Stacked Auto Encoder based Stock Price Prediction using Technical Parameters

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Abstract : Stock prediction is a type of time series prediction, which uses the time values to predict future values. For stock price or status prediction, historical time series data is used. As price of the stock varies over time, so, different techniques can be used to predict stock price and its behavior. In this paper, the proposed methodology is intended towards prediction of stock prices as well as behavior of the stock for investors whether to buy or sell the stock in order to get more profit and returns at lowest risk. In this research work, a deep learning approach is used to design an algorithm which is a basic hybridized framework of stacked deep auto encoder (SDAE) with random forest is formed to effectively predict stock market price from the historical dataset. Ten different technical indicators are extracted and used to predict stock price. Simulation results on different well-known stock market price like Adani Powers, BHEL, Reliance Industries, SBI, Infosys, etc stock exchange price are finally presented to test the performance of the established model. As result analysis shows that, the stock status is predicted more accurately with SDAE algorithm.

Keywords: Deep Auto Encoder, Stock Market Indices, Technical indicators, Stock Prediction.

1. Introduction

A stock price is that the price of one stock of a particular number of salable stocks of an organization, a by-product or alternative monetary asset. For the common person, the worth of the stock is that the highest amount that somebody is willing to get hold of the stock or the bottom amount that it will be purchased [1].

In economical and financial sector, research analyst analyzes the behavior of the stock price, exchange rates and commodity prices for long time for future investments. This observation assumes that investors act rationally and can hold the stock for future aspects. Apart from all these circumstances and evaluations, it provides efficient investment in the stock and new information seems to be randomly affect of the assets [2].

The researchers also observe that the price of stock also changes in stock markets from season to season or on some occasions. Generally, in month of January stock price fell more sharply as well as in week days on Monday stock price stock prices fell more sharply than all other days. Many stock market observers and experts note the effects in many different markets but didn't provide any explanatory and satisfactory explanation for consistency in the market [3].

Stock trading is the process for selling and buying of shares of any company or stock in exchange market with an aim for generating profitable returns. Like any other market, stock market is intended such that whenever any buyer wants to buy any stock at certain price, can buy the stock. Whereas, stock market also provide a platform for selling stock at offered prices. To provide a communicating channel between seller and buyer, a mediator caller broker is needed. All the transactions are mediated by these brokers at offered prices i.e. for buying and selling. Many firms are established for such transactions such as indiabulls, religare, hdfc securities, etc.

Brokers usually charge a commission fee for completed transactions (e.g., a set quantity for every transaction or a little proportion of the order total). Naturally, consumers wish to reduce the worth obtained the stock and sellers wish to maximize the selling price for the stock. The securities market is so ruled by identical elementary economic principles as the other economic market, particularly provide and demand [4].

Technical analysis uses most of the anomalies to extract info on future worth movements from historical knowledge. Viewed for long periods, the worth of the stocks is tied to the expectations of the company's future earnings and dividends. In brief periods, significantly for tiny and medium-sized enterprises, the quantitative relation between stock costs and dividends could also be terribly high [5,6].

The securities market forecast is an effort to see the future price of a listed stock or another monetary instrument. The positive forecast of the future worth of an action may generate a major profit. the belief of market potency suggests that stock costs replicate all presently accessible info and any worth changes that aren't supported new discovered information are thus inherently unpredictable. Others disagree, and those with this vision have numberless ways and technologies that ought to alter them to line costs within the future [7-9].

A lot of artificial intelligence methods have been developed and applied to forecast stock market indices, for instance, Artificial Neural Network (ANN, Support Vector Machines (SVMs), Rough Set Theory, Bayesian Analysis (BA)and K-Nearest Neighbors (KNN), Particle Swarm Optimization (PSO), Decision Tree (DT), and the evolutionary learning algorithms like Genetic Algorithm (GA).

2. Related Work

Lei [3] proposed an algorithm to improve the predictive ability of stock price developments based on Rough Set (RS) and Wavelet Neural Network (WNN). RS was introduced to reduce the size of the share price performance. On this basis, RS is reused to determine the WNN structure and obtain the stock price forecasting model. Finally, the model is used to predict the price course of the shares. Simulation results indicate that the structure of the WNN predictive model can be greatly simplified by reducing the RS attributes as the performance of the model improves. The direction of the symmetry values that predict that the ESS is compliant with the composite index, the CSI 300 index, the All Ordinaries, the Nikkei 225 index and the Dow Jones index, is 65.75%, 66, 37%, 65.97%, 65, 52% and 66.75%.

Bruno et al. [6] presented predictive system applications formed at pre-established periods without taking into account the new model updates. In this context, this study uses an automatic learning method called Regression Support Vector (SVR) to predict stock prices for large and small caps and in three different markets, where prices are used both days and at current frequencies. Forecasting errors are measured and the model is compared to the random walk model proposed by the EMH. The results suggest that SVR has predictive power, especially if a strategy is used to periodically update the model. There are also results indicative of greater forecast accuracy during periods of low volatility.

Salim Lahmiri [9] presented a model for predicting intraday stock prices, singular spectrum analysis (SSA) and regression vector support (SVR) associated with the optimization particle swarm (PSO) were used. In particular, the SSA divides the stock price series into a small number of independent components used as predictors. The SVR is applied to the predictive activity and the PSO is used to optimize the SVR parameters. The performance of our proposed model is compared to the power of four models that are widely used in financial forecasts: the wavelet transform (WT) coupled to the feedforward neural network (FFNN) mobile autoregressive media process (ARMA), polynomial regression (PolyReg) and naive model. Finally, the mean absolute error (MAE), mean absolute percentage error (MAPE) and the mean square root error (RMSE) are used as primary outcome measures. Through the application of all models of six times the intraday series price action, the simulation results show that the current SSA PSO-SVR classic WT FFNN, ARMA, polynomial regression and naive model in terms MAE, MAPE and RMSE far exceeds. Therefore, our proposed forecasting system SSA-PSO-SVR is a clear potential for the analysis of financial time series and forecast data.

Manas et al. [10] presented an intelligent and optimal market price forecasting model using the hybridization of the adaline neural network (ANN) and particle swarm optimization (PSO). The hybrid models associated with Adaline and PSO take into account the fluctuations of the stock market and use the OSP to optimize and update the weightings of the representation of Adaline to represent the open market price of the Bombay Exchange. The predictive power of the proposed model is compared with various representations such as interval measurements, CMS-PSO and Bayesian-ANN.

3. Methodology

In addition to minimizing the risks to equity investors, pricing strategies can also provide evidence of risk. Predictive studies, as presented here, help to develop cost-effective strategies, in particular risk-adjusted strategies, since greater predictability can affect the risk level of an investment portfolio. As a result, more accurate pricing forecasts can potentially provide investors with risk-adjusted returns.

The objective of this research work is to introduce a combined deep learning approach with technical indicators to predict future price of particular stocks.

The proposed methodology is performed as following:

- Data Extraction
- Finding Technical Indicators
- Predicting Closing Price
- Finding performance parameters for variable features with variable training and testing set.

A. Data Extraction

In order to perform modeling of stock market analysis, this paper collected historical datasheet for Technical feature extraction which is taken for different companies during year 2014-2018. Historical Dataset is taken from Yahoo finance website. For this simulation analysis 10 different companies historical dataset is created for three years i.e. from 2014 upto 2018. The dataset is acquired in order to predict the direction of any share or stock whether it will go high or low. All the available data is trained by supervised machine learning algorithm using stacked deep auto encoder (SDAE).

B. Technical Feature Extraction

Technical indicator is composed of data derived from the application of a certain formula to the past prices of a stock. In this research work 10 features are extracted for further analysis of proposed algorithm which is discussed in detail in previous section.

Moving Average Convergence Divergence (MACD)

Moving average convergence divergence (MACD) is used as an indicator that shows relationship between moving averages of stock prices. It is calculated as :

$$\text{MACD} = 26 - \text{day EMA} - 12 - \text{day EMA} \quad (1)$$

A signal line is plotted for nine-day EMA of the MACD functioning as a trigger for buy and sell signals.9-day MACD is allocated as a signal line which is used to buy and sell signal for any stock price.A sell (short) signal occurs when the MACD line crosses below the Signal line.A buy signal occurs when the MACD line crosses above the Signal line.

Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a comparison indicator between losses and recent gains and determines an overbought or oversold market. At time t, it has the form of Eq. 3.2. Typically, RSI is calculated over a 14 Day Period. The basic formula is:

$$\text{RSI} = 100 - 100/\,(1 + \text{RS}) \quad (2)$$

where, RS = (Average Gains) / (Average Losses)

For predicting stock position there are two lines i.e. 70 and 30.If the indicator is below 30, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above 70, then the asset is after a strong uptrend and could be overbought i.e. sell condition.

Momentum

One of the simplest oscillator is Momentum which is used to measure the frequency or intensity of price changes. For example, in ordet to construct a 10-day momentum line, simply subtract the closing price 10 days ago from the last closing price. The formula for momentum is:

$$M = V - Vx \quad (3)$$

Where V is the latest price, Vx is the closing price x number of days ago.

There is signal line plotted at 100 or zero line cross.If a stock is trending higher, only buy when the indicator falls below zero/100 line cross.

Simple Moving Average (SMA)

SMA is used to calculate the average price of stock over a period of time. The Simple Moving Average (SMA) is the arithmetic mean of T past prices C_i.

$$SMA = \frac{1}{t}\sum_{i=1}^{T} C_i \quad (4)$$

There are two basic signals in relation to the 200-day moving average. If the price is above the 200-day SMA this is a buy condition or long signal.If the price is below the 200-day SMA this is a sell condition or short signal.

Commodity Channel Index (CCI)

The CCI is used to compares the current mean price with the average mean price over a typical window of time periods.

CCI = (Typical Price- t-period SMA of TP) / (.015 x Mean Deviation) (5)

Where, Typical Price (TP) = (High + Low + Close)/3

Constant = .015

The indicator fluctuates between -200 and +200.If the indicator is below -200, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above +200, then the asset is after a strong uptrend and could be overbought i.e. sell condition.

Linear Regression Indicator (LRI)

The Linear Regression Indicator is used for trend identification and trend following, similar to a moving average. A trend line drawn with the linear regress always finishes with the LRI indicator point.

If/when the price closely approached the upper limit (max Value of LRI), then sell condition. If it is at the very bottom of the channel then buy condition.

Double Exponential Moving Average (DEMA)

The name double comes from the fact that the value of an EMA (Exponential Moving Average) is doubled. To keep it in line with the actual data and to remove the lag the value "EMA of EMA" is subtracted from the previously doubled ema. Double exponential moving average calculated as:

DEMA = 2*EMA-EMA(EMA) (6)

In DEMA two signal lines are plotted with time period 12 and 24.If output DEMA value is greater than both signal line then buy condition is established.Whereas DEMA value is lower than both signal line then sell condition is established.

Weighted Moving Average (WMA)

A Weighted Moving Average is calculated by multiplying each bar's price by a weighting factor. WMA is calculated as in equation 3.7.

$$WMA = \frac{PC_i + (P-1)C_{i-1} + \cdots + C_{i-P}}{P + (P-1) + \cdots + 1} \quad (7)$$

Where, P= Time period

C_i as either daily closing or up-to-the-minute prices

There are two basic signals in relation to the 200-day WMA. If the price is above the 200-day WMA this is a buy condition or long signal.If the price is below the 200-day WMA this is a sell condition or short signal.

Detrended Price Oscillator (DPO)

DPO is a technical indicator that uses displaced moving average in order to eliminate the long-term trends. This indicator is used to check the level of overbought and oversold efficiently.

$$\mathrm{DPO} = (\text{Price of } (n/2 + 1) \text{ periods ago}) - (n \text{ Period SMA}) \qquad (8)$$

Where, n = time period

Peaks in price are occurring look for sell/shorting signals that align with the stock price cycle.

Envelopes Trading Bands (ETB)

ETB is an indicator that is based on a simple or exponential moving average, and sets bands based on a set percentage deviation, thus creating envelopes. Envelopes define the upper and lower boundaries of a security's normal trading range. A sell signal is generated when the security reaches the upper band whereas a buy signal is generated at the lower band.

There are two signal lines termed as ETB lower line and ETB upper line.

ETB upper =Average of SMA+[Average of SMA *0.025].

ETB lower = Average of SMA-[Average of SMA *0.025].

If the indicator is below ETB lower, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above ETB upper , then the asset is after a strong uptrend and could be overbought i.e. sell condition.

C. Stock Price Forecasting

Data classification is the process of sorting and categorizing data into various types, forms or any other distinct class. Data classification enables the separation and classification of data according to data set requirements for various objectives. SDAE has been used in simulation experiments.

A stacked deep autoencoder is constructed by combining a stacked autoencoder, which comprises a desired number of cascaded autoencoder layers with a random forest classifier. For autoencoders networks, features learning phase is unsupervised since it's not using labeled data. The basic architecture of an unsupervised autoencoder is a move forward with an input layer, often one hidden layers and an output layer.

An autoencoder may be used for pre-training or for dimensionality reduction when the architecture takes the form of a bottleneck. For simplicity, consider an autoencoder with a hidden layer; autoencoder can then learn several levels of representations by stacking hidden layers. It is a features extraction algorithm; it helps to find a representation of data. The features generated by the autoencoders represent the data point better than the points themselves.

The layer of deep autoencoder contains input layer, hidden layer and output layer. It learns non-trivial features using a similar training strategy to that of a typical auto-encoder. An illustrated example of this is presented in Fig. 1. Hence, the deep learning power of SDAEs is combined with a shallow learning classifier. For shallow learning classifier, Random Forest is used as time series prediction of stock price.

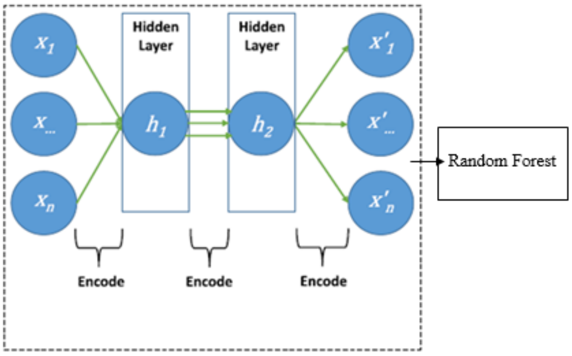

Figure 1: Stacked Deep Auto-Encoder with Random Forest Classifier

4. Performance Parameters

Mean Square Error (MSE)

MSE of any estimator (classifier) measures the average squares of errors or deviations, i,e. the difference between the estimator and what is estimated. MSE is a risk function corresponding to the expected value of the squared error loss.

$$MSE = \frac{1}{N}(Target_{value} - Obtained_{value}) \qquad (9)$$

Root Mean Square Error (RMSE)

RMSE is a parameter that determines the difference in squares between the output and the input.

$$RMSE = \sqrt{MSE} \qquad (10)$$

Mean Absolute Error (MAE)

MAE measures the average size of errors in a series of forecasts regardless of their direction. This is the average of absolute differences between prediction and actual observation, in which all individual differences are also weighted.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \qquad (11)$$

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a measure of the predictive accuracy of a forecasting method in statistics, for example in estimating the trend. It usually expresses the precision in percentage and is defined by the formula:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{Target_{value} - Obtained_{value}}{Target_{value}} \qquad (12)$$

5. Result Analysis

The result analysis is performed by analyzing the performance of Stacked Deep Auto-Encoders (SDAE). For evaluating the performance of this model, the stock market dataset for four years is taken and stock price is predicted for 30 days and 180 days. Further technical features are extracted from the dataset and finally dataset is divided into two groups i.e. training set as well as testing set. For performance analysis MSE, RMSE, MAE and MAPE are evaluated. As mentioned before, the evaluation parameters are mean square error (MSE) as well as root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The result analysis describes that out of 10 technical parameters which have impact on deciding stock price.

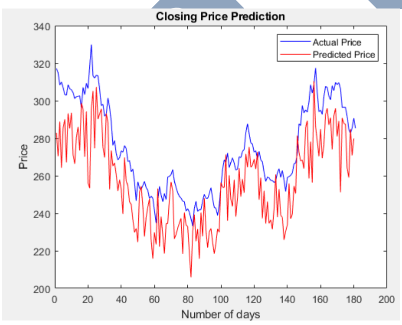

Figure 2: 180 days Ahead Price Prediction of Reliance Industries

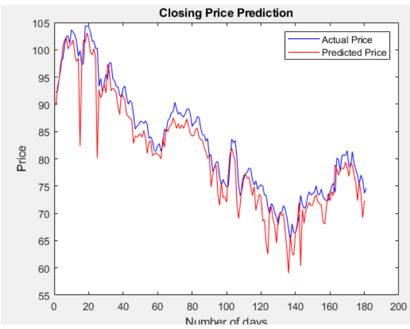

Figure 3: 180 days Ahead Price Prediction of SBI

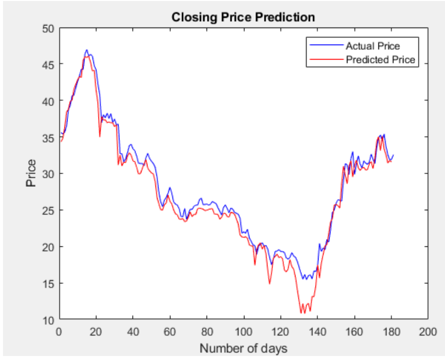

Figure 4: 180 days Ahead Price Prediction of Adani Powers

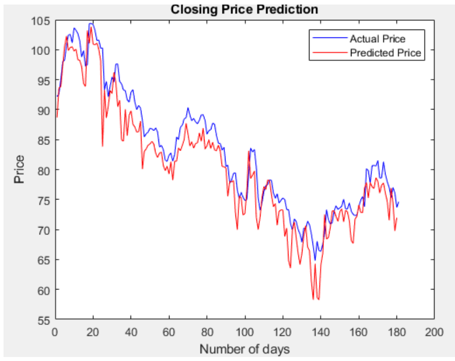

Figure 5: 180 days Ahead Price Prediction of BHEL

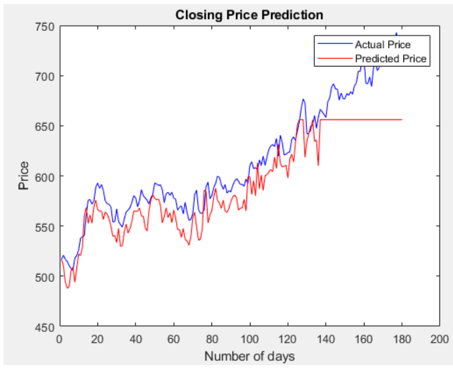

Figure 6: 180 days Ahead Price Prediction of Infosys

Whereas figure 2-6 shows the closing price prediction of the five different companies using proposed algorithm and from result analysis it is shown that the proposed algorithm outperforms better with respect to MSE, RMSE, MAE and MAPE parameters.

In this section, to analyze the performance of the proposed methodology are analyzed. In this case the stock price is predicted and RMSE and Accuracy parameters are evaluated and compared with existing works. Table I represents the comparison results of SDAE and PSONN are evaluated for stock closing price prediction. After result analysis it has been observed that proposed SDAE algorithm outperforms better with respect to MAPE and Accuracy.

Table I: Comparative Analysis for Stock Price Forecasting

Performance Parameters	Proposed	PSONN [39]
MAPE	0.02	1.1
Accuracy	99.382	98.9

6. Conclusion

The application of time series analysis and securities market forecasts is especially relevant for technical analysis, that uses historical values to get indicators that show attainable trends in share costs. In this research work, a hybridized framework composed of SDAE and random forest regression model is proposed and applied this framework to forecast stock market price. An important characteristic of this method is that the ten technical indicators are selected and classification using SDAE. This method has been compared with PSONN.

The results have led to following main conclusions:

1. Technical indicators are important factors for determining the long-term forecasting of the stock price. The proposed SDAE algorithm uses these features to determine whether to sell, buy or hold any stock.
2. On the basis of price forecasting the proposed algorithm can suggest whether to buy or sell any stock.

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