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Stock Price Prediction using Bi-directional Long-Short Term Memory based Deep Neural Network

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***Abstract*—In the area of finance, forecasting of stock price is becoming very popular increasingly. Predicting the stock price of a firm is very important to increase speculators interest in investing for a company and for growth of shareholders in that stock. In addition to a unique investment portfolio model based on the projections produced, this article suggests a novel method for time-series stock price prediction. To achieve this, a Bi-directional Long-Short Term Memory-based Deep Neural Network (Bi-LSTM-DNN) is equipped with novel regression technique. Once made, the predictions are utilized to build investment portfolio, more precisely, a projected portfolio. Numerous tests have been conducted using NIFTY-50 stock data that was acquired from Indian National Stock Exchange. The outcomes verify that suggested model performs better than a number of conventional prediction models and a number of conventional portfolio optimization algorithms. Reducing investing risks and increasing rewards are possible with an accurate stock price prediction. The Root Mean Square Error (RMSE) value for the proposed deep learning network for stock prediction using Bi-LSTM-DNN is 0.81.**

Keywords*—bidirectional long short-term memory, deep neural network, deep learning, indian national stock exchange, stock prediction.

I. INTRODUCTION

Since COVID-19 pandemic occurred in end of 2019 and early 2020, the globe has undergone significant transformation [1]. Every industry was impacted, either directly or indirectly, by this. Global stock markets saw a sharp decline in a short period of time [2]. Some investors saw this as a chance to purchase mutual funds, stocks, or equity-based assets since they would sell more units at a lower price and might be resold at a greater price in the future [3]. Covid-19 pandemic's effects on capital markets caused shift in stock price trends that no model had previously anticipated. Predictive analytics has advanced significantly, with new advancements being made on a daily basis [4]. In this research, a novel approach for stock forecasting more precisely, the prediction of stock prices has been implemented, along with the proposal of a new portfolio model. There has to be a shift in patterns of data from the Indian stock markets is when the country is experiencing second severe wave of the COVID-19 epidemic [5].

As a result, studies using sufficiently long time-series-based stock data have been investigated. To ensure that all patterns are covered, the time span spans from pre-COVID to the present. Multiple time scale characteristics may be learned using a hybrid end-to-end neural network to forecast stock values [6]. Through a self-learning process, they are able to recognize underlying dynamics, hidden patterns, and past information in data. Data generated in the stock market is enormous and extremely irregular [7]. As a result, a lot of researchers try to predict stock prices by using machine learning techniques like Support Vector Machines (SVM) and Neural Networks [8].

The contributions of the paper include:

- NIFTY-50 stock data that was acquired from the Indian National Stock Exchange was used for this research.
- When calculating a collection of variables that are independent as input data and their matching output as dependent variable using time series data, Autoregressive Moving Pointer Model (AMPM) is utilized.
- Bi-LSTM is used to forecast stock prices when various parameters are properly adjusted. It is used to capture stock movements to calculate final predictions.

The organization is as follows, Section 2 gives detailed description about literature review of previous models and section 3 gives detailed description regarding proposed methodology. Section 4 details about the results and discussions of the proposed model. Section 5 provides information about the conclusion and the future scope.

II. LITERATURE REVIEW

Xuan Ji et al. [9] implemented a deep learning-based to stock price prediction that combines social media text elements and conventional stock financial index variables as prediction model inputs. This technique builds lengthy text vectors of features from social media using Doc2Vec. To balance proportions between text attribute variables and stocks financial index variables, text feature vectors are subsequently reduced in size using stacked auto-encoders. Meanwhile, the wavelet transform is used to deconstruct stock price time series data in order to remove the random noise that results from stock market fluctuations. Lastly, the LSTM is used to predict future stock values by combining the text and financial data. The issue of imbalanced text and stock characteristics is resolved by SAE, which raises the accuracy of techniques for classifying stock prices.

Anika Kanwal et al. [10] suggested a Bidirectional Cuda Deep Neural Network Long Short-Term Memory (BiCuDNNLSTM) and a one-dimensional convolutional neural network (CNN) are combined in this hybrid deep learning-based stock price prediction model. To forecast stock prices accurately and on time. BiCuDNNLSTM combines two deep learning models: the CNN model and the bidirectional CuDNNLSTM. CNN is used to extract abrupt features from dataset of stock. A good hybrid model for forecasting stock prices is BiCuDNNLSTM-1dCNN, which can also point investors in the appropriate way so they may maximize their investment profits.

Burak Gulmez [11] implemented a model using an artificial rabbit optimization approach, a deep learning system is tuned to forecast stock prices. An artificial neural network type called LSTM is frequently utilized in time series research. It can handle data with numerous input as well as output time steps, which allows it to anticipate stock market values well. The accuracy of stock market forecasts can be increased by optimizing hyperparameters of an LSTM using metaheuristic algorithms like Artificial Rabbits Optimization Algorithm (ARO). To anticipate stock prices, an optimized deep LSTM network coupled with ARO model (LSTM-ARO) developed. The outcomes unequivocally demonstrate that, out of all the models, LSTM-ARO model produces most effective predictions. You may experiment with different metaheuristic algorithms. Either an automated stock market system or a dynamic trading system can incorporate this method.

Yanli Zhao et al. [12] presented an integrated architecture for predicting stock price movement that is based on deep learning. In order to anticipate stock market and simulation trading, one unique hybrid model called SA-DLSTM is developed. It combines LSTM, denoising AutoEncoder (DAE), and an emotion enhanced convolutional neural network (ECNN). First, stock market data was supplemented with user-generated comments from the Internet, and the sentiment representation was extracted using ECNN. Second, DAE extracts the important characteristics from stock market data, which can increase forecast accuracy. Thirdly, create more accurate and realistic sentiment indices by taking the timing of emotion on the stock market into account. In order to anticipate the stock market, the essential components of sentiment and stock data are finally input into LSTM. The findings of the experiment demonstrate that SA-DLSTM has better prediction accuracy than the other models that were examined. In the meanwhile, SA-DLSTM performs well in terms of risk and return.

Guangyu mu et al. [13] developed a stock price prediction model using optimized deep learning and investor sentiment. MS-SSA-LSTM is constructed using a mix of multi-source data that influences stock prices, sentiment analysis, swarm intelligence algorithms, and deep learning. The hyperparameters of the LSTM are optimized by Sparrow Search Algorithm (SSA). Lastly, LSTM is utilized to predict future stock prices by integrating sentiment index with fundamental trading data. Tests show that MS-SSA-LSTM performs better than others and has high degree of generalizability. To achieve the best prediction results, the LSTM parameters must be intentionally changed. Consequently, the SSA is selected to maximize the hyperparameters of the LSTM.

III. Proposed Methodology

The suggested approach is built in two stages: projecting stock returns is the first step, and creating an ideal portfolio is the second. Bi-LSTM-DNN is utilized to predict stock returns and a novel regression technique has been employed in this process. Instead of using actual returns in portfolio optimization, Bi-LSTM-DNN forecasts or projected stock returns have been employed. Fig. 1 shows the block diagram for stock prediction using Bi-LSTM.

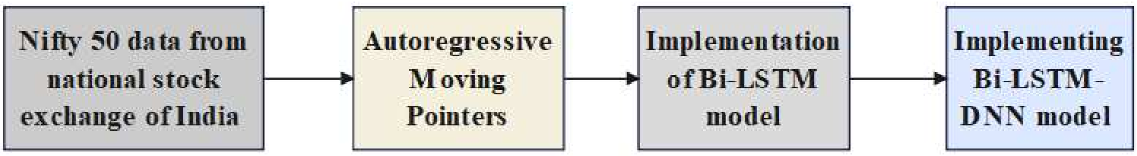

Fig. 1. Block diagram for Stock Prediction Network Based on Bi-LSTM-DNN

A. Dataset Description

The NIFTY-50 index, a stock market index that represents the 50 largest and most liquid Indian companies registered on the National Stock Exchange (NSE), is the subject of NIFTY-50 stock data, which includes both historical and current information. The information includes historical data, company-specific information, trading volumes, market capitalization, sector and industry representation, stock prices, and index composition. Investors, scholars, and financial experts frequently use the NIFTY-50 stock data to learn more about the Indian stock market and to help them make intelligent choices regarding investments.

B. Autoregressive Moving Pointer Model (AMPM)

The AMPM needs a variables set that are independent and dependent variable, just as others regression or auto regression-based models. If a collection of independent variables as input data and their matching dependent variable as output data is taken, AMPM produces same pairs of inputs and outputs on time series data [14]. Take time series data Y, where T is the duration of a previous historical series, as provided by (1).

$$y_t = \left(y_t -_{t-1,}\ y_t - 2, y_t - 1, y_t\right) \tag{1}$$

Two arguments of AMPM are i and j; formulated model can be as AMP $(i,)$ where chosen regression is given as i and in past historical time series reference point is j. The value is given as regression order obtained as j. (2) is determined using moving pointer variable.

$$M = y_t -_{(i-1)} - j \tag{2}$$

AMPM is finally shown in (3).

$$y_{t+1} - M = 1\delta\left(y_{t_{-(I-11)-M,\ldots,y_{t-11}-1M,y_t-1M}}\right) \tag{3}$$

If the dependent variable is $y_{t+1} - M$, the variables which are independent are displayed in right side and the predictor utilized is δ. It can be seen, moving pointer M has all variables deducted from it. The input layer has k neurons, which determine the AMPM regression's order. This is an example of a supervised network with the first hidden layer having 100 neurons ($h1,1$, $h1,2$,...$h1,100$); the second hidden layer also having 100 neurons ($h2,1$, $h2,2$,...$h2,100$); the third hidden layer having 50 neurons ($h3,1$, $h3,2$,...$h3,50$); and output neuron with the dependent variable $y_{t+11} - M$.

The data must then be fed into DNN utilizing Bi-LSTM to create LSTM-DNN. The AMPM-created input-output pairs may now be sent into the Bi-LSTM-DNN to execute the necessary heuristics [15]. (4) illustrates how the output from the Bi-LSTM-DNN is gathered and the M values were brought to get the final predictions.

$$y_{t+1} = y_{t+1} - 1M + 1M \tag{4}$$

Where y_{t+1} is used for final predictions.

C. AMPM rolling windows

Using overlapping rolling windows, training and test data are produced for each stock, and AMPM regression has to be done in each window. First, stock is to be divided into 2 sections: training section and testing section. Time series' historical data can serve as the training portion, while its most current data can serve as the test section. Each rolling window's size will be determined by the size of the training portion.

D. Bi-LSTM implementation

Finding information that has to be preserved and eliminated from Bi-LSTM cell as shown is the main job of the Bi-LSTM. This conclusion is reached by the sigmoid layer. It keeps the information if the output is a "1" and discards it if it is a "0."

- Planning on the data to be stored in Bi-LSTM cell is next stage. The two layers that make up Bi-LSTM cell assist cell in carrying out these functions. A sigmoid layer makes up the first layer. This layer establishes values that need to be updated in order to obtain the intended result.
- A tanh is the layer after that. The new candidate values are generated by this layer. In the future, we may use these values in Bi-LSTM cell. These two layers are then merged to construct a new Bi-LSTM cell state that only has information that is required in the following phase.
- Our cell state will be in a cleaner form after the Bi-LSTM. We mixed the output with sigmoid layer after the conversion. It gave reassurance that the throughput was reduced to meet our needs. Therefore, the result displayed just the pertinent data.

E. Implementing Bi-LSTM-DNN

Bi-LSTM-DNN's configuration was determined to be 4: 100:100:50 : 1, or 4 neurons in layer of input, 3 hidden layers (first and second levels each having 100 neurons), 50 neurons on third level and output neurons. For network, Mean Squared Error (MSE) is used as loss function.

IV. Results and discussions

This results section provides information regarding the experiment setup, evaluation metrics and simulation results for the prediction. This Deep Learning Network for Prediction of stock Using Bi-LSTM-DNN is performed by python tool in PC with the below specifications such as 16 GB RAM, Windows 10 0S and I5 processor.

A. Measures for evaluation

The accuracy for prediction is estimated using a variety of assessment indicators. Among these is the Root Mean Squared Error (RMSE). It is an achievement statistic that is frequently employed to quantify accuracy. Here, n is total quantity of data, and the original and anticipated values are indicated by y_i , respectively. (5) describes and provides this inaccuracy.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i)^2}{n}} \tag{5}$$

B. Performance analysis

This section includes the results for deep learning network for stock prediction using Bi-LSTM-DNN which is trained with the proposed criteria. Table I gives the information regarding the RMSE values of existing classifiers and proposed model. From the Table I, it clearly shows that Bi-LSTM-DNN accomplished better RMSE when compared with other existing classifiers.

TABLE I. Performance Analysis Of Existing And Proposed Classifiers

Existing classifiers	RMSE
LSTM	0.90
KNN	0.93
CNN	0.95
DNN	0.91
Bi-LSTM-DNN	0.81

To evaluate performance of suggested Bi-LSTM-DNN further, a comparison of RMSE between LSTM and Bi-LSTM displayed in Table II. From the Table II, it clearly shows that proposed Bi-LSTM-DNN achieved better RMSE of 0.00041 at 100 epoch which is better than LSTM which obtained 0.00048 respectively.

TABLE II. RMSE comparison for various epochs between the LSTM and Bi-LSTM-DNN

No of Epochs	LSTM		Bi-LSTM-DNN	
	RMSE	*Time (min)*	*RMSE*	*Time (min)*
11	0.00110	4	0.00071	9
21	0.00072	7	0.00064	16
51	0.00049	16	0.00042	41
100	0.00048	31	0.00041	71

Table II shows that when the total amount of epochs rises, the training model encounters an under fitting issue for the LSTM at a certain point, say after 100 epochs. But even over 100 epochs, Bi-LSTM-DNN performed well and produced predictions with a reduced RMSE. Based on this observation, it may be concluded that the Bi-LSTM-DNN outperforms LSTM since it uses backward propagation to forecast the data during each training cycle. Additionally, it is evident that as the number of hidden layers increases, efficiency of testing accuracy decreases for both LSTM and Bi-LSTM.

C. Discussion

Predictions are initially calculated by creating pairs of inputs and outputs using AMPM and passing them to the Bi-LSTM-DNN. In comparative analysis, LSTM and Bi-LSTM methods RMSE values are compared, it is proved that Bi-LSTM-DNN has the best testing accuracy that increasing hidden layers count. The suggested model's effectiveness is assessed using RMSE value of 0.81 which is better than other classifiers such as LSTM, CNN, DNN and KNN. Similarly, the process is analyzed under different epochs such as 11, 21, 51 and 100; in all the epochs, the conventional LSTM model has obtained 0.00110, 0.00072, 0.00049 and 0.00048 respectively; while the proposed Bi-LSTM-DNN has accomplished better RMSE of 0.00071, 0.00064, 0.00042 and 0.00041 respectively.

V. CONCLUSION

This study demonstrates the profound impact of deep learning algorithms on contemporary technology, particularly in creation of various time series-based models for prediction. Among all the regression models, they are able to produce the best degree of accuracy when it comes to stock price prediction. Stock prediction is computed using a novel regression approach that can be used to Bi-LSTM-DNN. The development of any prediction model necessitates the modification of these parameters since they have a substantial impact on forecast accuracy. Once computed, these forecasts are utilized to build an investment portfolio known as a projected portfolio. The portfolio uses entropy to accomplish diversification and a curve created from the likelihood of profits or losses to occur to graphically depict portfolio risk. The access time needed to compute predictions is model's restriction, non-stationary nature of data may cause process to lag even more. Lower RMSE is produced by Bi-LSTM-DNN than LSTM. Therefore, for stock market forecasting, both people and businesses can utilize our suggested prediction model that uses Bi-LSTM-DNN. This can maintain a sustainable atmosphere in the stock market while providing investors with significant financial benefits. The suggested Bi-LSTM-DNN for stock prediction network has an RMSE value of 0.81. In the future, needs to examine efficiency of this method by analyzing information from additional stock markets across various categories.

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