

An Intelligent-Hybrid Model for Pattern Detection to Predict Stocks Price Movement Direction

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Abstract: - In this paper, an intelligent-hybrid model for stocks price prediction is proposed. The model helps choosing the right investment action within a certain risk factor. It generates Buy, Sell or Hold signals based on the prediction of the market future direction. An intelligent hybrid fuzzy-neural multi-layer system is applied to generate the signal. The model increases the individual investors' local market understanding of market sentiments, breaking news and technical analysis expectations. An implemented system of the proposed model has demonstrated a promising performance of the applied test datasets containing 31 Stock Symbols over the past 9 years (January 2009-July 2018). The prediction accuracy of the model is computed by comparing the applied system predicted results against the actual results of the Egyptian stock market during the test period.

Key-Words: - Intelligent-Hybrid Model, Pattern Detection, Stocks Price Movement Direction, Kohonen self-organizing map, back propagation network, Fuzzy Logic.

1 Introduction

There are two main approaches for stock price prediction: fundamental and technical analysis. Fundamental analysis is a method to estimate intrinsic value of a stock by analysing various internal and external variables of a company. On the other hand, technical analysis is a method to find a pattern in the stock price fluctuations based on which investors can predict a future stock price [1].

The proposed model has to deal with huge data size, one record per tick, average 3 ticks per second. The average total records per day is $3 \times 60 \times 60 \times 8 = 86,400$ record, for a month 2,000,200 record. All these data will be: preprocessed, formulated, visualized, and analyzed. The model assumes that using Candlesticks pattern detection techniques can predict the trend of the financial time series by detecting certain patterns in the charts.

Using R-studio tools in the data preprocessing phase was very effective in the processes of:

- Prices data adjustments for stocks dividends, splits and elimination cases.
- Scaling, and chopping.
- Technical analysis indicators computation.
- Technical analysis patterns labeling.

This paper presents an intelligent hybrid model for stocks price movement prediction based on Artificial Neural Networks (ANNs) and Fuzzy Logic modules. The applied system of the proposed model is composed of 3 main modules; A Charting module, Sentiments web-based module and Signal module.

The Charting module provides the infrastructure needed for representing the stock price movements in various formats and applying different technical analysis techniques. Also, the Charting module represented the technical indicators, line studies and price representation styles (candlesticks, point and figure, etc.). The second part of the applied system is the Sentiments web-based module. It is a web-based solution that gathers the market sentiments from market audience and identifies whether the current market direction is Bullish or Bearish based on a predefined sentiment threshold. Finally, the Signal module which is a hybrid module consists of tradition pattern recognition techniques and a new intelligent module. The intelligent module used Kohonen's self-organizing neural network and a fuzzy-logic technique for candlesticks pattern recognition.

The paper is organized as follows: an overview of the related work in stock market price prediction then explaining the main features of the proposed system, and a representation of the system test results. Snapshots of the system outputs represented the test results. Finally, a conclusion about the current state and the future work that can be implemented to improve the system performance and accuracy, was added at the end of the paper.

2 Related Work

Turkish and Egyptian markets movements are tightly coupled so it was very helpful to study the

achievements that have been done in the Turkish stock market. [Şenol and Özturan] [3] applied advanced seven different prediction models combined in one system to predict the direction of the stock market index in Turkey. The study used a data set consists of more than 2000 records represents the daily closing prices of each stock in Istanbul Stock Index (ISE-30). The findings of this research showed that ANN model outperformed the other six used prediction models. The study claimed that ANN model can be a useful technique for prediction of the stock market direction, because it is capable of capturing unrealized relationships among the represented data even when it is hard to explain or describe it.

[Ajith, Baikunth and Mahanti] [4] introduced a Hybrid Intelligent Systems for Stock Market Analysis. The model applied a hybridized soft computing technique for automated stock market forecasting and trend analysis. The model used a neural network for one day ahead stock forecasting combined with a neuro-fuzzy model for analyzing the trend direction. The data set represented 24 months stock data for Nasdaq-100 main index as well as six of the companies listed in the Nasdaq100 index. The forecasting accuracy could have been improved if the model used individual neural networks customized for each stock instead of using a single generic network.

[Hepin, Chandima, and John] [5] presented a computational approach for predicting the Australian stock market index – AORD using multi-layer feed-forward neural networks from the time series data of AORD and various interrelated markets. A basic neural network with limited optimality was developed and achieved a correctness in directional prediction of 80%. The paper concludes that probability ensemble of neural networks is one of the most reliable directions for predicting stock markets direction.

Overall, these researches conclude that neural networks are suitable for use within trading systems, and that trading systems developed using neural networks can be used to provide economically significant profits.

3 A Kohonen's Self-organizing Maps Trading Model

The suggested model used Kohonen self-organizing map as part of its trading system. The Dataset contained 31 Stock Symbol continuous day trade. The period represented was over the past 9 years (January 2009-July 2018). Training set was 2/3

of the data set, and the remaining set was used for testing.

The total number of data points were 83700 values. Daily updates provided by a local data feed company were recorded for the period from March 1, 2009 till March 31, 2018. The statistics of the data is described as follows:

Mean = 0.309647

Standard deviation = .1553885

Maximum = .9201

Minimum = .1436

Figure.1. shows the graphical representation of the data set

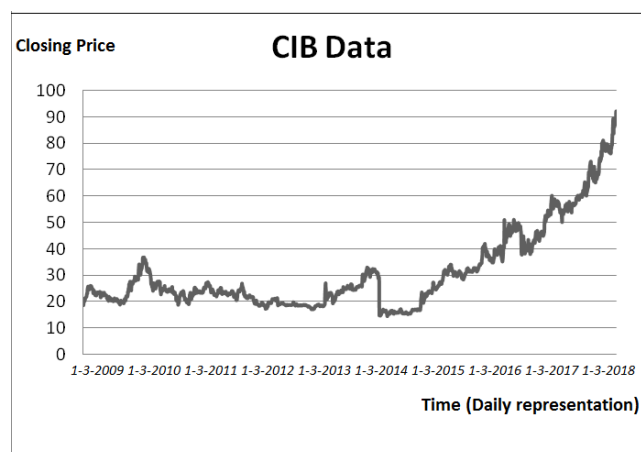


Fig. 1: Data set: CIB stock prices on daily up-dates (March 1, 2009 till March 31, 2018).

Data set analysis showed that the majority of the changes of the daily stock closing price occur to vary in the spectrum from 1% to 4%. (without taking to account the sign of the change). Therefore the model suggested 7 classes or intervals: (- ; -4.5%), (-4.5% ; -2.5%), (-2.5% ; -0.5%), (-0.5% ; 0.5%), (0.5% ; 2.5%), (2.5% ; 4.5%), (4.5% ; -).

This number of classes found to be large enough to contain the trading strategy.

The first dataset sliding window technique used in the model was set to 20 (4 weeks). The used input vector includes 27 items = 20 (day) + 7 selected Technical Analysis Indicators values (14 days EMA, Momentum, Stochastic, MACD, RSI, CCI, and OBV).

In the second dataset the input vector was the set of closing prices of the stock. In another data set, the window represented a set of the opening, closing, highest and lowest price of three or more trading days. The model examined both of these approaches and the better results were found to be that of the first one. The applied system consists of a number of sub models each of which has its own predictive power in a certain direction.

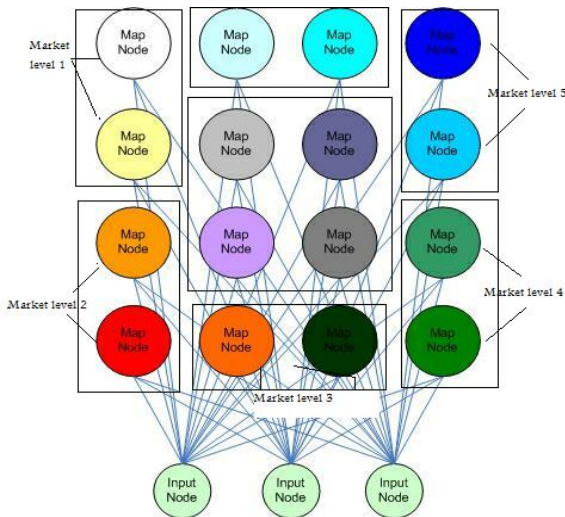


Fig. 2: Market 7 levels in Kohonen’s network

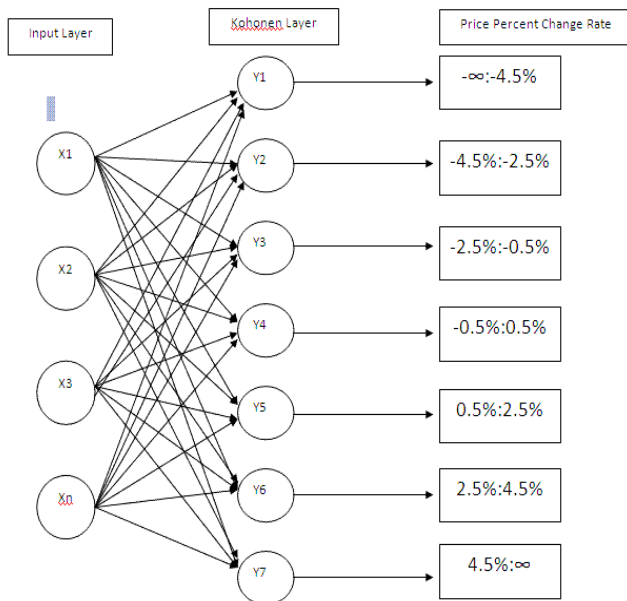


Fig.3: Kohonen’s network architecture for price prediction

Kohonen networks was used to split data into predefined classes. Each class with pre-determined intervals as shown in Figure.3.

The window size is relative to the number of input units (there are 20 units).

Number of clusters in the Kohonen layer is already determined (seven clusters). Each unit represents a cluster of neurons. Supervised learning approach was used for training as each cluster is trained individually. This is done by freezing all other neuron clusters while the inputs with the desired response identical to the given cluster are processed. Seven stages are needed to train this network accordingly to the number of classes we used for the CIB stock. After the learning is

completed, all clusters are de-frozen (all neurons may be active), and the network works in a normal manner.

The Kohonen SOM network model experiments is shown in Table1. The Kohonen SOM output vector produces one trading result:

- 1= Major Downtrend,
- 2 = Secondary Downtrend,
- 3 = Minor Downtrend,
- 4 = Sideways,
- 5 = minor Uptrend,
- 6 = Secondary Uptrend,
- 7 = Major Uptrend.

Table.1: Kohonen SOM Network Model Experiments

| Networks | RMSE Data | | | | |
|----------|----------------------|---------------|--------------|---------|---------------|
| | Input-Neurons-Output | Training (Tr) | Testing (Te) | Tr - Te | Learning Rate |
| 27-8 | 0.1789 | 0.1887 | - 0.0098 | 0.8 | 32,000 |
| 27-49 | 0.1325 | 0.1372 | - 0.0047 | 0.9 | 20,000 |
| 27-64 | 0.1113 | 0.1332 | -0.0219 | 0.7 | 20,000 |
| 27-81 | 0.1505 | 0.1934 | -0.0429 | 0.9 | 40,000 |
| 27-100 | 0.0912 | 0.1624 | -0.0712 | 0.7 | 30,000 |

The model used a simple back propagation network as well. It consists of 20 input neurons, 10 hidden neurons and 7 output neurons. The model used a set of last closing prices of the stock as input vector, to predict the market future direction. As shown in table 1 the best results were achieved with the look-ahead horizon of 4 weeks or 20 trading days.

Table.2: Back Propagation Neural Network Model Experiments:

| Networks | RMSE Data | | | | |
|----------|----------------------|---------------|--------------|---------|---------------|
| | Input-Neurons-Output | Training (Tr) | Testing (Te) | Tr - Te | Learning Rate |
| 27-3-1 | 0.0298 | 0.0559 | -0.0261 | 0.3 | 50,000 |
| 27-8-1 | 0.0156 | 0.0226 | -0.0070 | 0.3 | 50,000 |
| 27-16-1 | 0.0173 | 0.0374 | -0.0201 | 0.3 | 50,000 |
| 27-20-1 | 0.0169 | 0.0405 | -0.0236 | 0.3 | 50,000 |
| 27-27-1 | 0.0184 | 0.0174 | -0.0010 | 0.3 | 50,000 |
| 27-100-1 | 0.0168 | 0.0574 | -0.0406 | 0.3 | 50,000 |
| 27-27-1 | 0.0163 | 0.0575 | -0.0575 | 0.5 | 50,000 |
| 27-27-1 | 0.0188 | 0.0359 | -0.0171 | 0.1 | 50,000 |

The back-propagation network model produced also one trading result:

- 1= Uptrend.
- 0 = Sideways.
- 1 = Downtrend.

3.1 Trading Rules

The system processed a simple crossover method using the Moving Average (MA) technical indicator as a threshold:

Sample of the MA trading rules:

IF price crosses the MA from the upside to the downside THEN sell

IF price crosses the MA from the downside to the upside THEN buy

If signal correction chosen on using support or resistance levels, track the support and resistance value. Check for breaks out to fire signal.

Sample of the RSI trading rules:

B3:

RSI: Crossed 30 up.

B2:

RSI is moving up $50 < RSI < 70$

B1:

RSI is moving up $30 < RSI < 50$

RSI is moving up $RSI < 30$

RSI is moving up $RSI > 70$

S3:

RSI: Crossed 70 down

S2:

RSI is moving down $30 < RSI < 50$

S1:

RSI is moving down $50 < RSI < 70$

RSI is moving down $RSI > 70$

RSI is moving down $RSI < 30$

RSI horizontal same as previous signal

A snapshot of the system generated Buy/Sell signals using M.A. crossover is illustrated in Figure 4.



Fig.4: Snapshot of system generated Buy/Sell signals using M.A. crossover

3.2 The Voting System

A voting system generated the trading signal. A committee of networks with different time horizon generated:

Buy signal, when the majority of networks classify the input pattern as a rising case.

Sell signal, when networks predict price decrease.

Do nothing (untradeable day), when the committee have no or unambiguous answer.

Sample of the RSI trading rules:

If the BPN = 1 "Uptrend", and the SOM = 7 "Major Uptrend", and the pattern detection = Ascending Triangle "Continuation Bullish Pattern", and the 20-day EMA crosses above the 50-day EMA = Buy Signal.

If the BPN = -1 "Downtrend", and the SOM = 5 "Minor Uptrend", and the pattern detection = Rectangle "Continuation Pattern", and the 20-day EMA crosses the 50-day EMA to the downside = Sell Signal.

3.2 Fuzzy Logic Module

The system used candlesticks as a way to represent the daily stock prices, because it is the most widely used technique among stock market investors. It is also the most appropriate representation technique to detect the patters used in the prediction process. Figure. 5 shows an example of the daily candlestick chart for the stock market. Daily open, close, high, and low prices are recorded in the candlestick lines from day number1 till day number 10.

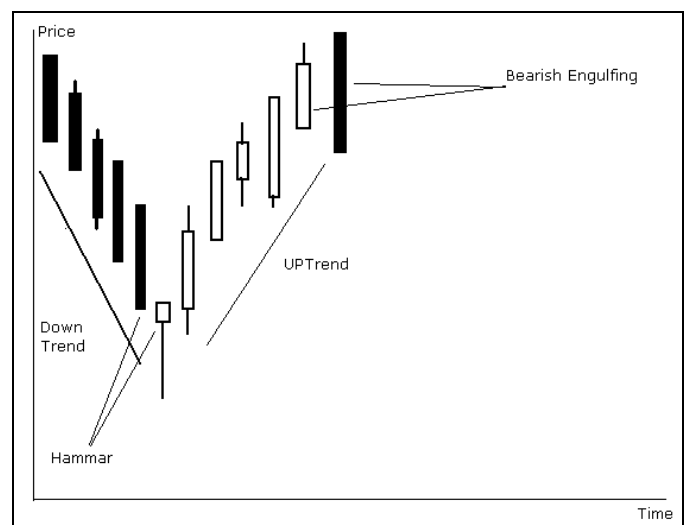


Fig.5: Candlestick pattern examples

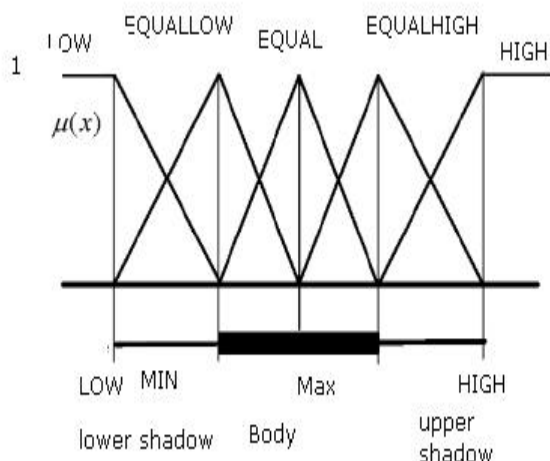


Fig.6: Fuzzy sets of the open style and close style

Figure.6. shows the membership function of the linguistic variables of the open style and close style. The candlestick line in the bottom of Figure 5 is the candlestick line of previous trading time. The unit of X axis is the trading prices of previous day and the unit of Y axis is the possibility values of the membership function. The Open, Close, High, and Low values are provided to the system, and five linguistic variables are defined to represent the open style relationships: OPEN LOW, OPEN EQUAL_LOW, OPEN EQUAL, OPEN EQUAL_HIGH, and OPEN HIGH, and five linguistic variables are defined to represent the close style relationships: CLOSE LOW, CLOSE EQUAL_LOW, CLOSE EQUAL, CLOSE EQUAL_HIGH, and CLOSE HIGH.

The following example demonstrates pattern representation

Pattern description part- Pattern information part

Pattern name: Bearish Engulfing

Confirmation suggest: Suggest

Previous trend: Uptrend Confirmation information:

The open price after the pattern should not be higher than the Open price of candle line 0.

Recognition rule:

1. A definite downtrend must be underway.
2. The second day's body must completely engulf the prior day's body.
3. The first day's color should reflect the trend: black for a downtrend and white for an uptrend.

Candle lines:

Candle line 0:

Open style: OPEN HIGH

Close style: CLOSE LOW

Upper shadow: null

Body: ABOVE MIDDLE

Body color: BLACK

Lower shadow: null

Candle line 1:

Open style: ABOVE OPEN

EQUAL_LOW

Close style: CLOSE HIGH

Upper shadow: null

Body: ABOVE SHORT

Body color: WHITE

Lower shadow: null

Interested time period: DAY

Pattern explanation:

The first day of the Engulfing pattern has a small Body and the second day has a long real body.

Another example is the Hammer

Pattern description part Pattern information part

Pattern name: Hammer

Confirmation suggest: Suggest

Previous trend: Downtrend

Recognition rule:

Uptrend must be identified before the pattern

Candle lines:

Candle line 0:

Open style: OPEN HIGH

Close style: CLOSE LOW

Upper shadow: null

Body: ABOVE EQUAL

Body color: BLACK

Lower shadow: double body n

Candle line 1:

Open style: HIGH

Close style: CLOSE LOW

Upper shadow: yes

Body: ABOVE SHORT | EQUAL

Body color: BLACK

Lower shadow: yes

Interested time period: DAY

Pattern explanation:

Hammer is a potentially bullish pattern which occurs during a downtrend. It indicates that the market is hammering out a bottom.

The applied system generates alerts during the construction of any candlestick pattern when its success probability exceeds 40%. For example, alerts for Hanging man or Doji pattern detection would be generated when their success probability exceeds 40%. However, at the end only a single pattern would be suggested at the end of the process.

4 Experimental Results

For the Kohonen NN the model findings are that to have a clear signal one Kohonen layer cluster should noticeably be higher than all the rest. With two or more neuron clusters are active, additional

interpretation is needed. Signals that are not occurring in contiguous neurons (clusters) should be ignored. If, for example, neurons 3 and 7 are active, the network is not able to classify the pattern. A simple buy signal is generated when neurons in the positive ranges are active, sell when neurons in the negative ranges are active and stand aside when neutral or conflicting activation occur.

Table.3. shows the back propagation and the Kohonen network prediction results on the training and on the test sets.

Training set was for the period from 1-3-2009 till 31-3-2016 (2/3 of the data set), and the remaining set was used for testing (1/3 of the data set).

Table.3: Training and testing results

| Data | Back Propagation | Kohonen |
|----------------------------|------------------|---------|
| Training Set: | | |
| Correctly classified cases | 79% | 85% |
| Test Set: | | |
| Correctly classified cases | 60% | 72% |

Here is a sample output to the applied model results. The samples are divided by symbols, and for each symbol a sample of two years was represented, i.e.2016/2017 & 2017/2018. The applied model gave the best results when using window size of 10 sticks up to 50. Table.4 describes an example of the test samples.

Table.4: Pattern detection results

| No. | Input dataset | Operation | Actual Output | Detected output |
|-----|------------------------|--|-----------------------------------|-----------------------------------|
| 1 | hrho1.csv ¹ | Downtrend pattern recognition | 9.downtrend patterns | 8.downtrend patterns |
| 2 | hrho1.csv | Uptrend pattern recognition | 7.Uptrend patterns | 6.uptrend patterns |
| 3 | hrho1.csv | Downtrend pattern recognition Uptrend pattern recognition | 7.Uptrend 3.downtrend patterns | 7.Uptrend 3.downtrend patterns |
| 4 | hrho2.csv ² | Downtrend pattern recognition | 2.downtrend patterns | 2.downtrend patterns |

A sample of the pattern detection results for the data files of Egyptian Financial Group EFG/Hermes Holding "hrho" were presented in Figure 7, 8, and 9. Egyptian Mobile Service "EMOB" in Figure 10, 11, and Orascom Telecom in figure 12.

1hrho1.csv: The trading data of the symbol hrho during the period 2014-2015

2hrho2.csv: The trading data of the symbol hrho during the period 2016-2017

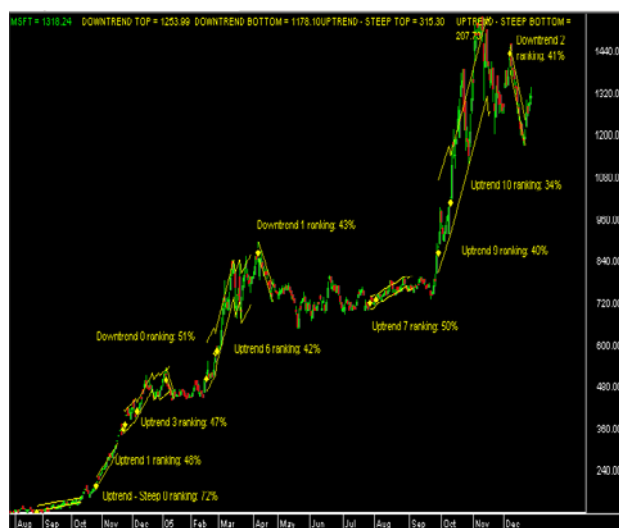


Fig.7: Pattern detection results for hrho data file (2014/2015), with window size (10-50)



Fig.8: Pattern detection results for hrho data file (2016/2017), with window size (10-50)

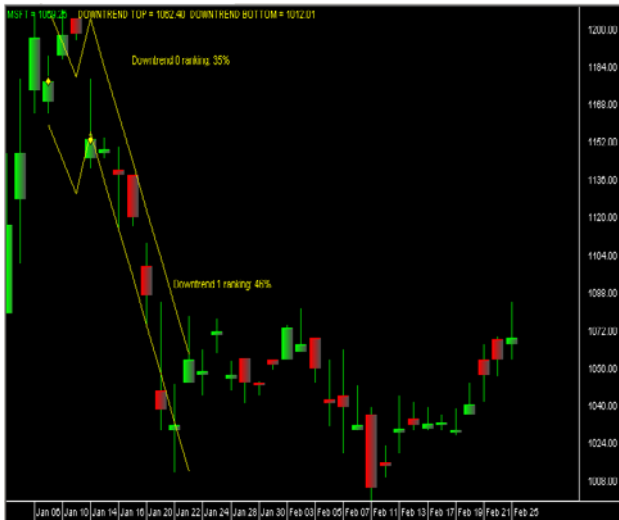


Fig.9: Pattern detection results for hrho data file (2018), with window size (10-50)



Fig.12: Pattern detection results for ORTE data file (2014/2015), with window size (10-50)



Fig.10: Pattern detection results for EMOB data file (2014/2015), with window size (10-50)



Fig.11: Pattern detection results for EMOB data file (2016/2017), with window size (10-50)

5 Conclusion

The model proposed a Kohonen self-organizing map to split data into predefined classes representing seven different market levels. In the multilayer model the back-propagation network was used to generate a final trading signal.

The proposed hybrid fuzzy-neural multi-layer model can enhance the performance of online trading by using ANNs voting system.

Using Fuzzy logic techniques in detecting candlesticks patterns in a multilayer soft computing model successfully predicted the change in the market direction.

6 Future Work

One of the limitations of using ANN in forecasting is the local maximum problem. Using genetic algorithms (GA) will be very useful to overcome this situation for nonlinear optimization problems.

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