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The Development of a Deep Learning Model for Predicting Stock Prices

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ABSTRACT

The volatility and complexity of the stock market make it difficult to predict stock values accurately. The primary goal of this paper is to overcome some of these difficulties by training the data to anticipate stock prices based on sentiment analysis of tweets. Using natural language processing (NLP) technology, the tweet sentiments were categorized into (positive - neutral - negative). The stock price was predicted using deep learning algorithms (CNNs, RNNs, LSTMs, BiLSTMs). Among the algorithms, (BiLSTM) achieved the best results in terms of accuracy (94%) and the others (CNN=90%, RNN=91%, LSTM=92%). The paper also confirms that the average MSE and RMSE (MSE=0.03552, RMSE=0.1882064) for the BiLSTM algorithm are achieved (MSE=0.03552, RMSE=0.1882064). As a result, the obtained results were better than previous studies.

1. Introduction

Forecasting stock prices has always been a difficult undertaking for investors and financial professionals [1-2]. However, there has been substantial progress made in creating more precise and trustworthy prediction models since the introduction of deep learning, a branch of machine learning [3-4]. With the use of neural networks, deep learning methods have transformed several industries, including banking, by sifting through massive volumes of historical stock data to identify significant patterns and linkages [5-7].

To anticipate future stock prices, deep learning algorithms for forecasting stock prices examine previous price changes, market trends, and other financial data [8-9]. models are capable of addressing the inherent risk and unpredictability of a stock market because they can handle large-scale datasets, capture complicated nonlinear relationships, and adaptively acquire information from the data [10-12].

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The basis of deep learning models is Artificial neural networks, which are mathematical representations drawn from the structure and operation of the human brain, input data is processed and transformed by these networks, which are made up of several interrelated layers of artificial neurons [13-15]. It can capture sequential dependencies as well as time series patterns making models based on deep learning, such as recurrent neural networks, or RNNs, and long short-term memory (LSTM) networks, (Bi-directional long short-term memory) and convolutional neural network (CNN), suitable for stock price prediction [16-18].

To create a deep learning system for forecasting stock prices, historical volume and price data are given into the neural network as input along with other pertinent variables like technical indications or news sentiment [19-21]. NLP-based sentiment analysis can be used as an additional tool for stock price forecasting. One can learn about sentiment in the market and investor opinions that could affect stock prices by looking at the feelings expressed in news stories, tweets, blog posts, reports on finances, and other written materials about stocks or businesses [22-23]. From this data, the model next learns to identify and generalize trends that can predict future price changes. To reduce the disparity between the actual and predicted values, the network's parameters are optimized during the training phase. From this data, the model then trains to identify and generalize features that can predict future price changes. To reduce the disparity between the anticipated and real stock values, the network's parameters are optimized during the training phase [24-26].

In the end, by utilizing the strength of neural networks and managing complicated patterns in enormous datasets, deep learning models have made considerable improvements to stock price prediction. They offer useful tools for investors to study past data and make more educated decisions, even if they cannot eliminate the risks and uncertainties that the stock market entails [27-28].

2. Related Work

Gupta *et al.*, [29] used StockTwits to predicate sentiment affects stock price forecasting. StockTwits is an online microblogging platform. Utilizing a set of text features and machine learning methods, specifically, evaluate StockTwits tweet data and extract economic emotion. algorithms that were used in this research (Naïve Bayes, Logistic Regression, SVM) applied to five companies (AAPL, GE, MSFT, TGT, and AMZN) were examined. For all five a company, the accuracy level achieved by the logistic regression and TF-IDF combo is between 75% and 85%.

Staffini [30] proposed a Deep Convolutional Generative Adversarial Network (DCGAN) structure to deal with the problem of fore-casting the final price of stocks. To assess the empirical performance of the proposed model, they use the FTSE MIB (Financial Times Stock Ex-change Milano In-dice di Borsa), the national stock exchange of Italy's benchmark stock market index. By doing either single-step or multi-step prediction, they find that recommended model outperforms commonly used, industry-standard techniques. This finding suggests that Deep Learning, and specifically GANs, is a potential area for financial time series prediction. GANs have a 95% confidence level, which indicates that using them in time series of financial prediction may be advantageous. The ARIMAX-SVR is the model with the fastest execution times, whereas our suggested GAN has the shortest execution durations among the models under consideration.

Yukhymenko *et al.*, [31] proposed an inventory asset price prediction model, which is built on generative key competitive networks (GANs). The GAN model consists of two models, a generator and a discriminator, where the former is trained to model new data from historical data and the latter learns to recognize real data among them. In addition to purely historical data, technical indicators such as moving averages of the last 7 and 20 days, Bollinger Bands, etc. are also calculated. However, technical indicators and net asset value still do not give a complete picture of the development of the stock market. Where they also used the method of Sentiment analysis is a text analysis technique that detects polarity (such as positive or negative opinion) in a text, whether it is a complete document, paragraph, clause, or sentence. In this paper, we will use the VADER model to assess the mood of a text. As an output, we receive the average sentiment index of all posts on the Twitter social network about the origin of the stock studied on a given day. The new data is fed into the GAN. The generator learns to generate new data samples from the learned distribution of the training data, and the discriminator learns to distinguish the generated data from the real ones. The effectiveness of the model is tested on expected and actual historical data for the studied period. Comparing the results of the model with other methods, we can note that the proposed model has good prediction results, despite the difficult macroeconomic climate at that time, which negatively affects the stock market and makes it more stable [31].

Lin *et al.*,[32] suggested a stock forecasting system that uses a Generative Adversarial Network (GAN) with Gated Recurrent Units (GRU) as a generator that takes historical stock price input and produces future stock cost and Convolutional Neural Network (CNN) as a tool for discrimination to distinguish between the real stock cost and generated stock cost. They found that the GAN model can enhance the GRU and LSTM models when compared to the standard models. Basic GAN and WGAN-GP both outperformed traditional models. One of the main conclusions of this research is that while basic GAN works better during times of normality, WGAN-GP performs better during unexpected events like COVID-19. To know that a GAN model with RNN, though, is unstable. Hyperparameter tuning for these models is difficult. You risk getting poor outcomes if your parameters are inadequate [32].

Lu *et al.*, [33] suggested using CNN-BiLSTM-AM to fore-cast the closing price of stocks the next day. Convolutional neural net-works (CNN), bidirectional long short-term memory (BiLSTM), and the attention mechanism (AM) make up this technique. To extract the features from the input data, CNN is employed. The stock close price of the following day is predicted by BiLSTM using the retrieved feature data. To increase forecast accuracy, AM is utilized to capture how feature states affected the closing price of the stock at various points in the past. The outcomes demonstrate that this technique performs best, with the lowest MAE and RMSE (21.952 and 31.694, respectively). The largest is R2, with a value of 0.9804. When compared to other approaches, the CNNBiLSTM-AM technique is better suited for stock price predict-ion and for giving investors a trustworthy means to choose which stocks to buy.

3. Methodology

3.1 Dataset

In the context of this study, the data on which the training process was conducted were used, and the test process was also conducted on it from Twitter. The size of the data set used is 80793, on which the test was conducted in previous research [31].

3.1 Analysis Data Using NLP

Analysis of the tweets of the companies that participate in the price shares, where the data of 22 companies were taken from Twitters the number of 80,793 tweets, where each tweet was defined as this tweet (positive, neutral or negative) depending on (NLP) and on the basis of the type of tweet predicted by deep learning algorithms as take AMZN company for analysis and forecasting stock prices as shown in Figure 1.

	Date	Tweet	Stock Name	Company Name	sentiment_score	Negative	Neutral	Positive
48351	2022-09-29 22:40:47+00:00	A group of lawmakers led by Sen. Elizabeth War...	AMZN	Amazon.com, Inc.	-0.0772	0.084	0.841	0.075
48352	2022-09-29 22:23:54+00:00	$NIO just because I'm down money doesn't mean ...	AMZN	Amazon.com, Inc.	0.25	0.158	0.684	0.158
48353	2022-09-29 18:34:51+00:00	Today's drop in $SPX is a perfect example of w...	AMZN	Amazon.com, Inc.	-0.3182	0.164	0.728	0.108
48354	2022-09-29 15:57:59+00:00	Druckenmiller owned $CVNA this year \nMunger b...	AMZN	Amazon.com, Inc.	0.2382	0.065	0.851	0.083
48355	2022-09-29 15:10:30+00:00	Top 10 $QQQ Holdings \n\nAnd Credit Rating\n\n...	AMZN	Amazon.com, Inc.	0.7783	0.0	0.799	0.201

Fig. 1. Classified Tweets by NLP

3.3 Deep Learning Technique

3.3.1 Convolutional neural networks (CNN)

Forecasting methods are a type of deep learning method that uses convolutional neural networks (CNN) to predict stock prices. CNNs can extract features from the input stock data, such as price trends, and market conditions. CNN forecasting methods can frame the stock price prediction problem as a binary classification or regression task, depending on the objective and the evaluation metrics. CNN forecasting methods can achieve high accuracy and low risk in predicting stock prices, especially for high-frequency trading [34].

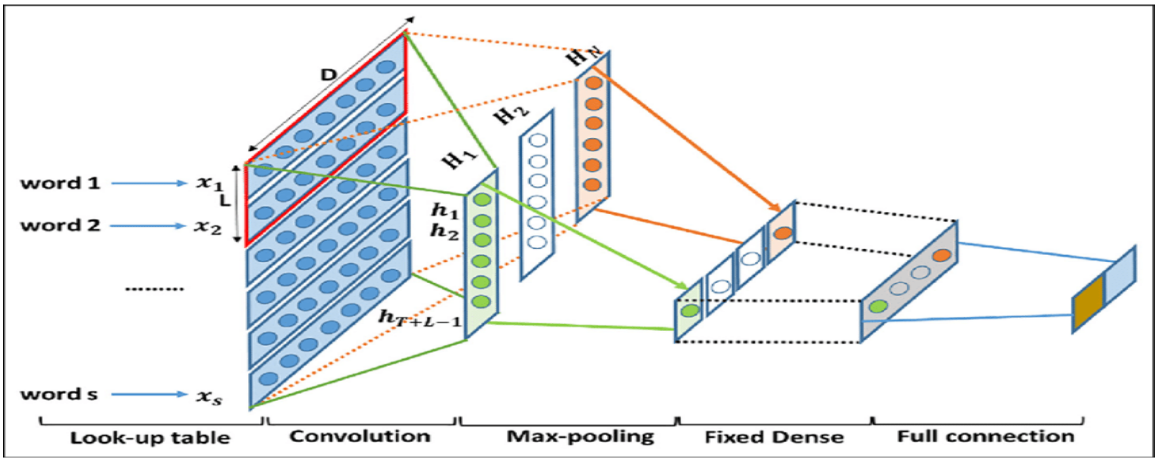

Fig. 2. CNN model structure diagram

3.3.2 Recurrent Neural Networks (RNN)

In this research, recurrent neural networks were used to predict stock prices. Historical data for prices and other variables is collected, data is prepared and divided into training and test sets, and the neural network is built using RNN layers such as LSTM or GRU, with other layers such as blur and projection. The networks trained on the training data and used to predict future stock prices [35].

3.3.3 Long Short-Term Memory (LSTM)

LSTM is a type of recurrent neural network (RNN) that can process sequential data such as time series. It is used to predict stock price movements based on historical data and other factors. It consists of four neural networks and several memory blocks in a chain structure. Three gates control the flow of information inside and outside the cell, and the cells remember values over different time intervals. LSTM improves the performance of traditional RNNs by solving the problem of vanishing or exploding gradients [36].

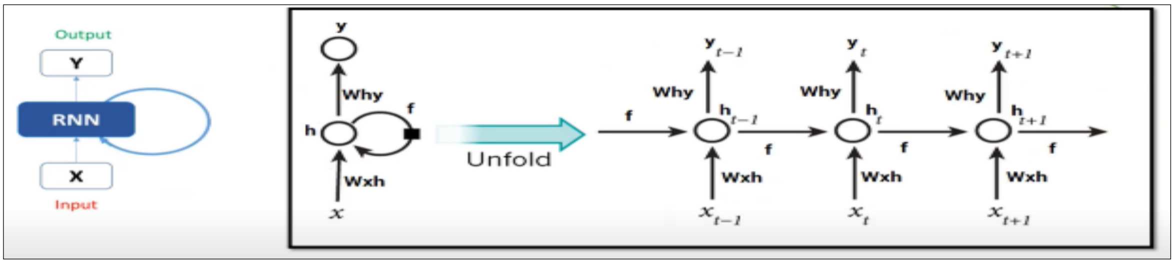

Fig. 3. RNN model structure diagram

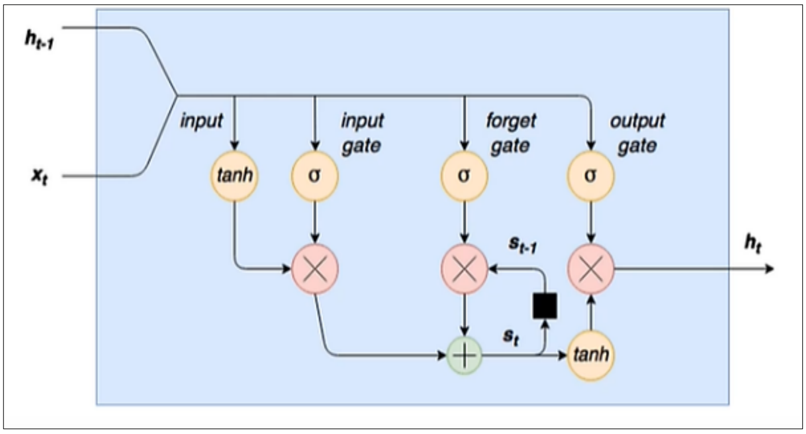

Fig. 4. LSTM model structure diagram

3.3.4 Bidirectional Long Short-Term Memory (BiLSTM)

An enhanced version of LSTM is called a Bidirectional Long Short-Term Memory (BiLSTM) neural network. BiLSTM is able to fully take into consideration past and future data by that link a for-ward LSTM layers and a back-ward LSTM layers which allows for both backward and forward sequential input, establishing the model more robust., while the traditional LSTM only forecasts the next moment's output by previous time series information. This study used the BiLSTM artificial neural network to fully utilize the long-term dependent feature the sample data to perform learning, learn the bidirectional in series features from the feature data that was extracted from the CNN layer, and then output the price predict-ion results via the fully connected layer [37].

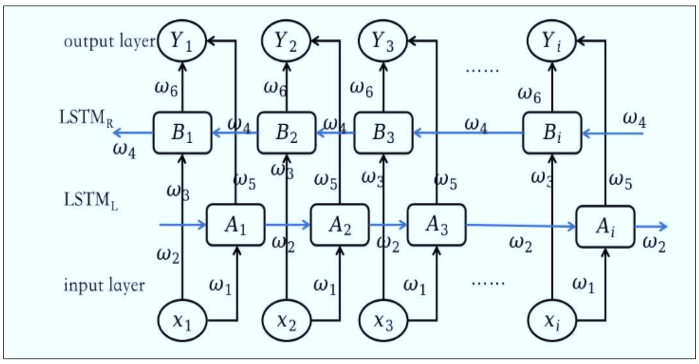

Fig. 5. BiLSTM structure model diagram

Below are the equations for each of the parts of BiLSTM.
Yi = F-3(ω-5 Ai + ω6 B-i), Ai = F-1(ω-1 xi + ω2 A-i−1), Bi = F-2(ω-3 x-i + ω4 B-i+1)
where the activation functions of their respective layers are f1, f2, and f3.

3.4 Training Process techniques

The training process techniques are as follow
1- Input data: - training data input for CNN-RNN-LSTM-BiLSTM.
2- Standardization of Input Data: - Given a significant data gap in the input, improving model training for data.
3- Network Initialization: - Initializing the CNN-RNN- STML -BiLST weights and biases for each layer.
4- Training depended on Algorithm
• CNN Layer Analysis The CNN layer's convolution layer and layer for pooling are successively applied to the input data, followed by feature extraction from the input data and out-put value generation.
• RNN Layer Analysis The RNN layer will process the input sequence and maintain an internal hidden state, which can be passed through fully connected layers to make predictions about the future stock price.
• LSTM Layer Analysis The LSTM layer processes the input sequence, updates its internal memory state, and generates outputs. It has several internal calculations, including input gate, forget gate, output gate, cell state update, hidden state output. The outputs can be either the hidden state at the last time step or all the hidden states at each time step.
• BiLSTM Layer Analysis the BiLSTM layer consists of two LSTM sublayers, forward and backward, which perform the same calculations as regular LSTM layers. The outputs are concatenated to form the final output and forecasting for stock price.
8-The output layer calculates the output value, which is com-pared to the actual value of this category of data to determine the associated error.
9- Calculation Error: This group of data's actual worth and the output value computed by the output layer are compared, and the related error is calculated.
10- Backward Error: Once the predicted error propagates the other way and each layer's weight and bias are changed, the approach repeats step 4 to resume network training.

4. Result and Discussion

The performance of each method was evaluated using the evaluation criteria after the deep learning algorithms had been applied to the data. The evaluation criteria were MSE and RMSE The following is the MAE (Mean Square Error) calculation the equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left|X_i^{\wedge} - X_i\right|$$

where *i* represents the expected value and X_i represents the actual value. The forecast is better the smaller the MAE.

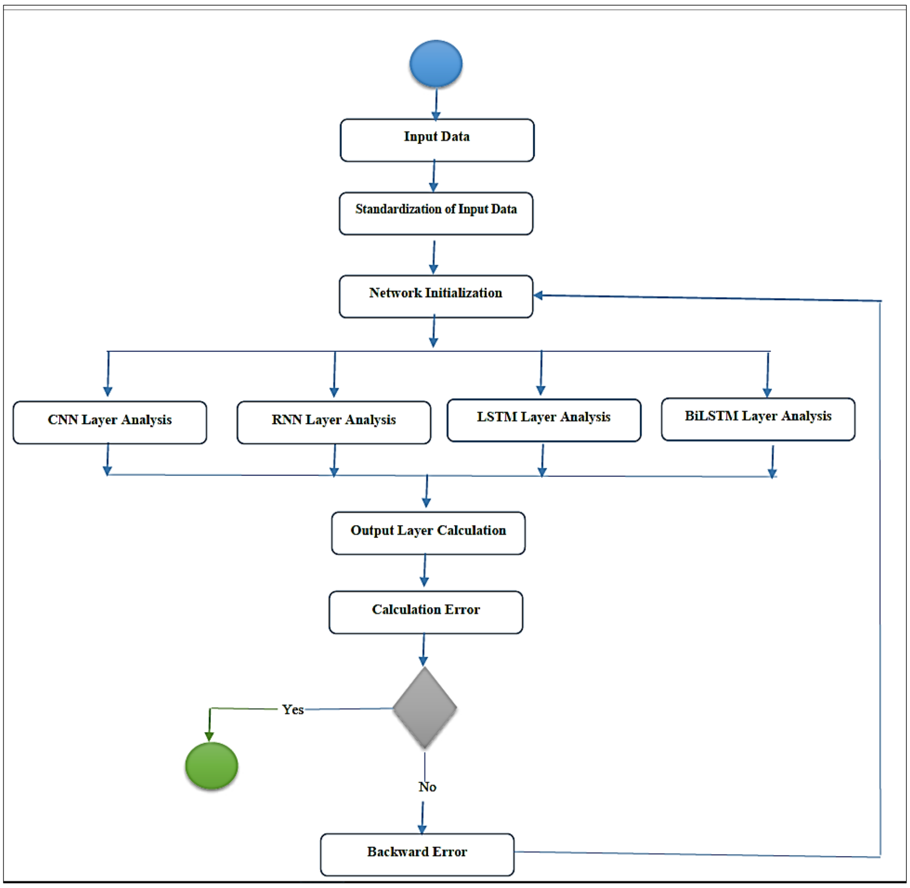

Fig. 6. Schema for Work

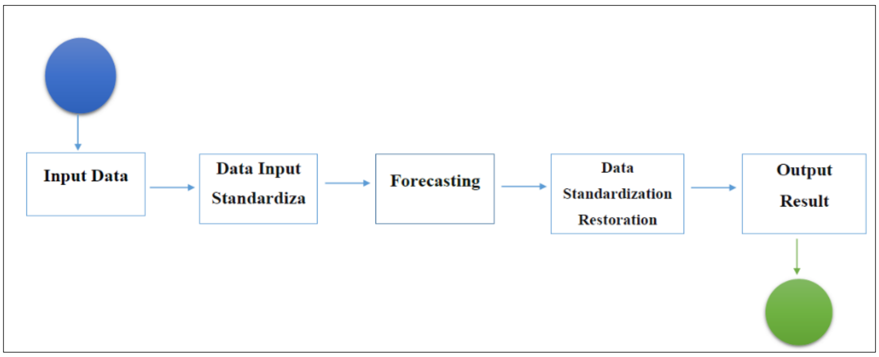

Fig. 7. Schema for forecasting

The following is the RMSE (Root Mean Squared Error) calculation equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|X\hat{}_i - X_i|}$$

where *i* denotes the anticipated value and Xi denotes the actual value. The forecast is more accurate the lower the RMSE.

As shown in the table below, 10 Epoch were chosen to assess how these criteria (MSE) and (RMSE) affected the algorithms (CNN-RNN-LSTM-BiLSTM).

Table 1
Calculate MSE and RMSE for CNN-RNN-LSTM-BiLSTM

Epoch	MSE CNN	RMSE CNN	MSE RNN	RMSE RNN	MSE LSTM	RMSE LSTM	MSE BiLSTM	RMSE BiLSTM
Epoch 1	0.1135	0.336898	0.0500	0.223607	0.0452	0.212603	0.0446	0.211187
Epoch 2	0.0477	0.218403	0.0407	0.201742	0.0378	0.194422	0.0394	0.198494
Epoch 3	0.0437	0.209045	0.0416	0.203961	0.0360	0.189737	0.0355	0.188414
Epoch 4	0.0390	0.197484	0.0514	0.226716	0.0362	0.190263	0.0369	0.192094
Epoch 5	0.0375	0.193649	0.0434	0.208327	0.0399	0.19975	0.0320	0.178885
Epoch 6	0.0359	0.189473	0.0397	0.199249	0.0403	0.200749	0.0344	0.185472
Epoch 7	0.0366	0.191311	0.0460	0.214476	0.0359	0.189473	0.0349	0.186815
Epoch 8	0.0358	0.189209	0.0382	0.195448	0.0328	0.181108	0.0343	0.185203
Epoch 9	0.0364	0.190788	0.0424	0.205913	0.0346	0.186011	0.0312	0.176635
Epoch 10	0.0323	0.179722	0.0362	0.190263	0.0372	0.192873	0.0320	0.178885
Average	0.0458	0.2095	0.0429	0.2069	0.03759	0.19369	0.03552	0.1882084

From the table above find calculating the MSE and RMSE values for each algorithm, it was discovered that the standard values were excellent for the algorithms generally, but it was evident that the best values were obtained for the (BiLSTM) algorithm, whose average MSE and RMSE values were superior to those of the other algorithms. It is well known that the values of the lower MSE and RMSE are the better the prediction accuracy.

The figure below shows a comparison between the value of the evaluation criteria between the deep learning algorithms that were chosen to work on in this research and the values of the evaluation criteria that previous research worked on, as the comparison showed that the values obtained in our research for MSE and RMSE are less than the results of the values found in previous works.

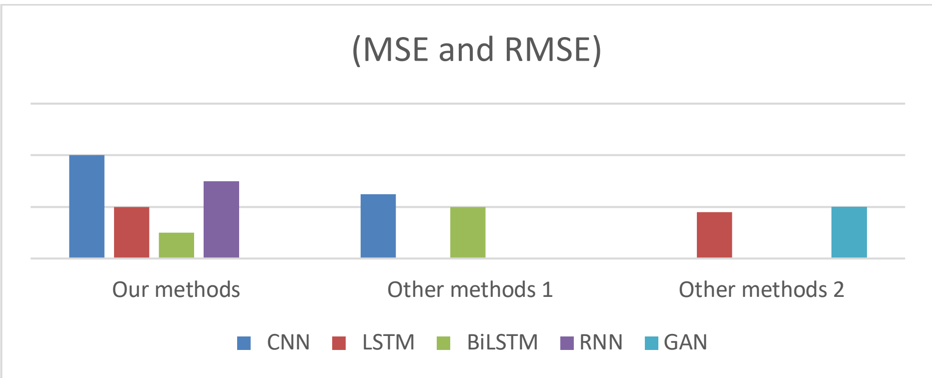

Fig. 8. Comparison criteria evaluation (MSE and RMSE)

The stock price data was trained and tested using the methods CNN-RNN-LSTM-BiLSTM. It was discovered that the best algorithm BiLSTM performs the best at predicting the stock price data, as shown in the illustration below

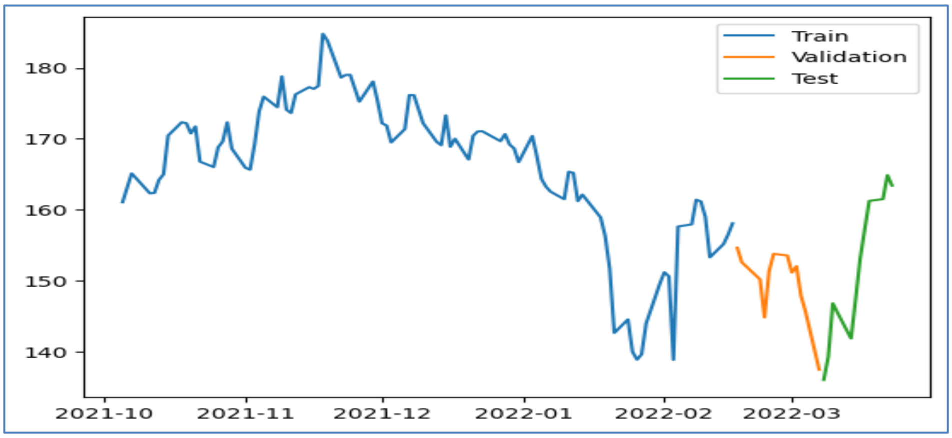

Fig. 9. Illustration predicting the stock price data

Table 2
Metrics for Measurement Perform on a Classification Test

	Precis Ion	Recall	F1-Sc Ore	Accuracy
CNN	0.90	0.89	0.90	0.90
RNN	0.92	0.92	0.92	0.91
LSTM	0.93	0.91	0.92	0.92
BiLSTM	0.95	0.92	0.93	0.94

Metrics that illustrate how well various models perform on a classification test are included in the table above.

• Precision measures the proportion of correctly predicted positive instances. A higher precision indicates a lower false positive rate.

• Recall: It calculates the percentage of positive cases that were correctly predicted out of all positive instances overall. A reduced false negative rate is indicated by a stronger recall.

• F1-score balances precision and recall, considering false positives and negatives. The F1-score is useful when you want to find a balance between precision and recall.

• Accuracy measures the accuracy of a model's predictions.

According on the provided metrics, it appears that the BiLSTM mod-el performs the best overall among the four models, having the highest precision, recall, F1-score, and accuracy. In the chart shown below, the results obtained in our research will be compared with the results obtained in previous studies depending on the accuracy.

From the below comparison, note that suggestion method results were equivalent to the results of the [33] search, which was based on the (GAN) algorithm, as well as better than the [29] [31] search, which was based on algorithms.

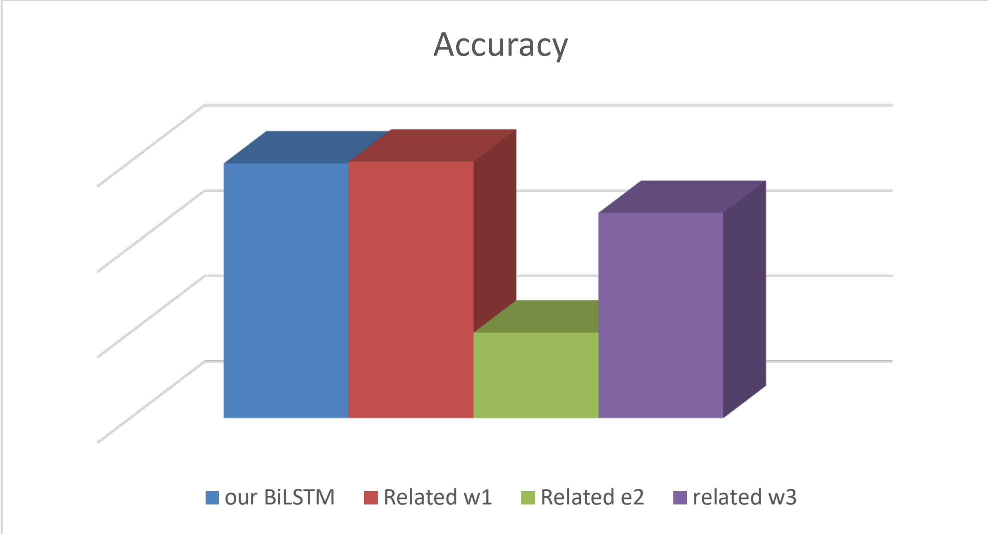

Fig. 10. comparison between accuracy suggestion method with previous Studies

5. Conclusion

This study suggests a CNN-RNN-LSTM-BiLSTM method to forecast the stock closing price of the following week based on the chronological aspects of stock price data. Where the tweets of the Amazon company were analyzed into positive - negative - normal tweets, then the data was trained through the deep learning algorithms that were worked on in this research (CNN, RNN, LSTM, BiLSTM) and where the evaluation criteria were calculated for each algorithm. The value of MSE for (CNN=0.0458,RNN=0.0429,LSTM=0.03759,BiLSTM=0.03552), and the RMSE for (CNN=0.2095,RNN=0.2069,LSTM=0.19369,BiLSTM=0.1882084). It was also found that the other measurements that were obtained for all the algorithms were excellent, equivalent and better results than the previous work algorithms.

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