DEEP LEARNING MODELS FOR NSE STOCK MARKET PREDICTION

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ABSTRACT

One intelligent data mining technology that has been used by researchers for the past ten years in a variety of fields is the neural network. In today's economy, stock market data analysis and prediction play a crucial role. The diverse algorithms employed for predicting can be divided into non-linear models (ARCH, GARCH, Neural Network) and linear models (AR, MA, ARIMA, ARMA).In order to anticipate a company's stock price based on existing historical data, we employ four different types of deep learning architectures in this paper: Multilayer Perceptrons (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). Here, the National Stock Exchange (NSE) of India and the New York Stock Exchange's day-by-day closing prices are being used.The network was trained using the NSE stock price of a single firm and was able to forecast the stock prices of five different NSE and NYSE companies. It has been noted that CNN performs better than the other models. Despite having been trained on NSE data, the network was nevertheless able to forecast for NYSE. This was made feasible by the internal characteristics that both stock markets have in common. When the findings were compared to the ARIMA model, it was found that neural networks were performing better than the linear model that was previously in use (ARIMA).

Keywords: Artificial Neural Network; Deeplearning; Mean Absolute Percentage Error; National Stock Exchange ;New York Stock Exchange.

1. Introduction

Initial Public Offerings (IPOs) bring new issues to the market in the primary market. Investors exchange securities they already hold on the secondary market. The time series data for the stock market is very erratic and non-linear. A set of data collected over time to determine the state of an activity is called a time series [6]. For stock market forecasting, linear models like AR, ARMA, and ARIMA have been employed [9][10]. The sole issue with these models is that they are only effective with specific time series data; for example, a model designed for one corporation may not work effectively for another.Compared to other industries, stock market forecasting carries a greater degree of risk because of the stock market's ambiguous and unpredictable character. It is among the main causes of the difficulties in predicting the stock market. This is where deep learning models are applied to financial [4] predictions. The usage of neural network design in deep learning models gave rise to the moniker "deep neural network." Another name for it is ANN. ANNs are capable of learning from experience and making generalizations, making them good approximators. The following qualities make ANN practical implementation in forecasting situations quite successful: ANN has been utilized for stock market prediction for the last few decades. As we can see in [1], comparison studies of various DL models for stock market prediction have already been conducted. Coskun Hamzacebi has experimented with directive and iterative approaches to forecasting [6]. Rout et al., Ajith Kumar, used a low complexity. Recurrent neural network for forecasting the stock market [7]. Using a given stock market input parameter, Yunus Yetis et al. used artificial neural networks (ANN) to predict the value of NASDAQ's (National Association of Securities Dealers Automated Quotations) stock [12]. Back propagation and RNN were used by Roman et al. to analyze multiple stock market returns [13]. In order to predict a company's stock value, Neini et al. conducted a comparison study between Elman Recurrent Network and Feed Forward MLP [18].Neural networks were used by Mizuno et al. in technical analysis as a predictionform [15]. A study on the efficacy of ANN in stock market forecasting was carried out by Guresen in 2011 [19]. They investigated the relationship between stock volume and price on a particular basis in [20].Quantity of nifty 50 listed businesses. Batres-Estrada provides an explanation of the various uses of DL models for time series analysis in [21]. A study on the combination of financial time series analysis and natural language processing (NLP) was carried out by X Ding et al. in [22]. For stock market prediction, they employed machine learning (ML) techniques like Particle Swarm Optimization (PSO) and Least Square Support Vector Machine (LSSVM) in [23]. Kim et al. presented an alternative method for stock market forecasting in [24]. To forecast stock prices, they introduced a Genetic Algorithm (GA) for discretizing features in ANNs.discusses wavelet transform and multi-stage fuzzy inference in [25].

2. A COMPUTERIZED NEURAL NETWORK

A computational structure called an artificial neural network (ANN) [16] functions similarly to biological neurons [8]. Its purpose is to use data to find an underlying trend and draw generalizations from it. As a non-linear statistical data tool, ANNs are regarded as such [2]. ANNs can be used to model the complex relationship that exists between inputs and outputs. The primary advantage of artificial neural networks (ANNs) is their ability to identify underlying patterns in data, an area where most traditional methods fall short [3]. Three layers typically make up an ANN: the input layer, the hidden layer, and the output layer. Except for the input layer, all nodes in hidden and output layers use non-linear activation functions. Every neuron in the subsequent hidden layer is connected to every node in the input layer.

2.1. NEURONS

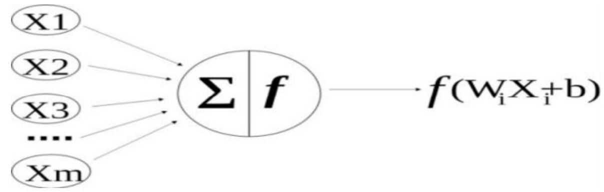

Fig. 1. Artificial Neuron

An artificial neuron, which is a basic processing unit modeled after a biological neuron, is depicted in the above figure [1] . A weighted link (wi) connects each of the neuron's'm' inputs (xi) to the neuron. Here, the neuron uses the equation below to add up the inputs multiplied by the weights.

A = Σ xiwi + b

Where A is the net sum and b is the threshold value.For getting the output this net sum is applied into a function called activation function F(A).

Output = F(A)

Here the input values and weights are real numbers. In some situations, the threshold value b is considered as an imaginary input x0 = +1 and a connection weight w0 for the simplicity of computation.

2.2. FEED FORWARD NETWORK

A basic neural network is the feed forward network [11], commonly referred to as MLP. Via a weighted matrix wki, each input neuron is connected to the neurons in the hidden layer that come after it. Three layers make up a network: input, hidden, and output layers [8]. The neurons found in the hidden and output layer [8], also referred to as [17], are artificial neurons. These neurons all receive inputs from a layer above. Neurons within the network are linked to neurons in the subsequent layer, but not to neurons within the same layer. Formula for activation function [14] of an ith hidden neuron is given by

$$h_i = f(u_i) = f\left(\sum_{k=0}^{K} w_{ki} x_k\right)$$

hi : ith hidden neuron , f(ui) : link function which provides non-linearity between input and hidden layer ,wki : weight in the (k, i)th entry in a (K X N) weight matrix , xK : Kth input value

$$y_j = f(u'_j) = f\left(\sum_{i=1}^{N} w'_{ij} h_i\right)$$

y j : jth output value

2.3. RECURRENT NEURAL NETWORK

RNN [18], in contrast to MLP, receives input from two sources: the past and the present. To determine how they respond to the new set of data, information is gathered from these two sources. A feedback loop, whose output at each instant serves as an input for the following moment, helps achieve this. It can be stated here that the recurring. A neural network is memory-based. Every input sequence contains a wealth of information, which recurrent networks store in their hidden state.

2.4. LONG SHORT-TERM MEMORY

One kind of RNN is called LSTM [19]. These networks can pick up on long-term dependencies with ease. In 1997, Hochreiter and Schmidhuber presented it. Although these networks are obviously made to avoid the issue of long-term dependency, they typically retain information for extended periods of time.

3. Methodology

3.1. DATASET 1

The dataset is derived from actively traded stocks in three distinct industries: the automotive, banking, and information technology sectors on the NSE. The stocks that correspond to these sectors are HCLtech, Axis Bank, and Maruti. Information such as the stock symbol, stock series, date of the previous closing, opening, high, low, last, closing, and average prices, total traded quantity, turnover, and number of trades are all contained in each. We only extract the day-by-day closing price of each stock from these datasets because it is the most preferred method for investors to make decisions about which stocks to purchase or forgo based on the market's closing price.ASSISTANCE. TATAMOTORS, a training dataset from the automotive industry, is used. The training dataset includes the closing price for 4861 days and spans the dates 1 JAN 1996 TO 30 JUNE 2015. The range of the training set is 58.79 - 1365.15. After being extracted, the data range between 0 and 1 was unified by normalization. To put all stock data into a single range, normalization of the data is performed. We require the data to fall within a common range because we are utilizing stock data from various markets. The equation was utilized in this procedure. x norm = (x − x min) / (x max − x min) (7) where x norm is the normalized value, x min and x max is the minimum and maximum value in the training dataset. This normalized data was given as the input to the network in a window size of 200 to predict 10 days in future. And the output from the network was subjected to a De-normalization process for acquiring original predicted values. The training of network was done for 1000 epochs. The window size was fixed by performing error calculation on each window size which varies from 50 to 250. Among this, the window size of 200 resulted minimum error than other window sizes.

3.2. DATASET 2

We attempted to predict the model using NYSE stock data in order to confirm whether the models identify the common dynamics between different stock exchanges. The information comes from Yahoo Finance. The two most actively traded stocks on the New York Stock Exchange that we have chosen are Chesapeak Energy (CHK) and Bank of America (BAC). The dataset's time span was from January 3, 2011, to December 30, 2016, and it was expressed in US dollars. We only extracted the day-by-day closing price from the dataset.

4. RESULTS AND DISCUSSION

Here, we've conducted an analysis using data from the NSE and NYSE stock markets. We had employed four different kinds of deep neural networks—MLP, RNN, LSTM, and CNN—for this. Tata Motors' NSE data, which is part of the automotive industry, was used to train each of these networks. Additionally, these networks were tested using information from the NYSE and NSE. We select data from the IT, finance, and automobile sectors for the NSE, and the financial and petroleum sectors for the NYSE.We have utilized the ARIMA model, a linear model, to compare linear and nonlinear models.

5. CONCLUSION

Four DL architectures were employed in this study to predict the stock prices of the NSE and NYSE, two distinct top stock markets globally. Here, we used the TATA MOTORS stock price from the NSE to train four networks: CNN, RNN, LSTM, and MLP. The resulting models were utilized to forecast the stock prices of CHESAPEAK ENERGY (CHK) and BANK OF AMERICA (BAC) from the NYSE as well as the stock prices of MARUTI, HCL, and AXIS BANK from the NSE stock market. It is evident from the outcome that the models are able to recognize the patterns that are present in both stock markets. This demonstrates that the two stock markets share underlying dynamics.Since linear models like ARIMA predict time series in a univariate manner, they are unable to reveal underlying dynamics in a variety of time series. We can infer from the outcome that DL models outperform ARIMA models. Because a specific window is used to predict the next instant, CNN has outperformed the other three networks in the proposed work, capturing abrupt changes in the system. The benefits of using a hybrid network, which combines two networks to create a prediction model, have not been examined in this work.

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