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Stock Price Trend Forecasting using Long Short Term Memory Recurrent Neural Networks

Mahdi Ismael Omar, Mujeeb Rahaman
Department of Computer Science Engineering, Institute of Technology, Jigjiga University, Jigjiga, Ethiopia

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ABSTRACT

The prediction of future stock price trend using current and historical stock market data is a research problem for traders and researchers. Recently deep learning methods shown promising performance to extract meaningful information from the given large data. In this paper, we proposed a system to predict the next trading session close price trend from historical stock trading data using long short term memory (LSTM) method. This is a classification problem next trading session close price trend can be uptrend, downtrend, or sideways trend. We built an automated trading system using the results of our classifier. We experimented with the proposed trading system on the American index stocks. Our experimental results show that the proposed method outperforms the buy-and-hold and decision tree-based method.

Keywords : Deep Learning, Long Short Term Memory, Stock Market

I. INTRODUCTION

The prediction of the future price of the stock is a very lucrative task for everyone involved in the stock market trading and investment directly or indirectly as a monetary benefit is involved. The stock price movement is very noisy and mostly non stationary. Many uncertain factors govern the movement of the stock price including geopolitical tension, weather, etc. People are trying for many decades to predict the future price of the stock. Traditional approaches used for stock price prediction are classified mainly as technical analysis and fundamental analysis. The technical analysis is useful for short term stock price prediction and it is mostly used by traders. It provides indicators for prediction using various combinations of moving averages. Its prediction is based on the historical and current transaction data. It also includes candlesticks and candlesticks charts. The fundamental analysis is useful for long term stock price prediction. Investors use fundamental analysis for long term investment. The fundamental analysis uses financial reports, the company's management performance, growth opportunities, etc. to predict long term stock price trends.

The modern tool in the stock market is computer programming. Its use is two-fold, firstly it can be used for automation of a trading strategy and secondly it can use for the stock price trend prediction. Nowadays Algorithmic Trading is a buzzword, It is a computer program written to take a trading decision (Buy, Sell, or Hold) and execute that decision in stock exchange automatically [1]. The trading strategy, automated by the Algorithmic

Trading can be static or dynamic. In static one rule to take a trading decision is predefined. In dynamic one, the Algorithmic Trading agent dynamically generated the rule to take a trading decision based on the variation in the stock price trend.

The majority of the Algorithmic Trading strategies are based on the prediction. Machine Learning methods play a vital role in the prediction of the future stock price trend using a computer program. In the literature, almost all the Machine Learning methods including supervised, unsupervised, and reinforcement learning methods used for the stock price or trend prediction. Authors in [2] used the ARIMA model to predict the volatility of the Indian index stocks. Stock price trend predicted using four Machine Learning methods namely ANN, SVM, random forest, and Naive-Bayes by the authors in [3]. The authors in [4] predicted the direction of the index stock trend. Authors in [5] used the Q-learning method of reinforcement learning to find an optimal dynamic trading strategy.

Deep learning shown promising performance in many applications including computer vision, image processing, etc. [6], Long Short Term Memory (LSTM) is a type of deep learning method use for sequence prediction i.e. for time series data. The LSTM method also used for the stock price or trend prediction as stock market data is time-series data. The authors in [7] used the LSTM to predict the future stock price trend. [8] combined the LSTM with multiple GARCH-type models to forecast the volatility of the index stock. The [9] used LSTM to predict the volatility of the index stock S&P 500 and individual AAPL. The authors in [10] used LSTM to know the future stock price trend of the china stock market. The LSTM based trading strategy is proposed by the [11]. [12] proposed a hybrid model using an autoregressive moving average model, exponential smoothing model and recurrent neural network to predict stock returns. [13] proposed a trading agent using reinforcement learning and the LSTM method.

In this research work, we proposed a binary classifier to predict the next trading day's t + 1 close price based on the previous trading day's transaction details and the next trading day's t + 1 open price using the LSTM. We experimented with the proposed LSTM based classifier with various lookback period and obtained the optimal lookback period. We also proposed a novel trading strategy based on LSTM based classifier. We experimented with the proposed trading strategy on the American index stocks DJIA and NASDAQ.

The proposed trading strategy outperformed the benchmark trading methods viz Buy-and-Hold and Decision Tree-based trading strategies. The main contribution of our work is two-fold, firstly we obtained optimal lookback period for the LSTM method. Secondly, we proposed a novel LSTM based stock trading strategy that outperformed Buy-and-Hold and Decision Tree-based trading strategies in terms of the % accumulated return. The remaining portion of the paper organized as Section 2 describes the LSTM Network in detail; Section 3 described the proposed system in detail; the experimental data and experimental results explanation are in Section 4; lastly, Section 5 concludes the paper.

II. METHODS AND MATERIAL

This section describes the methodologies used in this research work which includes Long Short Term Memory (LSTM).

2.1 LSTM networks

The Recurrent Neural Network (RNN) uses to learn sequential patterns but has a problem of vanishing gradient. The LSTM is a version of the RNN, that does not have the problem of vanishing gradient [14]. It has a set of repeating memory modules, each having three gates. A typical repeating memory module having tree gates shown in Figure 1. The C_t is the memory module cell state, x_t is an input to the module, and h_t is an output of the cell or module. The forget gate governs which content of the cell forget, the forget gate value is calculated using the following equations.

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

The input gate decides which new content to be stored in the memory cell, this gate also finds new cell state C_t. The input gate output is computed using the following equations.

$$C_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (2)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (3)$$

The output gate used to compute the output of the cell using the following equations.

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (4)$$

$$h_t = o_t * tanh(C_t) \quad (5)$$

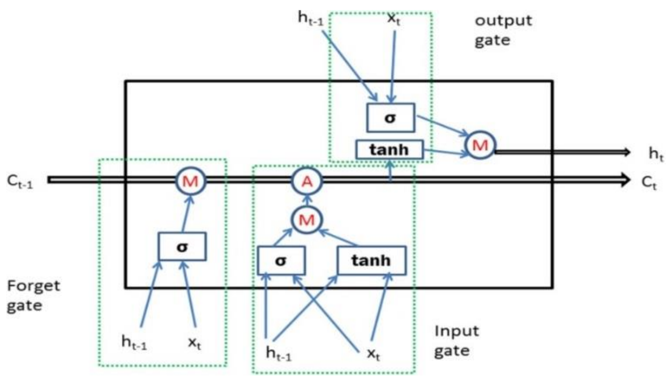

Figure 1 : A typical LSTM repeating memory module structure

III. PROPOSED SYSTEM

In this section, we proposed our proposed system using LSTM. Daily stock market data used for experimentation in this work. We have trained a binary classifier using LSTM to predict the next trading day's close price trend. A trading strategy based on the classifier's prediction developed to trade in the stock market. The experimentation performed on a single stock and only one trading action (Buy, Hold, or Sell) is permitted daily for simplicity. We experimented with the LSTM on different lookback periods ranging from 5 to 25. The transaction charges of 0.10% on Buy and Sell action are included in this study.

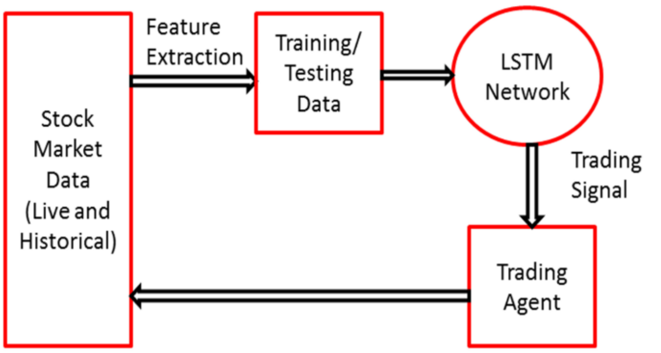

Figure 2: Proposed System

The proposed system is shown in Figure 2, the daily historical and live data is available in the form [Open, High, Low, Close, Volume]. We extracted some features from this raw data. This is a supervised learning problem, input features and output variable used to train and test the LSTM are described below.

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Input features

- Percentage variation of High price from Open price for the same day t.
- Percentage variation of Low price from Open price for the same day t.
- Percentage variation of Close price from Open price for the same day t.
- Percentage variation of High price from Low price for the same day t.
- Percentage variation of Open price on the day t from Open price for the previous day $t - 1$.
- Percentage variation of Open price on the day $t + 1$ from Open price for the day t.

Output variable

- Binary price trend (uptrend or downtrend) of close price on day t + 1 compare to the close price of the day t.

Close price of the day $t + 1$ is predicted based on the features derived from the price data of the day t and Open price of the day $t + 1$, the prediction is done at the opening of the trading day $t + 1$. In this way, training and testing data is generated. We divided the entire data in training and testing, 80% for training, and 20% for the testing. The LSTM classifier trained using training data. The classier output is trading signals (Buy, or Sell). We developed an algorithmic trading strategy based on the prediction result of the classifier, i.e. the Trading agent module shown in Figure 2. The trading agent takes a trading decision on the livestock market data.

IV. EXPERIMENTATION

This section describes in detail the experimental dataset and the experimental results.

4.1 Experimental Data

We experimented with the proposed system on the two American index stocks viz DJIA and NASDAQ. The Experimental data divided into training and testing data as indicated in Table 1 and Figure 3 shows the plots of the experimental index stocks. The experimental data fetched from Yahoo finance. The proposed system implemented using Python programming language, and Keras library used to develop the LSTM network.

Figure 3: Daily close price series for two experimental index stocks

Stock Name	Time	Total Period	Training Period	Testing Period
DJIA	Start	2010-01-01	2010-01-01	2018-07-06
	End	2020-07-30	2018-07-05	2020-07-30
NASDAQ	Start	2010-01-01	2010-01-01	2018-07-10
	End	2020-07-30	2018-07-09	2020-07-30

Table 1: Experimental Data of the American index stocks DJIA, NASDAQ

4.2 Experimental Results

Our experimental results are two-fold, first is the performance of the binary LSTM based classifier, and second is the performance of the trading strategy based on the prediction of the LSTM classifier. We experimented with the proposed classifier on different lookback sequence length ranging from 5 to

25. The accuracy of the classifier on the experimental dataset DJIA and NASDAQ on different lookback period showed in Table 2. Similarly, the average F-measure score indicated in Table 3.

Stock Name	Lookback				
	5	10	15	20	25
DJI	0.5508	0.5639	0.5639	0.4492	0.4568
NASDAQ	0.4229	0.5470	0.4229	0.4229	0.4229

Table 2: Accuracy of the proposed model on test dataset

Stock Name	Lookback				
	5	10	15	20	25
DJI	0.36	0.45	0.52	0.31	0.40
NASDAQ	0.30	0.46	0.30	0.30	0.30

Table 3: Average F-measure on test dataset

The performance of the classifier in terms of accuracy and F-measure score increases up to lookback period 15 and then starts degradation in the performance for a further increase in the lookback period for the index stock DJIA. Similarly lookback period 10 is optimal for the index stock NASDAQ. The performance of the classifier in terms of accuracy and F-measure score increases up to lookback period 15 and then starts degradation in the performance for a further increase in the lookback period for the index stock DJIA. Similarly lookback period 10 is optimal for the index stock NASDAQ.

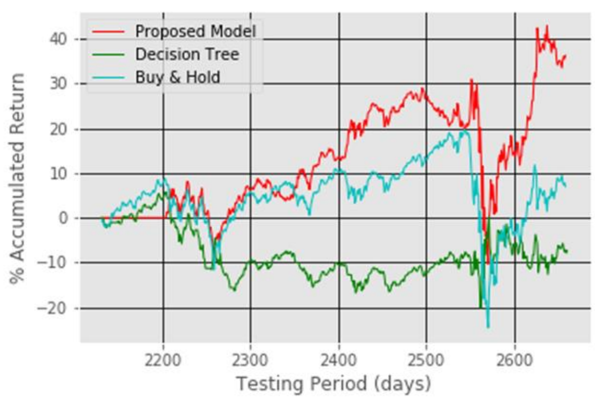

Figure 4: Performance of the three trading strategies on DJIA index stock on the test set in terms of percentage Accumulated Return

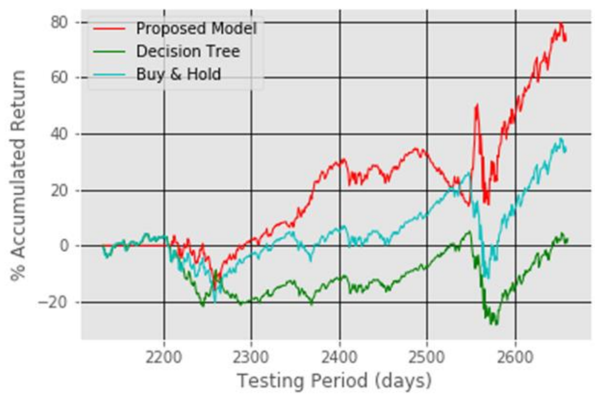

Figure 5: Performance of the three trading strategies on NASDAQ index stock on the test set in terms of percentage Accumulated Return

Stock Name	performance evaluation metrics	Buy-and-Hold	Decision Tree	Proposed Model
DJIA	Accumulated Return (%)	7.63	-7.49	36.28
NASDAQ	Accumulated Return (%)	35.48	3.13	73.17

Table 4: Performance of all three trading methods on two index stocks

We compare the performance of the proposed trading strategy based on LSTM prediction with the Decision tree-based trading strategy and Buy-and- Hold trading method. The performance of these trading strategies in terms of % accumulated return on DJIA depicted in Figure 4 and Figure 5 shows similar performance on the index stock NASDAQ. The proposed trading strategy outperformed the Decision tree-based and Buy-and-Hold trading strategies as indicated in Table 4 in terms of % accumulated return.

V. CONCLUSION

In this research work, we proposed a stock trading strategy based on the prediction of LSTM. We trained the LSTM to predict the next trading day close price trend (uptrend or downtrend) compared to the current trading day close price. Here the LSTM work as a binary classifier. We experimented with the proposed classifier by varying the lookback period from 5 to 25. Our experimental results on the American index stocks conclude that the lookback period of 10 to 15 is the optimal lookback range to train LSTM for stock price trend prediction.

We proposed the stock trading strategy based on LSMT. We compare the performance of the proposed trading strategy with the two benchmark trading methods viz Buy-and-Hold and decision tree-based trading strategies. Our pro- posed trading strategy outperformed the benchmark trading strategies in terms of percentage accumulated return.

We experimented with the proposed method on daily stock market data. In the future, the proposed method can be tested on stock market data of different frequencies such as weekly, monthly, even hourly.

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