Stock Price Prediction Using Deep Learning Model

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Abstract

Prediction and the analysis of data obtained from the stock market both plays a significant part in the economy of today. The neural network is one of the sophisticated data mining techniques that has been employed by academics in a variety of fields over the last several decades. These researchers have been looking into a wide range of topics. Linear models and non-linear models are two classifications that may be used to the many different methods that are employed in forecasting. Deep LSTM underpinned the stock market prediction model. This model accurately predicts the stock market. This research yielded two stock market forecasting improvements. This scenario modifies the deep LSTM classifier to predict stock market. The Time series approach is used to train the deep LSTM, which approximates hyperparameters using step size and sparse gradient factor, that provide significant improvement in the prediction.

Keywords: - stock price, prediction, deep learning, LSTM, time series.

I. Introduction

Stock markets now a days drives the economy of the world. According to the Efficient Market Hypothesis, stock prices reflect current information. The stock market is dynamic since it has many stocks and prices vary over time. Stock market forecast involves time-based market patterns. Every stock market investor wants to increase profits and reduce risks. Even if political events, investor emotions, economic constraints, and other variables impact the stock market [1], shareholders value stock market index forecasts [2]. The stock market drives economic growth, therefore behaviour study and prediction may help achieve economic goals. Thus, stock market prediction requires a trading system including prediction, trading policy, and risk analysis components. Trading element creates a group of equities that improve return relative to risk [3].

Data pertaining to stock markets are organised in time series and also include highly variable non-linear data. The data that is collected throughout time periods show distinct activity statuses that may be estimated using the passage of time[4]. The accurate forecasting of future events relies on a number of well-known phenomena, including data, economic activity, climatic indicators, and temporal behaviours. Aside from this, the forecast of the stock market is a crucial performance that personal depositors and economic enterprises engage in when deciding how to allocate their investments. The stock market is a non-linear dynamic and evolving system, however it is difficult to make accurate predictions about the stock market[5]. The determination of a potentially profitable rate at which firm shares may be traded on exchange is the primary goal of stock market prediction. Additionally, reliable classifications of future stock values have the potential to generate big gain [6]. In general, there are three categories of forecast movement: short, medium, and long. These categories are as follows: The act of forecasting the time in a matter of minutes, hours, or days within a week is referred to as short, whereas the act of predicting the time in a matter of weeks to months is referred to as medium. In a similar vein, a prognosis with a time frames of one year or longer indicates long term [7]. According to [8], research on the stock market highlights two fundamental trading attitudes, which are known as the technical and fundamental methodologies [9][10]. Price changes on the stock market may be determined using relative data when using a fundamental methodology[11].

In addition, fundamentalists rely on numerical information for making predictions about the future, such as managerial efficiency, ratios, and profitability [12]. Similarly, in the market for technical systems, timing is seen as an essential component, and methodologies based on modelling and charting are used in order to forecast developments in volume and price. In addition, subsequent persons place a significant amount of weight on previous information when making predictions about the future outcome [13]. Because both technology and the economy are advancing at a rapid pace, the stock market has become an increasingly important component of modern life.

II. Literature Review

The three-stage methodology was used to simulate stock market prediction [14]. Using Multiple Regression Analysis, financial and economic factors with a greater association were identified. The prediction model was created using Differential Evolution-based type-2 Fuzzy Clustering. Fuzzy type-2 Neural Network prediction was the last step. This technique has significant computational complexity but decreased prediction inaccuracy.

Predicted the stock market using Interrelated Time Series Data [15], this approach retrieved time series data and forecasted stock interrelationship changes. Foreign exchanges, global stock market indexes, and oil prices are in the time series. Prediction and interrelation discovery stages comprised this prediction approach.

LDA-Online stock market prediction system [16], a historical stock data training suited the learning model. LDA-Online made batch learning online. The LDA-Online technique incorporated fresh data in the training set for model fitting. This strategy examined forecasting data before the predetermined number of days and indications of the forecasted day. It ran faster and computed better. The limited indications and characteristics employed for stock market prediction made this strategy inaccurate.

stock market forecasting via newspapertitles[17], the words were converted into nouns and vectorized for skip gramme extraction. The CNN predicted stock market movements after vectorization. CNN's feature map forecasted market volatility. This approach had average accuracy but failed to assess how stock type affected method performance.

Multi-classifier stock market prediction system[18], the approach anticipated the stock market using Dow Jones Industrial Average time data. Time series demonstrated that periods were not random, making prediction problematic. The Hurst exponent accurately predicted the timeframe to overcome this impact. Hurst exponent predictions guided data selection. To save time, Hurst exponent-rich time series were employed for prediction. False closest neighbour and auto-mutual information were utilised to determine training pattern parameters. Decision tree, artificial neural network, and k-nearest neighbour classifiers learned patterns. This approach predicted averagely. Stacking ensemble and simple voting mechanisms gave this system good predictive correlations.

Stock market prediction using ANN[19], the stock was predicted using short-term and weekday stock prices. The ANN trained to predict. It successfully anticipated the stock exchange rate, although calculation was difficult.

Stock market forecast hybrid ANN models[20], Hamony Search and Genetic Algorithm created the hybrid ANN. Hybrid ANN chose significant technical indicators. Hybrid ANN assessed hidden layer neurons and input variables. The dataset was first separated into testing and training datasets, and then subsets were created from the training dataset to evaluate ANN generalization. Overcoming under- and over-fitting, the hybrid ANN technique performed well. As the hidden layer increased, this approach took longer, and the transfer function and training function influenced ANN quality. This technique fails to remove ANN-affecting parameters.

ANFIS, AI, and Swarm Intelligence were used [21] to simulate stock market prediction. ANFIS used recurrent technique, wavelet transform, and artificial bee algorithm. This approach correctly anticipated the stock market but allocated little memory.

Deep learning to forecast stock markets[22], Predicting the stock market using financial news characteristics. Predictions used the financial emotion dictionary and Fast text. The stock's hourly closing price determined the class labels' movement direction. Finally, various LATM networks predicted. This approach effectively predicted hourly stock direction. This procedure was computationally and time-consuming.

Ensembled stock market learning approach[23] using DBN and HS algorithms. The HS algorithm and DBN were used to identify the hidden layer network, indicators, and structure. The hybrid technique prepared datasets for testing and training. The dataset has five training subsets for simultaneous reinforcement learning. Finally, the HS algorithm evaluated the network structure with minimal mistakes. This strategy enhanced predicting and simplified calculation. This approach did not dynamically alter or optimize HS settings.

Stock market neural network[24], the learning function normalized data. Bipolar, unipolar, tan hyperbolic, and Radial Basis Function learning functions predicted. Open price, characteristic date, peak price, and low price were used to forecast stock market closing price. Backpropagation neural networks with learning functions forecast the stock market. The unipolar sigmoid function improved stock market prediction accuracy but not computing complexity.

Sentiment analysis and machine learning to forecast stock markets[25], Data was pre-processed for trustworthy prediction analysis. Pre-processing matched the data with stock price history. Sentiment then classified the news piece as good or negative. Using the Naive Bayes Classifier and lexicon, sentiments were categorised. This approach assessed public mood from large-scale news and economic and financial newspapers. However, this strategy addressed the association between newspaper readers and investment choices, which was unnecessary for stock market prediction.

Stock Market Prediction model[26], this model uses LSTM and sentiment analysis. This stock investing strategy mimicked investors, traders, and analysts. Fundamental study of headlines and technical analysis of equities based on numerical data dictated stock market behavior.

III. Proposed Model

a. Dataset: The information comes from India's National Stock Exchange (NSE), and it consists of the price histories and trading volumes of the fifty equities that make up the NIFTY 50 index. All of the statistics are broken down by day, and the price and trade figures are segmented accordingly. cvs files for each stock in addition to a metadata file that contains some macro-information on the stocks themselves. The data ranges from the first of January in 2000 to the thirty-first of April in 2021.

b. Deep Long short-term memory (LSTM) Model

The RNN model is further developed into the LSTM neural network. Both LSTM and RNN will have a time dimension added to their input data, which has the potential to enhance the performance of time series prediction. When compared to RNN, LSTM adds three distinct gates—the forget gate, the input gate, and the output gate—in order to tackle the gradient disappearance issue. This problem has seen widespread use in the context of time series modelling. As a result, we have decided to use it as our final model of prediction. The Long Short-Term Memory (LSTM) is made up of many neurons. The forget gate is the initial stop for data as it travels through each neuron. The forget gate is responsible for selecting the input data that will be ignored so that it does not influence the update performed by the subsequent neuron. In the second phase of the process, the input gate makes the decision on which kinds of information may be added. The sigmoid function and the tanh function are applied to the output of the neuron that came before it and the input of the neuron that is now being considered. This causes two outputs to be produced. Next, depending on these two outcomes, a determination is made as to which pieces of information need an update. The findings will be kept for the output gate in this case. Last but not least, the output gate is responsible for deciding which of the results produced in the input gate may really be created. The output of one neuron's gate will be sent into the next neuron, and so on and so forth.

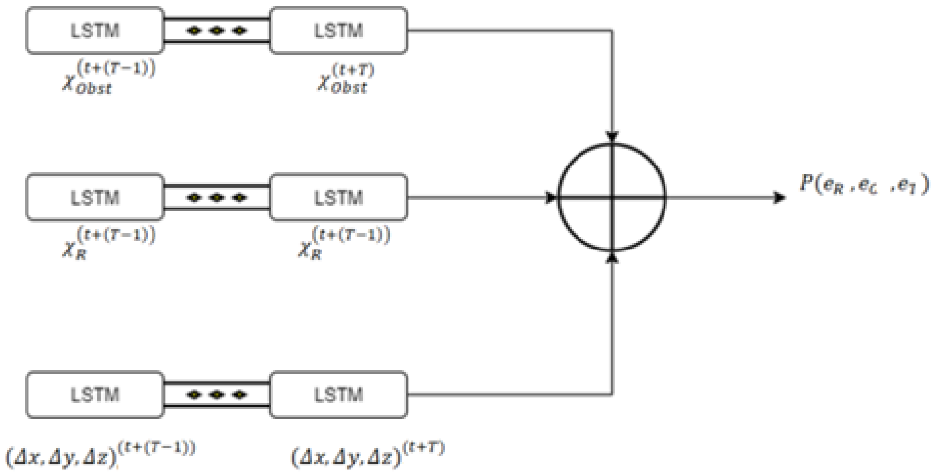

Figure1. Deep Long short-term memory (LSTM) Model

IV. Results and Discussion

A fresh approach to estimating future stock prices is shown here. This technique uses Doc2Vec to learn from documents found on financial social media and to extract text feature vectors. The dimension of the text vectors is then reduced with the help of SAE in order to prevent a significant imbalance between the text characteristics and the financial data. In addition, in order to prevent random noise in stock price data from having an effect on the prediction model, we utilize the Haar wavelet transform to create denoised stock price timeseries data. This helps us avoid the influence that random noise may have. In the end, we forecast future stock values by combining the text characteristics with the financial variables and using the LSTM model. The suggested technique outperforms previous baseline methods in terms of the mean absolute error and root mean square error, according to the findings of the experiments.

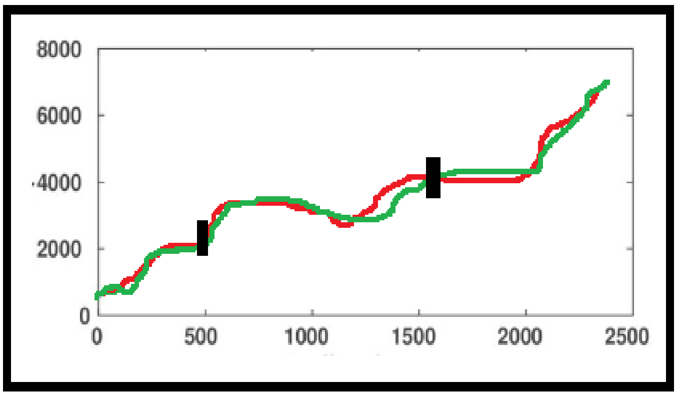

Figure2. Training results for Deep Long short-term memory (LSTM) Model

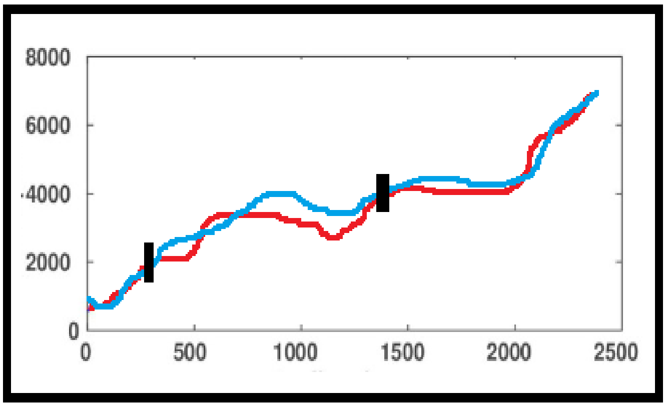

Figure3. Validation results for Deep Long short-term memory (LSTM) Model

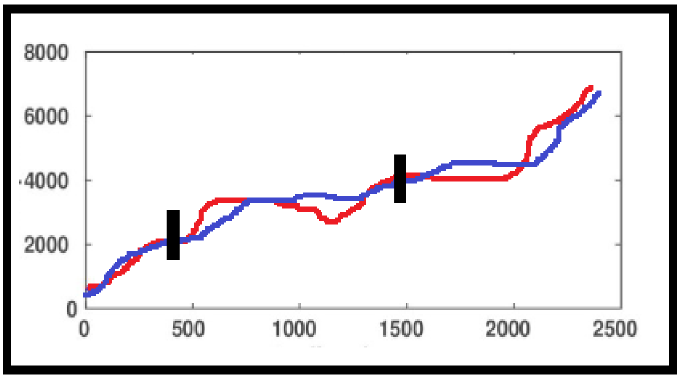

Figure4. Testing results for Deep Long short-term memory (LSTM) Model

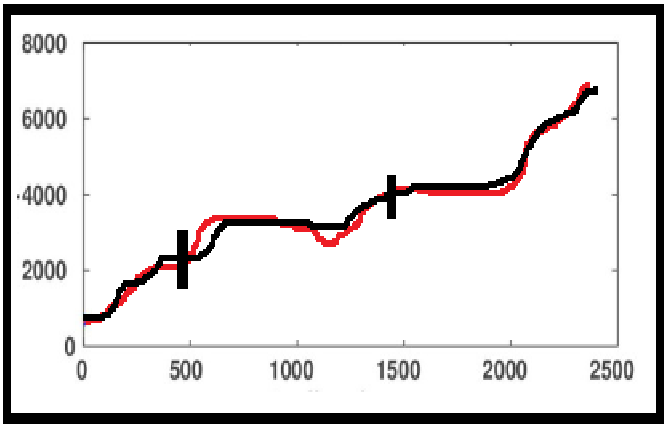

Figure5. Final prediction results for Deep Long short-term memory (LSTM) Model

The standard deviation of the residuals is referred to as the root mean square error (RMSE) (prediction errors). The residuals provide a quantitative representation of the degree to which the data points deviate from the regression line. The root-mean-square error, abbreviated as RMSE, is a measure of how these residuals are distributed. To put it another way, it gives an explanation of how the data tend to cluster around the line that provides the best fit. In addition to that, it is the square root of MSE. As the RMSE values decrease, the performance becomes more favorable. It should be low since it measures more mistakes than the other metrics do, therefore it can't be very accurate. If the model has a score of RMSE that is more than 0.5, it shows that the model is not very good at accurately forecasting the data. When the RMSE score is between 0.5 and 0.3, the model will make more accurate projections of the upcoming data.

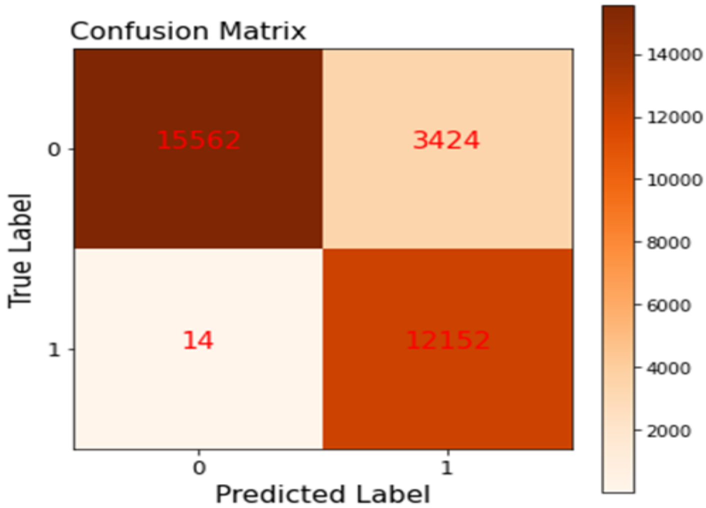

Figure6. Confusion Matrix for DLSTM Model

The mean absolute error (MEA), which does not take into consideration the direction of a mistake, is a measurement that determines the typical magnitude of errors across a set of forecasts. When determining the average absolute difference between the forecast and the actual observation, the weight that is given to each individual difference in the calculation is the same. The most important thing that it does is determine the difference between the actual values and the anticipated values. Let's assume that the MEA value is 5, and that the actual value is 20, whereas the projected value is 25. On the other hand, MAE does not penalize incorrect predictions.

	precision	recall	f1-score	support
0	0.81	0.89	0.85	18986
1	0.80	0.68	0.74	12166
accuracy			0.81	31152
macro avg	0.81	0.79	0.79	31152
weighted avg	0.81	0.81	0.81	31152

Figure7. Result Parameters for DLSTM Model

V. Conclusion:

The modelling of the sampling process, which was a difficult topic in stock market prediction, was the most important contribution that we made. The process of picking the testing and training datasets was another difficult challenge. When developing the model that is used to forecast what would happen in the stock market, the Deep LSTM algorithm was employed as the basis for the construction of the model. The forecasts that this model has made on the stock market have shown to be rather accurate. As a direct outcome of this research, two innovative approaches that make accurate forecasts of the stock market have been established. In this case, the deep LSTM classifier is altered so that it can make accurate predictions about the stock market. In addition, the deep LSTM is trained by using the deep LSTM approach that is given, with the efficiency of adaptive learning rates, and it employs step size and sparse gradient factor in order to estimate hyperparameters. The deep LSTM algorithm proved successful in achieving this goal. By making use of the projections that have been made about the stock market, investors may increase their capacity to make judgements regarding investments in stocks that are right for them.

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