Stock Price Prediction Using Deep Learning

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Abstract : Short-term price movements are highly volatile and unpredictable in nature and they challenge investor capital utility in the securities market. Accurately predicting the price variations in stock market has a extensive economic advantage. This can be achieved by fundamental analysis, which involves the study of company performance based on reports published in the public domain. However fundamental data is published once every quarter making short term decision making impossible. Another method, which is undergoing a lot of research work, is to create a predictive algorithmic model using machine learning. This method utilizes the technical analysis as a basis for decision making where Deep Neural Networks are utilized to develop a short-term prediction model. The paper discusses the features and methods that can be utilised in implementing Feed Forward Neural Networks and Recurrent Neural Networks. In future the various approaches could be enhanced to achieve higher levels of accuracy and profitability.

***IndexTerms* - Deep Learning, Artificial Neural Networks, Multilayer Perceptron, Stock Price Prediction, Technical Analysis.**

I. INTRODUCTION

As of late estimating stock prices is increasing in more consideration, perhaps in view of the way that if the prices are effectively anticipated the traders might have proper direction while taking decisions. The profit returns realized from stock markets heavily depend on market analysis. If by any chance any framework be created which can reliably forecast the prices of the dynamic securities exchanges, it would make the proprietor of the framework well off. Moreover, such predictions will assist the controllers of the market in planning restorative measures in extreme cases.

Another inspiration for this research work is that it has numerous hypothetical and test challenges. One such critical hypotheses is the Efficient Market Hypothesis (EMH)[1].The hypotheses cities that in a proficient market, stock prices completely reflect accessible data about the market and its constituents and hence any chance of acquiring over abundance benefit stops to exist. However, there exists a counter postulate called Inefficient Market Hypothesis (IMH), which presents that monetary markets are not constantly productive, the market is not generally in a random walk, and inability exists[2].

Numerous scientists and specialists have proposed many models for stock price prediction, utilizing different fundamental, technical and analytical methodologies. Fundamental analysis includes the comprehensive reasoning in terms of extrinsic macroeconomic factors to address the changes in stock prices. The examination of the financial variables is subjective as the elucidation absolutely lays on the intelligence of the analyst. On the other hand, technical analysis fixates on utilizing value, volume, and other financial factual graphs to foresee stock developments. The preface to technical analysis is that the greater part of the intrinsic and extrinsic elements, which influence a market at any instance of time are already calculated into the market's cost[3].

With the hope of predicting markets movements, utilization of neural networks in securities exchange forecasting problems is extremely encouraging because of some of their exceptional qualities.

Firstly, neural networks exhibit striking capacity to extract context from convoluted or estimated information. They are utilized to derive patterns and determine trends that are too convoluted to be in any way be comprehended by either humans or other conventional computer processes.

Secondly, neural networks exhibit a nonlinear nature and are favored over the conventional linear models.

Thirdly, a neural network trained to a specific dataset of a specific domain; can be effortlessly re-trained to another condition to forecast at similar level of conditions. Also, when the framework in review is continuously changing and updating, neural networks have the capability to accordingly alter their weights.

Stock market in itself is a highly non-linear, perplexing, dynamic and perpetually evolving framework. Neural networks, with the majority of their, aforementioned features, are the ideal answer for forecasting price of stock market.

II. METHODOLOGY

Multilayer Perceptron (MLP)

The multilayer perceptron is a sort of artificial network which uses forward propagation. An MLP consists of at least three levels of nodes: an input level, a hidden level and an output level. Each node has a neuron that uses a non-linear activation function except for the input nodes. Backpropagation, a supervised learning technique, is used by MLP for training. MLP is differentiated from a linear perception in its multiple layers and nonlinear activation .It is possible to distinguish data that can not be separated linearly.

If a multilayer receptor has a linear activation function in every neuron then linear algebra indicates that any number of levels can be decreased to an input of two output model layers. In MLPs, some neurons use a non-linear activation function that has been advanced to model the frequency of action possibilities, or activation, of biological neurons.

MLP consists of three or more levels (one of input and one of output with one or more hidden levels) of non-linear activation nodes. Because the MLPs are completely connected, every node in a layer connects with a certain weight to every node in the next level. Learning occurs in the perceptron when connecting weights are altered after every piece of data is refined, based on the quantum of the lapse in the outcome compared to the anticipated result.

Learning occurs in the perceptron when connecting weights are altered after each piece of data is processed, based on the quantum of lapse in the output compared to the expected result. This is an case of supervised learning, and is done through backward propagation, a conclusion of the average least squares algorithm in linear perception.

Long short-term memory (LSTM)

Long-term memory units (LSTMs) are units of a recurrent neural network (RNN). An RNN composed of LSTM units is generally called an LSTM network. A common LSTM unit consists of a cell, an entrance door, an exit door and a forgotten door. The cell remembers the values at arbitrary time intervals and the three ports coordinate the flow of information that enters and leaves the cell. There are considerable LSTM unit architectures. A common architecture consists of a memory cell, an entrance door, an exit door and a forgotten door.

An LSTM cell takes an entry and stores it for a period of time. This is identical to applying the identity function (f (x) = x) to the input. Because the derivative of the identity function is consistent, when an LSTM network is trained with backward propagation over time, the gradient does not disappear.

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The function of activating LSTM ports is usually the logistic function. Naturally, the input gate dominates the extent to which a new value flows into the cell, the forgotten gate dominates the extent to which a value remains in the cell, and the output port dominates the extent to which the value in the cell is used to calculate activation of the LSTM unit output.

III. DATA

The complete snapshot of the market data of all the tools is available on websites such as Yahoo Finance and Google Finance. It includes the Volume, OHLC and Open interest fields and the complete depth of the supply / demand market, among others.

3.1 OHLC

An Open-High-Low-Close (OHLC) is a type that is normally used to illustrate movements in the price of a financial instrument over time. Each vertical row in the table shows the price range (the highest and lowest prices) in a unit of time, such as a day or an hour. Verification signs project from each side of the line indicating the correct opening price. Bars can be displayed in different tones depending on whether prices have increased or decreased during that time.

3.2 Volume

In capital markets, trading volume or volume, it is the quantity (total number) of a value (or a certain set of values or an entire market) traded over a given period of time.

The average volume of a guarantee over a longer period is the total amount negotiated during that period, divided by the duration of the period. Therefore, the unit of measurement for the average volume is represented by shares per unit of time, generally per trading day.

3.2 Market Depth Market Depth

The depth of the market is where you can get the best five offers and offers / requests for a particular tool. If we consider that markets are driven by supply and demand, this has a very important effect on market fluctuations.

IV. FEATURES

Technical indicators, also known as "technicals", concentrate on historical trading data, such as price, volume, and open interest, rather than the fundamentals of a enterprize, like earnings, revenue, or profit margins. Technical indicators are commonly used by active traders, since they're designed to evaluate short-term price movements, but long-term investors may also use technicals to determine entry and exit points.

4.1 Trend Type

These indicate whether the price is bullish or bearish and consist of moving average(short), moving average(long), exponentially weighted moving average(EWMA) and moving average deviation rate(MAD).

Moving Average (SMA)

A moving average is a extensively used indicator in technical analysis that helps ease out price action by refining out the “noise” from random price variations. Simple moving average (SMA), which is the simple average of a stock over a prescribed number of time periods.

Exponential Moving Average (EMA)

The exponential moving average (EMA), which gives greater value to more recent prices. The most common applications of moving averages are to determine the trend change, and to determine support and resistance levels.

4.2 Oscillator Type

These indicate the possibility of turnaround of an ongoing trend. This type includes indicators like moving average convergence/divergence(MACD), rank correlation index(RCI) and relative strength index(RSI).

Moving Average Convergence Divergence (MACD)

Moving average convergence divergence (MACD) is a trend-following momentum indicator that displays the association between two moving averages of prices. The MACD is computed by subtraction of the 26-day exponential moving average (EMA) and the 12-day EMA. A nine-day EMA of the MACD, termed the "signal line", is then displayed above the MACD, working as a trigger for long and short signals.

Relative Strength Index (RSI)

The Relative Strength Index - RSI is a momentum indicator that calculates the significance of recent price differences to evaluate overbought or oversold conditions. It is primarily used to attempt to determine overbought or oversold positions in the exchange of an asset.

4.3 Momentum

The impulse calculates the amount of rise or fall in stock value. From the perspective of the trend, momentum is a very crucial indicator of strength or weakness in the price of the security. History indicates that the momentum is much more useful in growing markets than in those in decline; The fact that markets rise more usually than they fall is the cause for this. In other terms, bull trends tend to last longer than bear markets.

V. Conclusion

The aim of our research study is to help the create a deeper understanding about the various possibilities that can be used to create a dynamic predictive model using neural networks. This paper establishes a basic premise upon which researchers can further their exploration in the the field of stock market prediction.

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