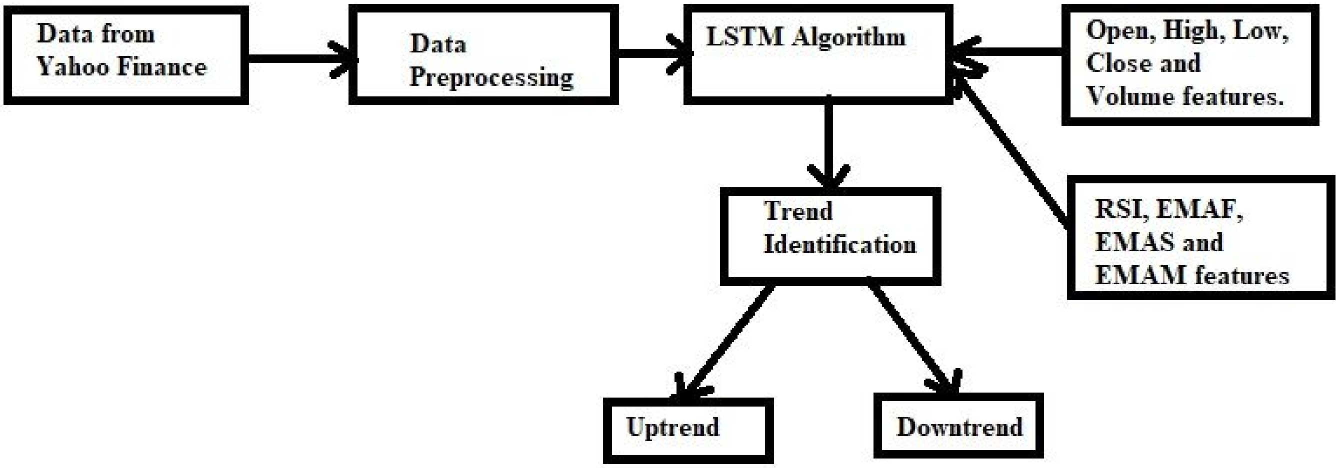

Figure 2

Architecture of the LSTM Prediction Model

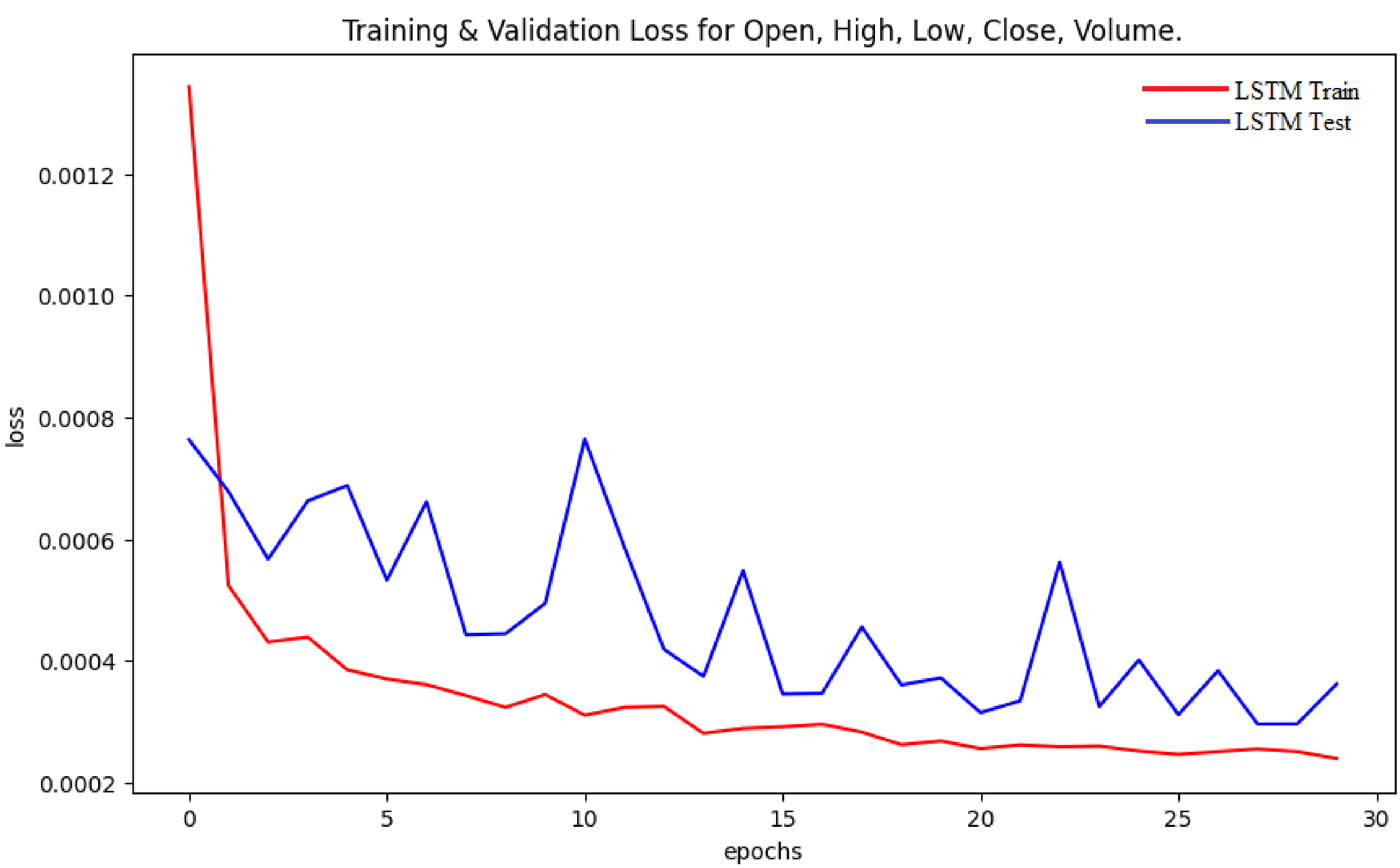

Figure 3

Training and Validation Losses for Open, High, Low, Close, and Volume

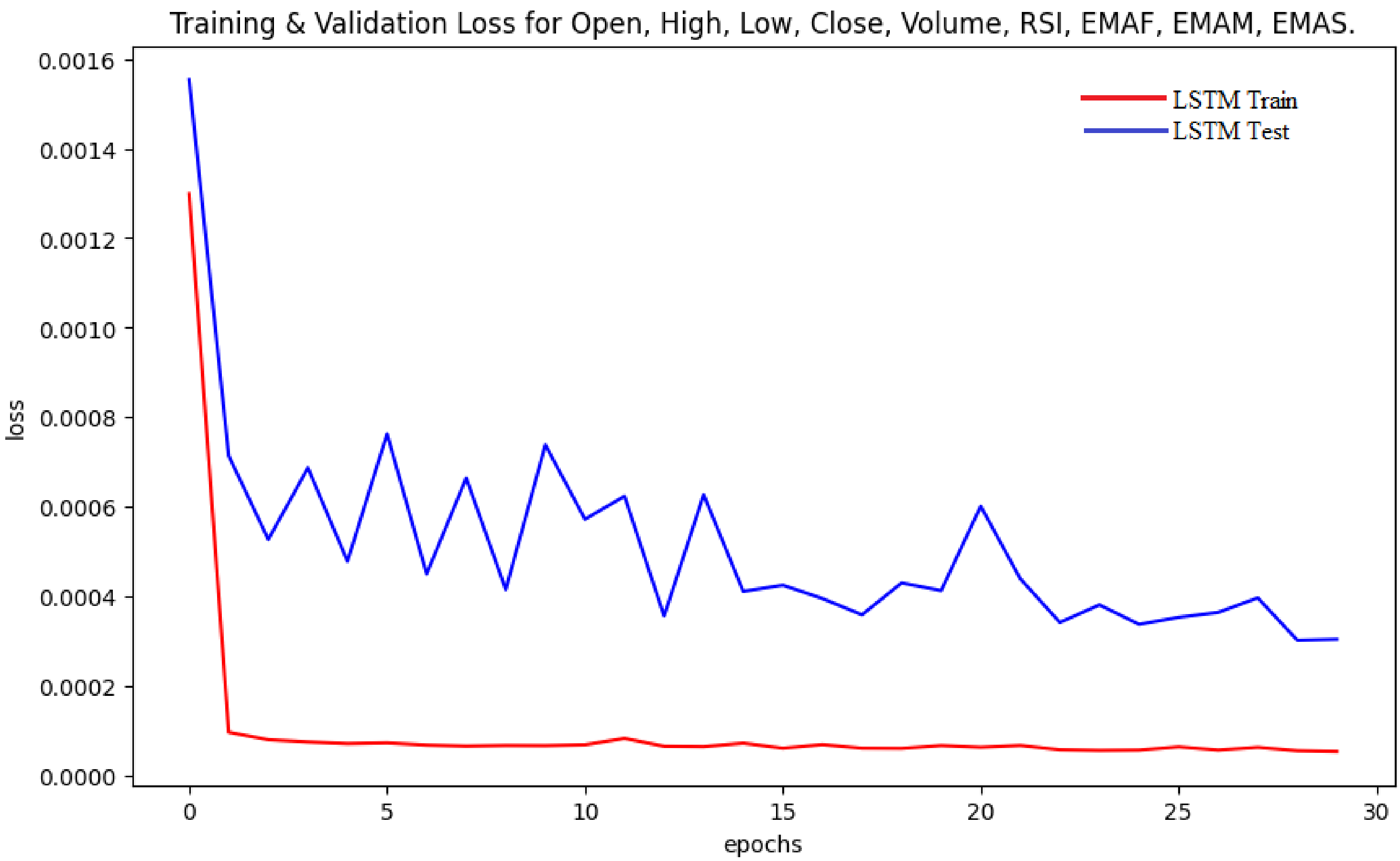

Figure 4

Training and Validation Losses for Open, High, Low, Close, and Volume with RSI and EMA

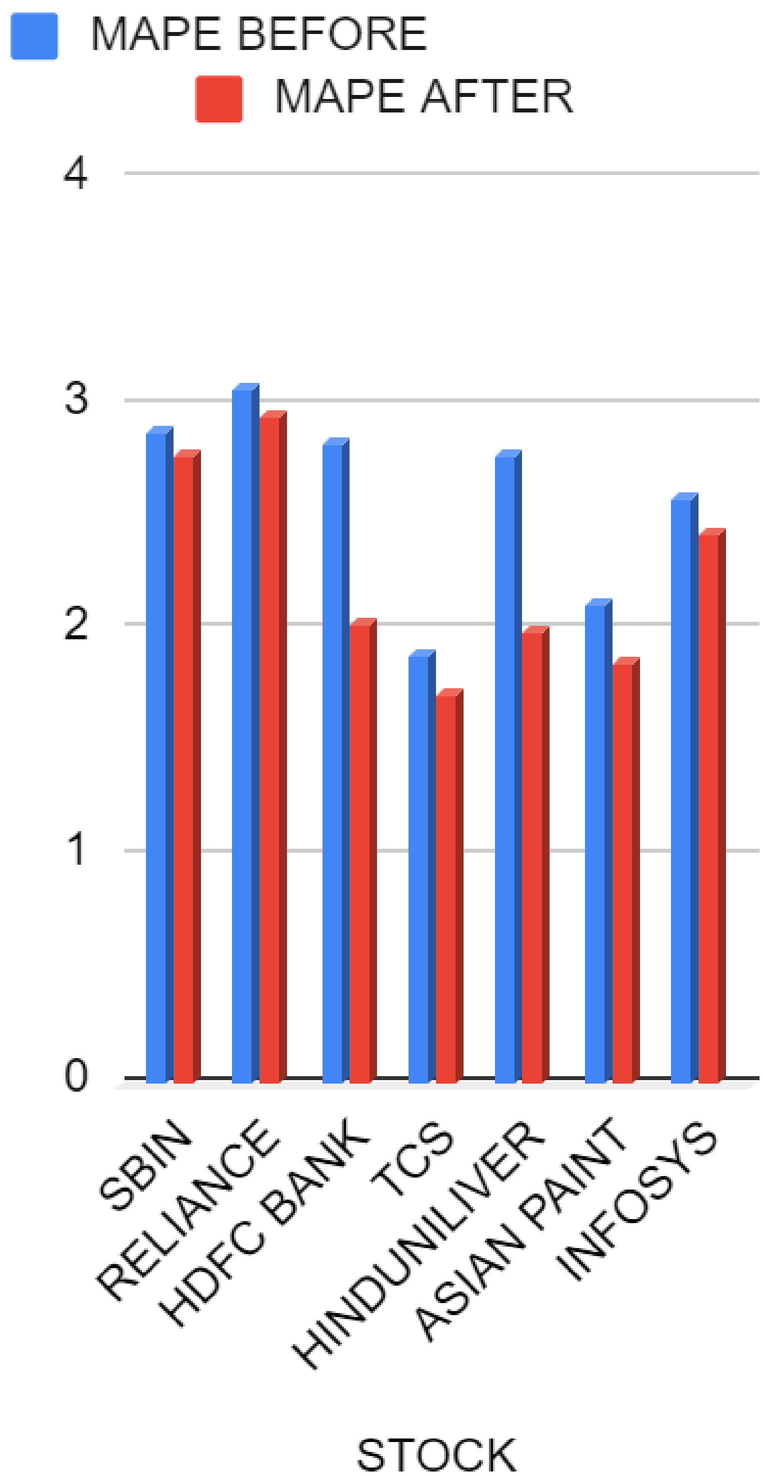

Figure 5

MAPE before and after applying RSI and EMA features.

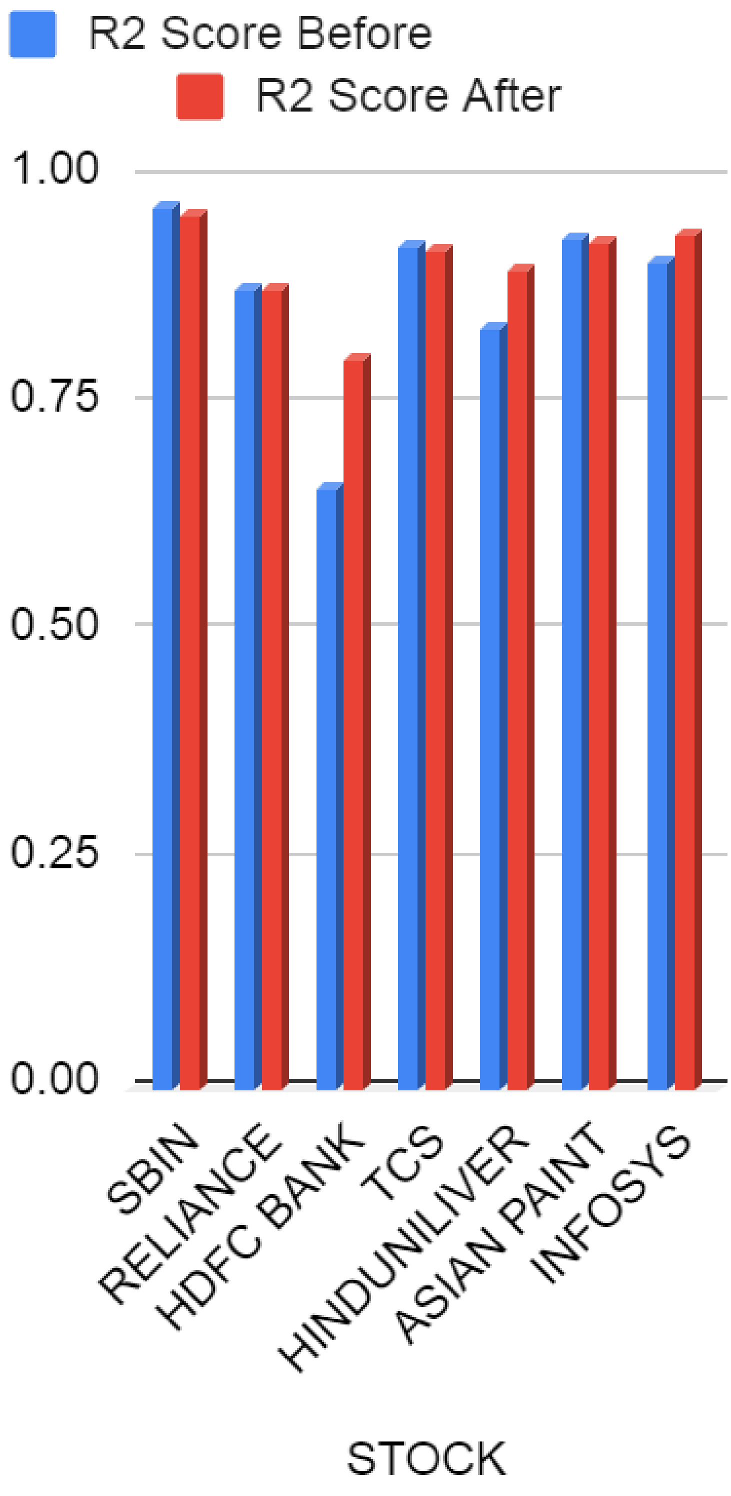

Figure 6

R2 score before and after applying RSI and EMA features.