Using Deep Learning Algorithms Prediction of the Closing Price of Stocks with Indication Features

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***Abstract*—Stock market price forecasting is currently a hot topic for research in the artificial intelligence field. It is quite challenging to correctly forecast stock market returns because of the financial stock markets' significant volatility and non-linearity. Programmable methods of prediction are now more accurate at predicting stock values thanks to developments in artificial intelligence and computational power. In the present study, stock price data from five different sectors with 10 years of history has been collected, and the closing price for each stock has been predicted using Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) models. The comparison between the metrics has also been shown in the following study. Two new features from the momentum indicator and long-term and short-term moving averages of the stock price have been engineered as two newly introduced indicator features in the machine learning algorithms. The closing price of stocks has been predicted in this study with the help of existing and newly introduced features.**

***Keywords*—stock price prediction, bollinger band, long-term Moving Average (MA), short-term Moving Average (MA), Long Short-Term Memory (LSTM), Artificial Neural Network (ANN)**

I. Introduction

Unpredictability, non-linearity, and volatility are hallmarks of the stock market. Since stock values depend on numerous factors, including the political environment, the status of the global economy, the firm's financial performance, and others, it can be challenging to predict stock values.

Inspecting the trend over the past few years, it may be possible to anticipate stock prices in advance, which might be very helpful for making stock market moves. There are two ways of predicting stock prices using historical data. Usually, the stock prediction takes place depending on the main features of the stock price data: open, low, high, and closing prices, along with volume and adjacent close values. The stock prediction process has two basic categories: One is the fundamental way, and another is the technical way. In our paper, a fundamental way, the qualitative analysis is taken based on the profile of the company, market sentiment, and geopolitical scenarios. Technical analysis is built on the tenet that a security's historical price and volume activity can forecast future price changes. Technical analysis presupposes that past trends and trading patterns of previous investors will persist. For the stock market analysis, the data size is particularly large and non-linear.

To handle this diversity of data, a powerful model that can uncover buried patterns and complex relationships in this vast data collection is necessary. Machine learning techniques in this area have been proven to boost efficiency by 60–86% [1] compared to earlier methodologies. Convolution Neural Network (CNN) has been used in a case study on the Thai stock exchange for the purpose of referencing valuable stock price fluctuations [2]. In recent technical advancements, machine learning algorithms are used for the prediction of stock prices. For the purpose of increasing the speed of the model and forecasting stock price, an improvised SVM has been used [3]. In a recent study, Vijh *et al.* [1] proposed the artificial neural network and random forest regressor model for the prediction of next-day stock prices depending on the historical data of stock prices. In another study by Illa *et al.* [4] a profitable stock market strategy has been developed based on the application of an SVM and Random Forest. Another significant research on the application of Generative Adversarial Network (GAN) has been done on stock price prediction by Polamuri *et al.* [5]. In this model, the comparison study and combined study of multi-Model based Hybrid Prediction Algorithm (MM-HPA) and GAN-HPA have been shown for price prediction. Another predictive model has been proposed by Kanwal *et al.* [6] where Bidirectional Cuda Deep Neural Network Long Short Term Memory and a one-dimensional CNN have been combined as a deep learning predictive strategy for the stock prices. A study by Weng *et al.* [7] that coupled the stock price data with the market sentiment and utilized LSTM to predict the stock price for the following day provided yet another important discovery. For the purpose of predicting stock prices using 1200 days of data from the Indonesian stock exchange, Wiiava *et al.* [8] has implemented the GC and DC on technical analysis. By pitting the gradient boosting method against the naive Bayes, a model on the accuracy of stock price forecasting has been developed [9]. For the purpose of predicting the movement of stock prices, [10] coupled a self-regulated GAN and a cooperative network. The model achieved the novelty of a state-of-art model compared to some recent advancements in the studies in this field. In a recent study by Xu *et al.* [11], the visual signals of the stock price were investigated with the use of VAR, followed by the GFFN. A recent study by Lei [12] shows that more neurons in the hidden layers and a smaller number of LSTM layers give better metrics for the prediction of stock prices depending on the historical data. Moreover, a literature review [13, 14] reveals the fact that LSTM and GRU give better predictions in most of the studies done in this field. In another recent work by Parida *et al.* [15], Kernel Based Extreme Learning Machine (KELM) has been implemented for the extraction of the features from the historical data of the stock price. A comparative study on deep learning-based strategy vs conventional machine

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learning approach has been discussed in [16]. In metaheuristic approach by Mahdavi and Khademi [17], ANFIS algorithm has been used for the prediction of oil consumption using historical data. In most of the studies, different Machine Learning (ML) or Deep Learning (DL) algorithms have been applied for stock price prediction, feature extraction, or signal detection. No work has still been done based on feature engineering of the present data and using the volume indicator and momentum indicator as feature variables. The present study proposes the application of ML on the derived features from the existing stock price data for price prediction. Mainly the Bollinger Upper Band, Lower Band, short, and longtime Moving Average (MA) has been derived as the new feature variable for stock price forecasting, and the ML algorithms have been used to find the price movement.

II. Methodology and Data

A. Data Description

The data has been collected from Yahoo Finance [1] for five different companies: Microsoft, Pfizer, Shell, IBM, and Netflix. The historical data ranges from 1/1/2013 to 4/17/2023. The data has initial feature variables such as opening price, low price, high price,_and volume. The target variable has been extracted as the next-day "closing price" of the stock. The dataset has been split into training and testing set, and the date has been set as the index of the dataset. According to the date-time index in Table 1, the training and testing datasets are denoted as follows: From the existing features, a few new features were generated for the regression problem. The newly generated features are the Bollinger Upper and Lower band, 14 days (Short-Term) and 50 days (Long-Term) Moving average

Table 1. Description of the dataset with reference to time

Dataset	Time Index
Training	2013-03-14 to 2021-04-08
Validation	2021-04-09 to 2022-04-08
Testing	2022-04-11 to 2023-04-17
Total Data set	2013-01-02 to 2023-04-17

Fig. 1 depicts the split of the data set into training, validation, and testing set. It is also evident from Fig. 1. that the data we have considered is nonstationary and nonlinear in nature.

Fig. 1. Train, validate, and test dataset for IBM stock closing price.

B. Bollinger Band

Bollinger Band is a momentum indicator for stock prices. In this indicator, 2 standard deviations are taken into consideration for the upper and lower indication of moving averages. In the present study, for the middle band, 20-day moving average has been taken and 2 standard deviations were considered. At first, the Typical Price (T_p) has been determined by

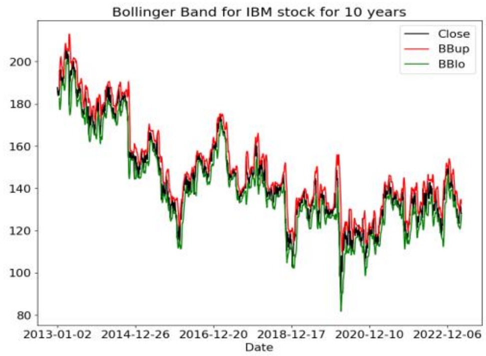
$$T_p = \frac{High\ price + Low\ Price + Closing\ price}{3}$$

Then the upper and lower band has been determined from the following formula

$$\text{Bollinger Upper band} = MA(T_p, i) + n(\sigma(T_p, i)) \quad (1)$$

$$\text{Bollinger Lower band} = MA(T_p, i) - n(s(T_p, i)) \quad (2)$$

Here i is the number of days for rolling mean i.e., 20. n is the number of standard deviations = 2, and $\sigma(T_p, i)$ is the standard deviation of T_p over last 20 days. The following Fig. 2 shows the Bollinger bands for 5 different stocks over 10 years.



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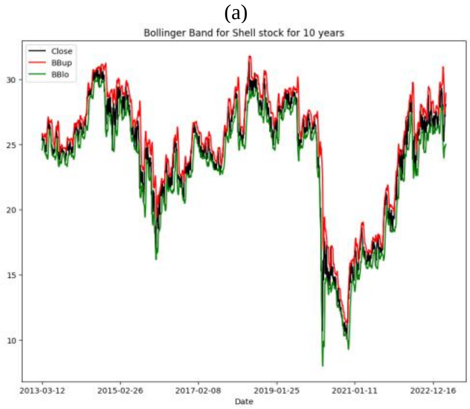

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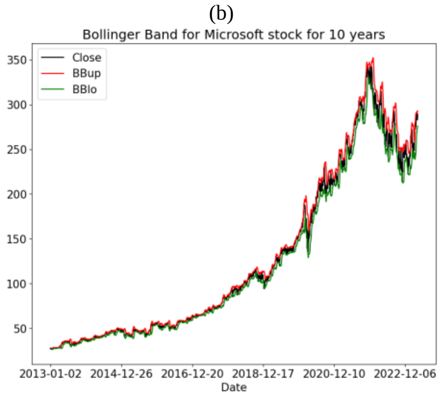

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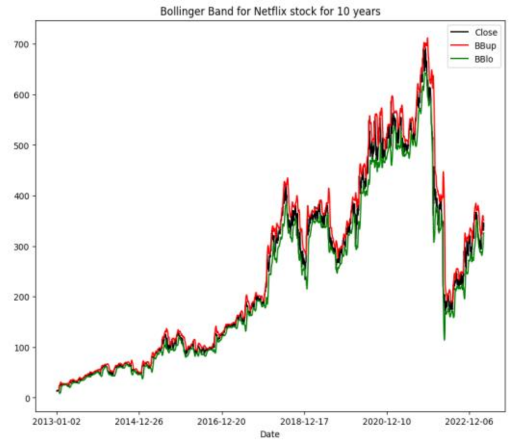

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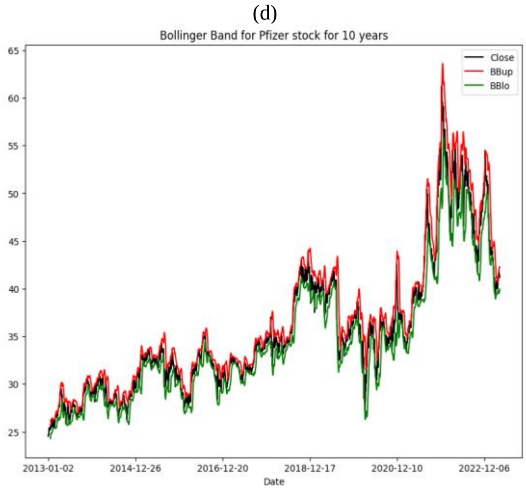

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Fig. 1. Bollinger upper and lower bound for IBM, Microsoft., Pfizer, Netflix, and Shell over 10 years. (a) Bollinger band of IBM stocks; (b) Bollinger band of Shell stocks; (c) Bollinger band of Microsoft stocks; (d) Bollinger band of Netflix stocks; (e)Bollinger band of Pfizer stocks.

C. Moving Average

Moving Average (MA) is a technical analysis of price by taking the average over a certain period. In the present study, a simple MA has been considered. Simple MA has been implied on the high price data over 75 days (Long-Term MA) and on the opening price of the stock over 14 days (Short-Term MA). The impact of quick changes in the opening price and the long-term reaction of high stock prices (slower reaction) have been featured in the proposal. The average is calculated with the following formula:

$$MA = \frac{x_1+x_2+\cdots+x_k}{k} \tag{3}$$

where x_k is the price (open/close/low/high) of the stock at period k, and k is the number of total periods.

D. Artificial Neural Network

Computer models called Artificial Neural Networks (ANNs) are based on how the human brain functions. They are made up of several interconnected nodes that individually carry out a straightforward mathematical operation. This process, together with some node-specific parameters, determines the output of each node. It is possible to learn and calculate extremely complicated functions by combining these nodes and carefully adjusting their settings. Table 2 shows the model summary of the present ANN model.

Table 2. ANN model summary

Layer (type)	Output Shape	Params
dense_4(Dense)	(None, 300)	3000
dense_5(Dense)	(None,200)	60,200
dense_6 (Dense)	(None,150)	30,150
dense 7 (Dense)	(None,100)	15,100
dense_8(Dense)	(None,50)	5050
dense_9(Dense)	(None,20)	1020
dense _10(Dense)	(None,10)	210
dense_11(Dense)	(None,5)	55
dense_12(Dense)	(None,2)	12
dense_13(Dense)	(None,1)	3

The input neurons have been treated as nine input variables in the current study: the opening price, high price, low price, Bollinger upper band, lower band, Long-Term MA of high and opening price (2 variables), and Short-Term MA of high and opening price (2 variables). Fig. 3 shows an illustration of the ANN model

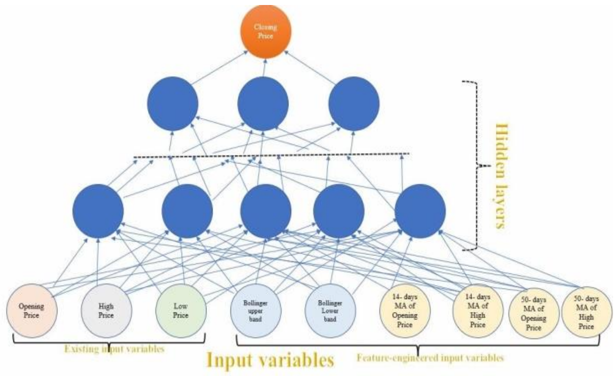


Fig. 3. ANN model for closing price prediction.

E. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) model is a Recurrent Neural Network (RNN) model that is widely used in time-series data for forecasting. For modeling sequential data and capturing long-term dependencies, Recurrent Neural Networks (RNNs) of the LSTM type are a good choice. Because it can recognize patterns and correlations in time-series data, which are frequently necessary for precise forecasts, LSTM can be useful in the context of demand prediction. The study may use LSTM to overcome the shortcomings of conventional approaches in capturing complex temporal dynamics and enhance the precision of demand forecasts in end route sectors. In this model, a very significant characteristic of deciding the storage of particular data and discarding non-relevant data exists. In this present study, we formulated a multi-layer LSTM for the prediction of the last value of the sequence of closing prices of stocks. In the present study, LSTM has been built with 64 neurons, three hidden layers, and one output layer. Table 3 represents the model summary of LSTM.

Table 3. LSTM model summary

Layer (type)	Output Shape	Params
lstm (LSTM)	(None,64)	16,896
dense (Dense)	(None,64)	4160
dense_1 (Dense)	(None,32)	2080
dense_2 (Dense)	(None,16)	528
dense_3 (Dense)	(None,1)	17

Table 4. Metrics of the training, validation, and testing of all stock price data

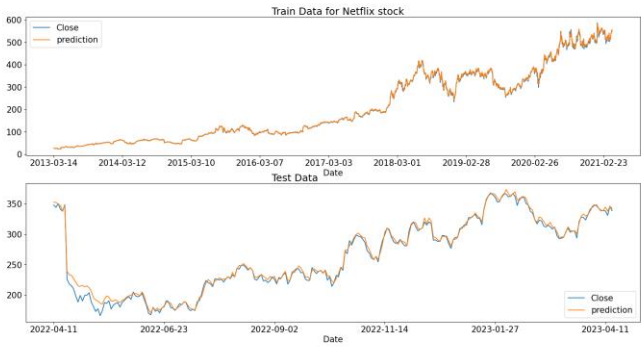
Stocks	Algorithm	Train dataset			Test dataset		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE
Microsoft	LSTM	2.517	1.302	1.887	68.9	6.645	2.51
	ANN	4.549	1.642	1.806	27.91	4.66	1.82
Pfizer	LSTM	0.132	0.306	0.936	15.16	3.07	6.12
	ANN	0.779	0.8547	2.58	1.695	1.25	2.63
IBM	LSTM	0.791	0.672	0.472	0.777	0.698	0.577
	ANN	1.092	0.818	0.571	1.15	0.872	0.648
Shell	LSTM	0.033	0.571	0.642	0.071	0.564	0.741
	ANN	0.027	0.124	0.555	0.055	0.175	0.664
Netflix	LSTM	49.43	4.2703	1.948	255.9	10.19	4.81
	ANN	8.253	1.751	0.831	12.01	2.913	1.116

III. Results and Discussion

Table 4 consists of metrics of training, validation, and testing of 5 stock prices with LSTM and ANN. From the metrics, it is observed that in almost all the cases ANN outperforms the prediction of stock closing prices more than LSTM. The best metric of ANN is obtained for the test data: RMSE (0.055), MAE (0.175), and MAPE (0.648) [17]. The metric MAPE came to less than 10 in every prediction, which is a significantly good value for price forecasting. MAE is particularly useful when one wants to understand the percentage error in prediction relative to the magnitude of the actual values. It is also easily interpretable and can help assess the quality of the forecast in terms of relative error. RMSE is widely used as it is sensitive to large errors and penalizes them more heavily than MAE. It provides an absolute measure of forecast accuracy.

The training and test of each stock's closing price prediction by ANN and LSTM are given as follows in Figs. 4 and 5 respectively.

From the comparison of Fig. 4(b) and Fig. 5(b), it is clearly observed that the test result for ANN gives a better prediction than LSTM for the closing price of Pfizer. For Microsoft and Netflix stock price prediction, LSTM performs badly in test data checks. The performance of ANN is showing very good performance for closing price prediction of all the stocks in terms of the metrics and graphical presentation.



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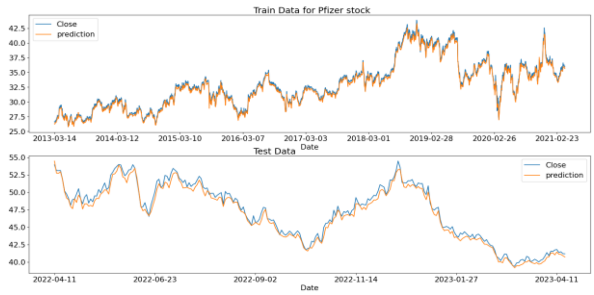

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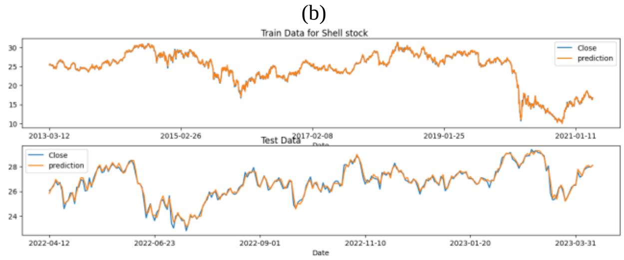

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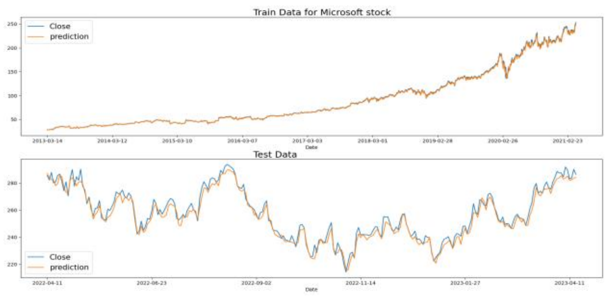

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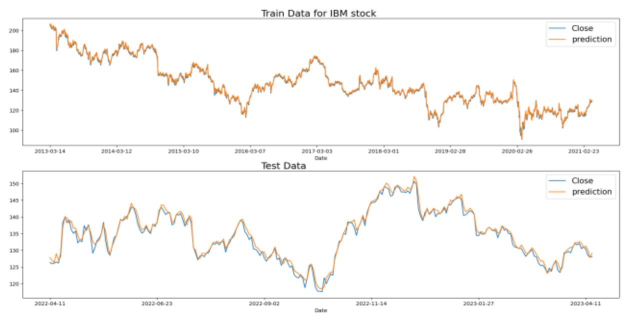

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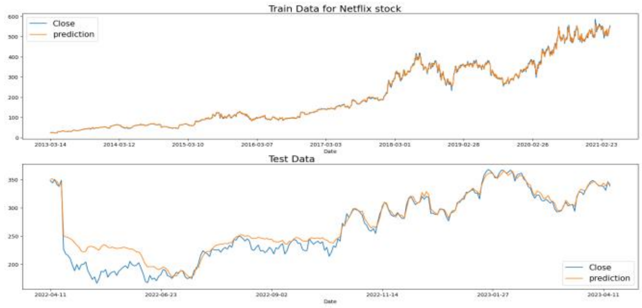
Fig. 4. ANN results for training and testing in 5 stocks. (a) Test and Train Prediction of Netflix Closing Price; (b) Test and Train Prediction of Pfizer Closing Price; (c) Test and Train Prediction of Shell Closing Price; (d) Test and Train Prediction of Microsoft Closing Price; (e) Test and Train Prediction of IBM Closing Price.



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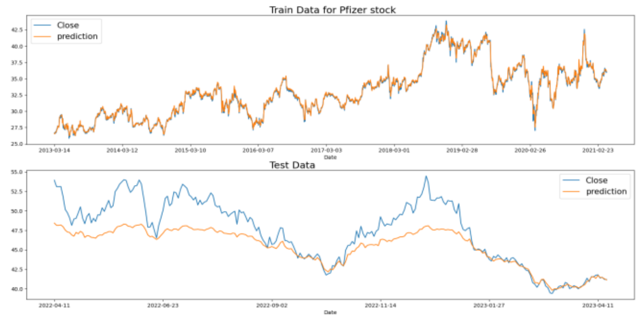

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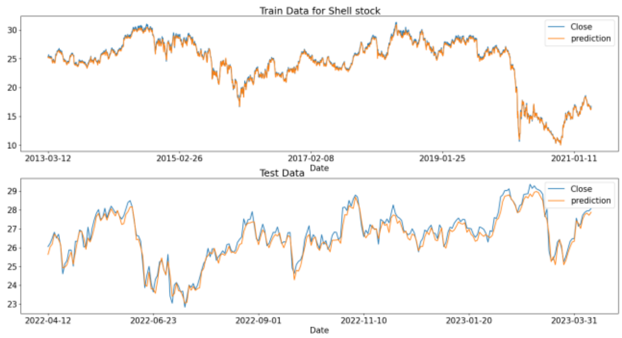

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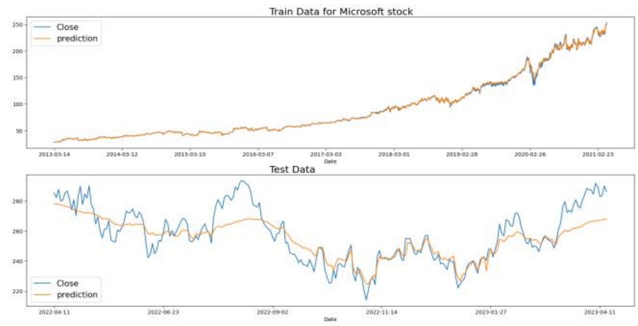

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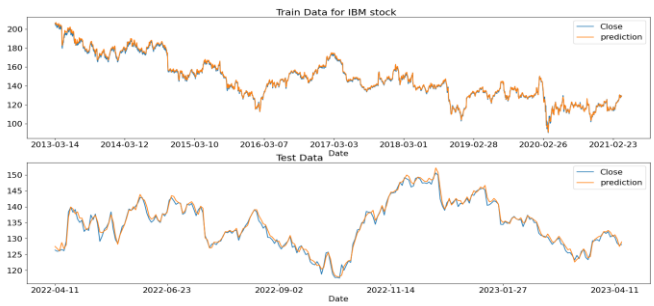

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Fig. 5. LSTM results for training and testing in 5 stocks. (a) Test and Train Prediction of Netflix Closing Price; (b) Test and Train Prediction of Pfizer Closing Price; (c) Test and Train Prediction of Shell Closing Price; (d) Test and Train Prediction of Microsoft Closing Price; (e) Test and Train Prediction of IBM Closing Price.

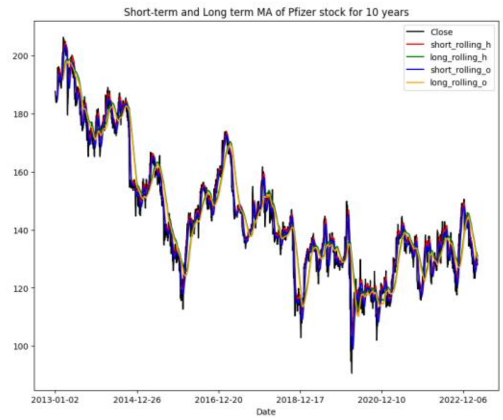
IV. Conclusions and Future Scope

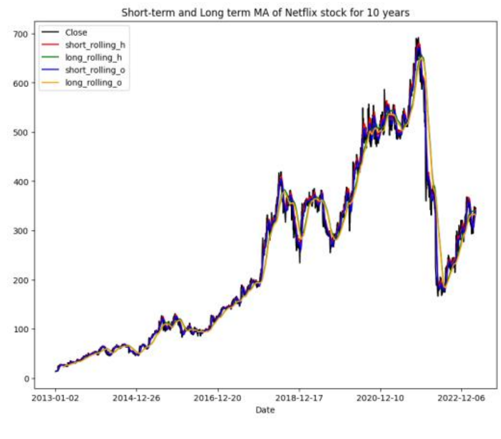
Because stock values frequently fluctuate and depend on numerous factors that create complex patterns, predicting stock market returns is a difficult task. Only a small number of inadequate characteristics, such as the high, low, open, close, and adjacent close values of stock prices, the number of shares traded, etc., are included in the historical dataset made available on the company's website. Feature engineering has been done in the present study to introduce momentum indicators as new features and also Long-term, and short-term MA for the impact of quick and late reactions of price volatility. ANN and LSTM have been applied to find the prediction performance of the time-series data and ANN outperforms LSTM for all the stocks from different business sectors. MAPE values for training, validation, and testing by ANN always came significantly low and advocated the fact of closer prediction value to the actual observation. In the future, Deep learning models can better be modified, and predictions can be featured with Japanese candlestick charts in an easier way for better understanding.

Appendix

List of Abbreviations

MM-HPA	multi-Model based Hybrid Prediction Algorithm
CNN	Convolutional neural network
SVM	Support Vector Machine
GAN	Generative Adversarial Networks
BiCudNNLSTM	Bidirectional Cuda Deep Neural Network Long Short-Term Memory
GFFN	Gaussian Feed Forward Neural network
VAR	Vector Auto-Regression
MA	Moving Average
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory
GRU	Gated recurrent unit





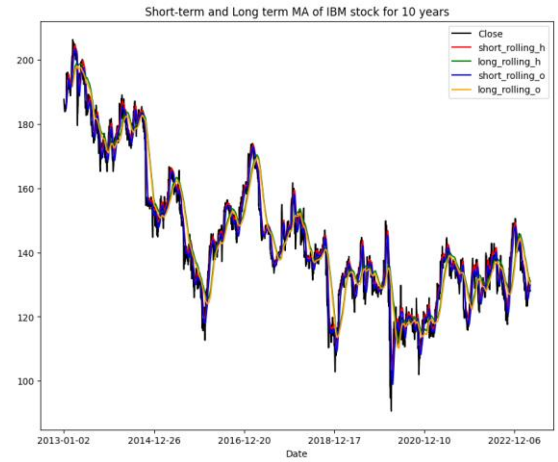


Fig. 1A. Sample short-term and long-term MA of opening and high prices of some stocks for 10 years.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yoon Kong conducted the conceptualization, investigation, solution methodology, analysis, software, fund acquisition, draft writing, and review. Uddalok Sen conducted the supervision, data creation, software, review, and editing. All authors had approved the final version.

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