FORECASTING OF STOCK MARKET TRENDS USING NEURAL NETWORK TECHNIQUES

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ABSTRACT

The task of predicting future value of company stocks accurately is Stock Market prediction. Successfully estimating the future price of a stock will result in great profit. In this paper, we explore different kind of non-linear models for predicting the stock behavior. We would be implementing three popular algorithms for stock prediction namely – convolution neural network (CNN) using 1d convolution, Long Short-Term Memory (LSTM) and the recurrent neural network (RNN) to gain profits by buying shares which have the potential to be sold at a much higher rate resulting in significant profit. At last, a comparison will be done between the three algorithms stated above to find out which among them was the most effective one and hence could yield a maximum profit when invested in a stock market.

Keywords: Convolution Neural Network, Recurrent Neural Network, Time Series Analysis, Logic Gates, Predictive Models, Forecasting, Data Models.

INTRODUCTION

Usually, stock prices prediction is very difficult and involves a series of algorithm for predicting the path that it is going to take in future and still some of the algorithms fail in showcasing the correct behavior. In this paper, we have used 3 algorithms - convolution neural network – 1 D convolution, long short-term memory (LSTM) and the recurrent neural network to predict the stock prices. We will be taking input as univariate data of a time series dataset using sliding window approach [1].

The time series data of the previous 30 min of closing rates of a particular stock are converted into vector and provided as input [2]. The change in price of the stock in the next few minutes is then predicted by our model [3]. The given three algorithms implemented will take up the input to predict the probable outcome if the algorithms used correctly predicts price ups and downs, by buying the stocks which are predicted to inflate and selling them in the next few minutes can help us get a great profit [4]. We will also be showing the variation of the expected behavior vs. the actual behavior. In order to have an idea of how much the algorithms were able to predict the correct behavior and also at last, a comparison will be done to find out which was the most appropriate method to do a stock analysis or prediction.

LITERATURE REVIEW

Prediction of some future event or happening through the previous records is done for a lot of applications; in our case it happens to be stock analysis which is very common

Citation Information: Neema, R; Rajkumar, R.; Shaik, D. A. & Masih, J. (2021). Forecasting Of Stock Market Trends Using Neural Network Techniques. *Journal of Management Information and Decision Sciences*, *24*(S3), 1–7.

nowadays. In stock analysis, we identify hidden patterns, trends and cycles by analyzing the time series data. Studying such patterns is very crucial in finding the fastest growing companies over a certain time period [5] Therefore, time series analysis and forecasting crucial areas of research.

The method used for the prediction of stock analysis is with the help of analysis of time series data. The algorithms used for this purpose are classified into two types, they are: -

Linear Models

Non-Linear Models

To fit a statistical model to the input stock data in time series format in the mathematical equation, different linear models use predefined equations. The sole drawback of linear models is that, they do not take latent dynamics present in the data into account whereas Non-linear models mainly utilize deep learning algorithms for predicting future stock prices [6]. Deep neural networks can direct non-linear functions by functioning as their non-linear approximates. The ideal deep neural network to be implemented in a scenario depends on the type of application. Multi-layer perceptrons (MLP), Recursive Neural Networks (RNN), Long Short-Term Memory (LSTM), CNN (Convolutional Neural Network) etc. are some of the most popular Deep neural networks [7]. They are very effective in several fields like image processing, natural language processing and time series analysis.

Deep learning algorithms are exceptionally strong, they have an intrinsic self-learning process which helps them in finding hidden insights and underlying patterns present in the data. The data generated from stock markets is massive and greatly non-linear. We require models that have the potential to analyze such dynamic data and find out valuable hidden patterns. The underlying patterns which are hidden in the data can be identified by deep learning techniques with the help of a self-learning process [8]. Deep learning algorithms perfectly fit the non-linear data generated by the stock markets and provide exceptional predictions by analyzing the data. In the time series, data is analyzed using several popular deep learning algorithms. In this we use a neural network model on a financial time series for the first time [9]. This attempt helps us understand how to decode the non-linear issues in stock market price changes for IBM using a neural network model. This work was confined; however, it is helpful in providing great points against EMH [10].

The future stock value was predicted by researchers by using various input variables for time series problems using NN models. In a few models, the inputs were data obtained from only one specific time series alone. Some of the works contained heterogeneous market information and other macroeconomic elements. NLP, along with financial time series analysis is used in. The financial time series are modelled using deep learning techniques. For predicting the Shanghai stock market, a new approach is used which consists of a NN model with technical analysis variables. This work is focused on showing the difference in performance between both the learning algorithm and both two weight initialization methods [11].

From the results we can see that using a conjugate gradient learning accompanied by multiple linear regression weight initializations will improve the effectiveness of back propagation.

Back propagation and RNN models were fitted to five different stock markets for predicting the future values of the stocks in 1996. In, various new methods like application of time delay, probabilistic and recurrent neural network models were incorporated for predicting the stocks on a daily basis [12]. S&P 500 stock market is predicted by applying various ML

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algorithms such as PSO and LS-SVM. Genetic algorithm and artificial neural network were used together for forecasting. In this work both of these models were combined. Genetic algorithm was used to calculate the weights of NN. Even by using such models, the final accuracy of prediction turned out to be low. Wavelets transforms were incorporated in the models for prediction [13]. These wavelets transform presents various short-term patterns in the stock market movements. The process of analyzing time series data became more productive by using LSTM, which has the potential to hold the information from the past. Such models are used and to predict the stock values [14].

MODELS

CONVOLUTION NEURAL NETWORK (CNN)

The initial step in the process of predicting stocks behavior involves building and using a CNN to obtain stock related information from previous day's data that can provide minute wise data for any specific stock. Data of stock value was converted into 1D-vectors consisting of past 30mins as the model requires us to use sequence of data. The inputs are provided to the model and its value after a particular time (for instance, 5 mins) is predicted, if the prediction says that the value of the stock will increase (decrease), the stocks are bought (sold) in the present and sold (bought) later (after 5 mins) which would eventually lead to a profit. NumPy array is used to create the vectors of the inputs provided to the model which are 30x1 matrixes of high and low values of stock for each 30-minute window.

Further in this project, the CNN is trained by using l^2 loss function. This approach is chosen as this particular function is ideal for regression related problems in the finance sector. However, in the future various other loss functions may be used for this problem. The l^2 regression along with the EUCLIDEAN LOSS layers is highly favorable for this model. The first network structure that researcher will be using for repeated convolution is –separable convolution with 32 filter and 5 kernel size followed by a convolution 1d and maxpool layer with pool size=2 and at last two fully connected layers.

$$L2LossFunction = \sum_{i=1}^{n} (y_{true} - y_{predicted})^2$$

L2 Loss Function

RECURRENT NEURAL NETWORK (RNN)

Predicting the movement of stock market indices is a commonly studied time-series learning problem. While previous studies rely on non-recurrent and shallow algorithms, deep RNNs are highly suited for sequential time series data as they share the same weights on several time steps and can easily extract important features from the feature set. Researcher will be implementing a 12-layer GRU on a benchmark dataset for predicting stock market movement achieving state-of-the-art status on the benchmark dataset when area under the ROC curve (AUC) is the evaluation metric.

RNN's are very good at keeping long term memories especially GRUs and LSTMs, using the memory storing mechanism of recurrent neural network to predict stock prices is one of the main focus of this project. The random sequences of input data are processed using RNNs by utilizing their internal memory. RNN has multiple computing units and each of them comprises of a real valued activation which changes with time and an adjustable weight. When

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similar sets of weight are applied by recursion over a graph-like structure, RNNs are created. The weights of the hidden units of an RNN are generally defined by using equation below:

$$h^t = f(h^{t-1}, x^t; \theta)$$

The input size of the model learned by using RNN always remains the same since it is defined with regard to transitions between states. At each step of the RNN architecture, the exact same transition function along with the same parameters are used [15].

LONG SHORT-TERM MEMORY (LSTM)

In 1997, Hochreiter and Schmidhuber developed a new type of RNN known as LSTM. Its architecture contains LSTM cells in the place of hidden layers. These cells regulate the flow of input with the help of several gates present in them. Each cell of an LSTM contains various gates such as input gate, cell state, forget gate, and output gate. Additionally, it also has a tan (h) layer, point wise multiplication and a sigmoid layer. The different types of gates and their purpose are mentioned below:

Input gate: Input is present in the input gate.

Cell State: It can add more data or delete existing data by using gates. It is present throughout the network.

Forget gate layer: Determines the amount of information to be permitted.

Output gate: The output produced by the LSTM is stored in this gate.

Sigmoid layer decides the fraction of each component to be allowed by creating numbers bounded by 0 and 1.

The state is updated with a new vector created by the tan (h) layer. The various outputs from all the gates decides the next state of the cell state. These gates can be denoted as mathematical equations as follows: -

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$$

$$c_t = \tanh(W_c.[h_{t-1}, x_t] + b_c)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(c_t)$$

Where xt, ht, ct, ft, it, ot are the input, output, cell state vector, forget gate vector, input gate and the output gate vector respectfully. The parameter matrix is denoted by W and b is its vector.

RESULTS AND DISCUSSION

Three different deep learning techniques were used to perform this experiment. Table 1, comprises of each model's highest error percentage for predicting future stock prices. CNN is clearly ahead of RNN and LSTM models in terms of accuracy from the table. Using CNN results in higher accuracies as it only uses the present window and does not consider any past information for making predictions. The dynamic movements and patterns going on in the present window are understood by the CNN model. Whereas the RNN and LSTM models depend on the previous information to make predictions. This quality causes these models to fail to fully understand the current changes and movements in the erratic and unpredictable

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stock market which results in poor learning by these models about the current window which is crucial for prediction.

TABLE 1
EACH METHOD AND THEIR ERROR PERCENTAGE

METHOD	ERROR PERCENTAGE
CNN	2.36
RNN	3.90
LSTM	4.18

FIGURE 2
PREDICTION OF S AND P USING RNN

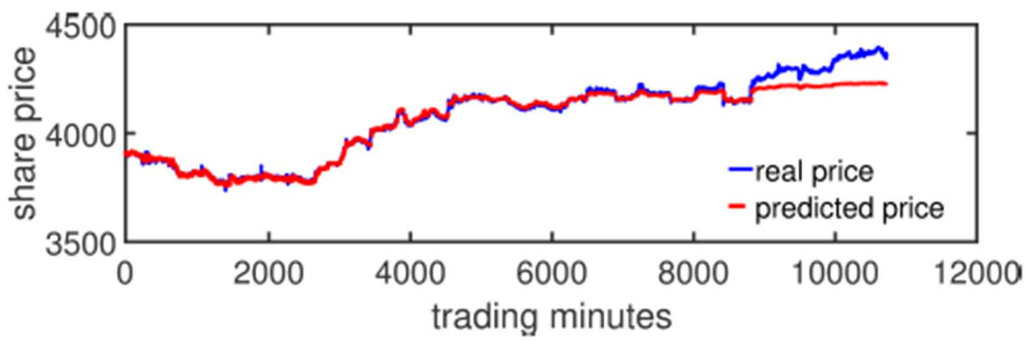
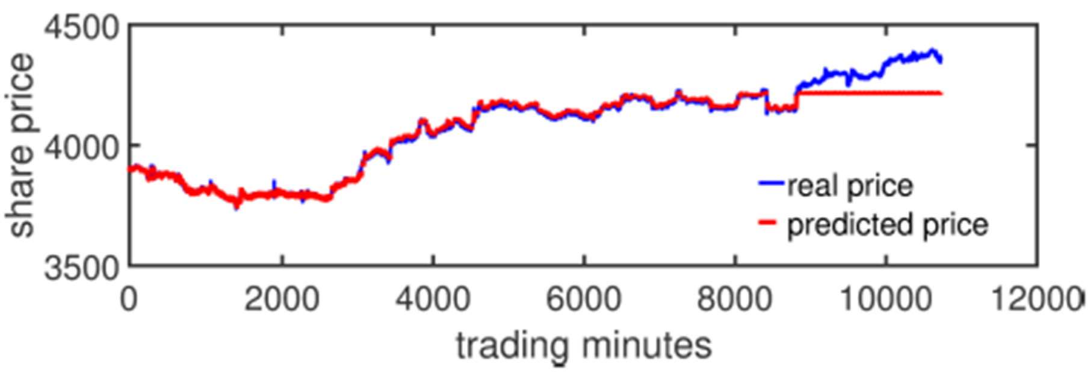


FIGURE 3
PREDICTION OF S AND P USING LSTM



1532-5806-24-S3-114

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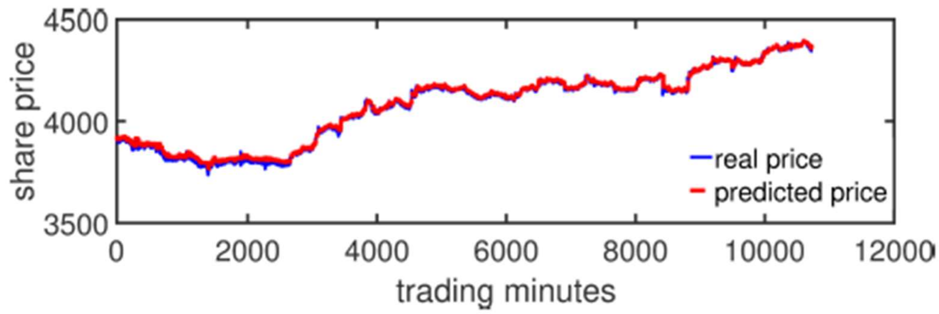
FIGURE 4
PREDICTION OF S AND P USING CNN



RNN and LSTM models perform very poorly in the 9000-to-11000-time frame as they cannot recognize the dynamic changes in trend which can be seen in Figure 2 and Figure 3. This happens because this particular time period has a drastically different pattern relative to the previous patterns. From Figure 4, we can clearly make out that CNN model excels in catching the variation in trends between 9000 and 11000 time period.

CONCLUSION

From the experiment we can conclude that CNN outperforms all the other models. It learns from the real time data and captures the dynamic changes in trends and predicts the future value accurately. RNN and LSTM are used in several other scenarios and perform well where time dependent data is involved, however they tend to fail in this case and are easily beaten by the CNN model. This happens as the stock market is highly unpredictable with its sudden variations in trends. The dynamic movements in the stock market never tend to follow a particular cycle or a pattern which makes them very erratic. The time period of the variations and cycles depends on various factors such as the companies' financial condition and the general market. Analyzing these fashions and patterns will help gaining significant profit. To analyze such information, we must use networks like CNN as they rely on the current information.

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