The Success Prediction Ratio (SPR): A Simplified Generalized Technique to Compare and Validate the Performance of the Stock Price Prediction Model

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Abstract*— Stock market direction prediction has always been a subject of interest for most market participants. It was observed in most of the literature, related to stock price prediction, they found difficult to compare and validate the performance of their price prediction models or methodology. To overcome this problem here we proposed a simplified generalized technique called Success Prediction Ratio (SPR) to compare and validate the performance of the stock price prediction model. In this study, we developed price prediction model using artificial neural network following technical analysis approach. Ten well known and reputed stock of National Stock Exchange has selected for analyzed the prediction performance of the model. At the last, we validate the performance of the model using Success Prediction Ratio. The study results show that proposed model outperforms in terms of percentage prediction and profitability.

***Keywords*— Success Prediction Ratio, SPR, Stock market prediction, price prediction model, model validation**

I. INTRODUCTION

Stock security price highly depends on various parameters such as company fundamentals, stock security demand-supply, government policy, global policy, inflation, interest rate, etc. These parameters are uncertain and in dynamic nature. For this reason, predicting the stock market is not a simple task. On every tick, a huge amount of bid places by plenty of traders/investors. The numbers of bid successes/fails are not constant and hence, the stock price fluctuates by these success/fails of the bid. At the result, this will create high randomness into the stock price. There is no relationship between stock raw data point.

There is two hypothesis related market prediction; Random Walk Hypothesis (RWH) and Efficient Market Hypothesis (EMH). The RWH state that there is no relation between future price data with a historical price. The patterns and trends of price changes in a market cannot be used to forecast the future value of financial instruments. The RWH model is related to another concept of finance literature that is market efficiency. Fama initially introduces Efficient Market Hypothesis concept in early 60's [1], [2]. Efficient Market Hypothesis (EMH) states that current stock prices contain and reflect the all kind of relevant information and market is efficient. Fama state that there are three forms of EMH; Weak form EMH, semi-weak form EMH and strong EMH. To make a profit higher than market return is not possible in the efficient market. The validity of both the hypothesis is always debatable. The technical analysis approach proved that using various technical indicators it is successfully possible to build a relation between historical stock price data and in a shorter time, effectively price trend prediction has possible.

Nowadays, emerging markets, such as National Stock Exchange (NSE), are gaining popularity due to high return as compared to the developed market. For this reason, emerging markets attract many investors. The benchmark index of Indian stock market, NIFTY 50 (referred as NIFTY), was launched in April 1996 by National Stock Exchange (NSE). Nifty, which is the main market indicator of the NSE, is a market capitalization-weighted index. The proposed work select 10 most prominent stock from the NIFTY index as a processing data for the model. The feedforward multi-layer neural network selected as a processing unit of the model for forecasting next day direction on collected stock securities data

The remaining paper organized as follows: The seciton II highlights the import research works have been done related to financial market prediction. In section III represents the predction model implimentation detail. This is crusial part of this reasearch study. This section represnts database selection for the model, database distribution for the model, neural network parameter set detail, the model training and testing. In section IV, new term, Success Pridiction Ratio introduce with its important. Section V represents exprimental results. In section VI, the model validation is done using SPR. Finaly, the study represents conclusions in Section VII.

II. LITERATURE REVIEW

Wu [3] assessed the weak-form proficiency of the Shanghai and Shenzhen stock markets and did not discover weak form efficiency at the bottom line. Dahel and Laabas [4] studied the efficiency of Gulf Cooperation Council equity markets. Their [4] conclusion is that the stock market of Kuwait follows the weak form of efficiency. Abraham et al. [5] tested the RWH and market efficiency supposition for Saudi Arabia, Kuwait and Bahrain. The research study [5] indicated that Saudi and Bahraini markets follow the hypothesis of a random walk, but the market of Kuwait is inefficient and hence did not follow the RWH.

There exist vast research literature, which concentrates on forecasting of financial markets. These study used various types of ANN to predict accurately the stock price return/direction of its movement. ANN model [6]–[10] has provided satisfactory forecasting result. The research paper by Chen [9] attempted to predict the direction of return on the Taiwan Stock Exchange Index. The Probabilistic Neural Network (PNN) was used to forecast the direction of index return. Statistical performance of the PNN forecasts is compared with that of the generalized methods of moments (GMM) with Kalman filter and the random walk prediction models. Kyoung-Jae Kim [11] proposed an advanced genetic Algorithm approach to instance selection in ANNs for financial data mining. Using this approach the study could avoid the basic limitations of ANNs such as inconsistency, problems in prediction for noisy data, etc. The study [11] produces a satisfactory forecasting in the direction of change in Korean Stock Price Index (KSPI) using GA based ANN (GANN).

Lawrence [12] reveals the ability of the neural network to discover patterns in the nonlinear and chaotic system more accurately than other current forecasting tools. The study [12] proposed that in 91 percent cases neural networks correctly predicted the future price trend as compared to 74 percent using multiple discriminate analysis (MDA). Yakup Kara [13] compare the prediction performance of ANN with Support Vector Machine (SVM) and conclude that average performance of ANN model (75.74%) was found better than that of SVM (71.52%).

By going through various literature studies it has been found that artificial neural network is effective tools for solving non-linear time series such as stock price time series. The input used in most artificial neural network architecture is technical indicators.

III. THE PRICE PREDICTION MODEL IMPLEMENTATION

The research data used in this paper is the daily closing price of ten selected stock from NSE. The historical data collected from Yahoo Finance web source. Table 1 shows ten selected stock security description, their core sector and the data collection periods. There is no global database availble to compared model performance.

TABLE 1: INPUT DATABASE OF THE MODEL

Stock Security	Description	Sector	*The Data Collection Period*
COALINDIA	Coal India Ltd.	Mining & Minerals	*13-Dec-2010 To 30-May-2017*
HDFC	Housing Development Finance Corporation	Finance	*05-Aug-2002 To 30-May-2017*
HINDUNILVR	Hindustan Unilever Ltd.	Personal Care	*05-Feb-2002 To 30-May-2017*
ICICIBANK	ICICI Bank Ltd	Finance	*05-Aug-2002 To 30-May-2017*
INFY	Infosys	Information Technology	*05-Feb-2002 To 30-May-2017*
ITC	Imperial Tobacco Company	FMGC & Cigarettes	*05-Feb-2002 To 30-Mar-2017*
ONGC	Oil and Natural Gas Corporation	Oil	*05-Feb-2002 To 30-May-2017*
RELIANCE	Reliance Industries	Refineries & Petro-Chamical	*05-Feb-2002 To 30-May-2017*
SBIN	State Bank of India	Finance	*05-Feb-2002 To 30-May-2017*
TCS	*Tata Consultancy Service*	*Information Technology*	*29-Sep-2004 To 30-May-2017*

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

TABLE 2: THE MODEL PROCESSING DATA DISTRIBUTION

Stock Security	Total Data Sample	Tuning Data Sample	Holdout Data Sample	Testing Data Sample
COALINDIA	1586	836	250	500
HDFC	3654	2904	250	500
HINDUNILVR	3782	3032	250	500
ICICIBANK	3656	2906	250	500
INFY	3780	3030	250	500
ITC	3742	2992	250	500
ONGC	3782	3032	250	500
RELIANCE	3782	3032	250	500
SBIN	3755	3005	250	500
TCS	3115	2365	250	500

These data distributed into three major segments; Tuning dataset, Holdout dataset and Testing dataset for predicting next day price direction using neural network model. The Tuning dataset consists of 60% of total dataset, Holdout dataset consists of 20% of total dataset and Testing data consisted 20% of the total dataset. Table 2 shows the entire collected database distribution. The most recent approximatly one-year data used for testing the model prediction performance. The most recent after the testing dataset data approximatly two years used for selecting reliable prediction model. The remaining dataset belongs to the tuning dataset. The tuning dataset is further divided to training dataset, validating dataset and testing dataset for the model. We have around 66% of training dataset of Tuning dataset, 17% validating dataset of Tuning dataset and 17% testing dataset of Tuning dataset for model training. The training dataset helps neural network model to learn important pattern from historical data. The validating dataset takes care model overfitting and testing dataset used for neural network output performance.

After going through a study of various research works, it has found that properly tuned back-propagation feed-forward Neural Network (NN) can effectively predict the direction of the stock market. The feedforward backpropagation neural network selected as processing unit for the prediction model. The input layer has five nodes. The five technical indicators; Moving Average Conversion and Diversion (MACD), Relative Strength (RSI), William %R, Accumulator/Distribution and On Balance Volume (OBV); has selected as inputs for the neural network. The selection of five technical indicators is done by the review of domain experts and prior researchers [11], [14], [15]. Table 3 shows the description for selected five technical indicators as an input variable to the NN. The Levenberg-Marquardt [16], [17] back-propagation learning algorithm used to train the three-layered feed-forward ANN. The mean square error (MSE) used to evaluate the performance of the ANN model.

TABLE 3: TECHNICAL INDICATORS DESCRIPTION

Indicator	Description	Type
MACD	Difference of two EMAs that shows a stock's momentum and direction	Trend oscillator
Relative Strength Index (RSI)	Shows how strongly a stock is moving in its current direction	Trend Strength oscillator.
William %R	Uses Stochastic to determine overbought and oversold levels	Stochastic
Accumulator/Distribution	Combines price and volume to show how money may be flowing into or out of a stock	Volume-based Indicator
On Balance Volume (OBV)	Combines price and volume in a very simple way to show how money may be flowing into or out of a stock	Volume-based Indicator

The output layer has one node. A hyperbolic tangent sigmoid transfer function used at both hidden layer and output layer. The output of neural network produced a value between 0 and 1. If the output of the model is greater than 0.5 then the direction of stock price is considered as "1" (Up) otherwise direction of stock price is considered as "0" (down). This way, the model output vector is prepared on the Testing dataset. An output vector of the neural network compared with the respective stock security's targeted vector and hit rate calculated. Based on hit rate percentage prediction and percentage Rate of Return (ROR) evaluated.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

The three-layered feed-forward NN was trained for the 100 epoch for each of the selected stock security using Training dataset. Training is stopped if maximum validation fails reaches to 6 or goal reach to 0 or training epoch reaches to 100 any of condition is true. To test the reliable tuned neural network, holdout dataset applied to trained neural network and output prediction calculated based on hit rate. If the prediction performance on holdout data above the 52% then considered the neural network tuned properly otherwise retrain again. To evaluate the prediction performance the model, Testing dataset applied to the properly tuned neural network and output of the model performance measured in terms of percentage prediction and percentage ROR for each of the selected stock securities. The above process repeated for each of the selected stock securities and five CASEs are prepared. The hidden layer's nodes are empirically selected by applying one epoch training using holdout dataset. The selected number of nodes for the hidden layer for respective stock security shows in Table 4 for all generated CASEs.

TABLE 4 THE NUMBER OF HIDDEN LAYER'S NODE FOR RESPECTIVE STOCK SECURITIES

Stock	Hidden Node
COALINDIA	30
HDFC	20
HINDUNILVR	25
ICICIBANK	20
INFY	20
ITC	15
ONGC	25
RELIANCE	30
SBIN	25
TCS	15

IV. SUCCESS PREDICTION RATIO

It has found in various literature related to prediction the market that research community face difficulty to the measured overall performance of their model in the single measuring unit when they used different performance measures. The reason is that there might different performance measured used by researchers while evaluating their model performance. The advantage of the SPR is that it provides single measurement unit that can measure the model overall performance with different performance measurement. That might make comparison ease for various performance measures for model performance.

TABLE 5: THE GENERALIZED REPRESENTATION OF EXPERIMENT'S RESULT-MATRIX

Stock Security	CASE1	CASE2	CASEm	Total Cases With (ξ>λ)
Stk_1	$\mu_{1,1}$	$\mu_{1,2}$	$\mu_{1,m}$	$\sum_{j=1}^{m}(\mu_{1,j} > \lambda)$
Stk_2	$\mu_{2,1}$	$\mu_{2,2}$	$\mu_{2,m}$	$\sum_{j=1}^{m}(\mu_{2,j} > \lambda)$
Stk_s	$\mu_{s,1}$	$\mu_{s,2}$	$\mu_{s,m}$	$\sum_{j=1}^{m}(\mu_{s,j} > \lambda)$
Total Cases With (ξ >λ)	$\sum_{i=1}^{s}(\mu_{i,1} > \lambda)$	$\sum_{i=1}^{s}(\mu_{i,2} > \lambda)$	$\sum_{i=1}^{s}(\mu_{i,m} > \lambda)$	$\Phi = \sum_{i=1}^{s}\sum_{j=1}^{m}(\mu_{i,j} > \lambda)$

Where Stk is any stock security/index, s is Total stock securities, m is Total generated cases, μ is the performance value of the Model, λ is Constant Value, ξ is Performance Measure and Φ is Total success prediction test.

The SPR is defining the ratio of total success prediction test vs. total prediction test. The formula for calculating SPR as expressed Equation (1).

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

$$SPR = \frac{\Phi}{s \times m}$$

Where s is total stock securities, m is total cases and Φ is total success prediction test.

SPR value 0 indicates 100% failed in all test and SPR value 1 indicates 100% success in all test. The value of SPR higher than 0.5 suggests that model will outperform with respect to performance measure and less than 0.5 suggest that model will underperform. Table 5 shows model output in form of result-matrix for various treatments. This research study uses ten different stock securities and five cases of each of the selected security for test the performance of model output.

V. EXPERIMENT RESULTS

TABLE 6: THE PERCENTAGE PREDICTION OF THE MODEL

Stock	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	50.6	52	53.2	48	49.8	3
HDFC	49.2	48.6	49.2	53.8	49.8	1
HINDUNILVR	53	49	55.2	50.8	53.4	4
ICICIBANK	51.6	53.2	51.4	52.4	53.8	5
INFY	48.2	48.4	46.2	46.8	45.6	0
ITC	52.4	49	52	51.8	52.2	4
ONGC	51	48	48.8	48.4	51.2	2
RELIANCE	54.4	55.2	57	49.4	56.4	4
SBIN	49.2	53.4	49.8	51	51.2	3
TCS	48.2	52	50.4	53.8	48.4	3
Total	6	5	6	6	6	29

s=10, m = 5, ξ is prediction (%), μ= prediction (%), λ is 50 (%), Φ=29, SPR=0.58

TABLE 7: THE PERCENTAGE ROR OF THE MODEL

Stock	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	11.37	-6.83	-1.80	-58.31	-18.49	1
HDFC	22.41	-16.94	25.08	54.45	6.15	4
HINDUNILVR	42.69	1.91	27.53	-20.81	44.92	4
ICICIBANK	19.41	76.65	33.34	58.60	80.35	5
INFY	8.17	4.33	-31.82	-11.48	-32.36	2
ITC	-1.12	10.50	26.47	24.23	51.88	4
ONGC	30.25	30.04	-8.22	-6.12	68.23	3
RELIANCE	58.56	57.89	125.74	-30.69	94.57	4
SBIN	3.02	28.71	32.41	9.95	23.61	5
TCS	-61.92	24.69	-8.84	37.21	-20.22	2
Total	8	8	6	5	7	34

s=10, m = 5, ξ is prediction (%), μ= prediction (%), λ is 0, Φ=34, SPR=0.68

Model performance has measured in terms of percentage prediction and model positive percentage ROR. The percentage prediction of the model represented as result matrix for the five generated different CASEs for each of stock security is illustrated in Table 6. The SPR value evaluated as per Equation (1), which is 0.58 in Table 6 suggests that model outperforms in terms of the percentage prediction above 50%. The percentage ROR of the model represented in form of result matrix for the five generated different CASEs for each of stock security is illustrated in Table 7. The SPR value of 0.68 in Table 7, which is above 0.5 suggests that model outperforms in terms of the percentage positive return.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

VI. VALIDATION OF THE MODEL USING SPR

Model prediction validation is done against randomly generated buy/sell trade. Instead of going after the model buy/sell trade, simple random buy/sell trade is initiated on a number of the testing data sample and vector prepared. This randomly generated output has a value between 0 and 1, with 0.5 mean and 0.2 standard deviation values. This randomly generated vector compared with the targeted vector of each of the respective stock and hit rate calculated. Based on hit rate, the percentage prediction and percentage ROR is calculated for random data.

The percentage prediction of randomly generated data result-matrix illustrated in Table 8. The SPR value 0.36, which is lower than 0.5 suggests that randomly generated data has failed to outperform in terms of percentage prediction.

TABLE 8 THE PERCENTAGE PREDICTION OF RANDOMLY GENERATED TARGET VECTOR

Stock	CASE1	CASE2	CASE3	CASE4	CASE5	*Total*
COALINDIA	48.4	49.2	47.4	53.8	51	*2*
HDFC	46	52.2	49.8	48	49.6	*1*
HINDUNILVR	52.4	48.4	48.6	48.2	50.2	*2*
ICICIBANK	49.8	47.2	53.4	51.6	49.2	*2*
INFY	48.2	48	51.2	50	47.4	*1*
ITC	49	50	47.8	54	52.2	*2*
ONGC	49	47.4	46.4	51.8	56.8	*2*
RELIANCE	47.8	49.4	49.4	51.2	47.6	*1*
SBIN	50.8	52.4	49.4	48.2	49	*2*
TCS	55.6	49	51.6	45.2	50.6	*3*
Total	*3*	*2*	*3*	*5*	*5*	*18*

s=10, m = 5, ξ is prediction (%), μ= prediction (%), λ is 50, Φ=18, SPR=0.36

The percentage ROR of randomly generated data's result matrix illustrated in Table 9. The SPR value 0.40 from Table 9 indicats that randomly generated failed to outperform in terms of percentage ROR.

TABLE 9: THE PERCENTAGE ROR OF RANDOMLY GENERATED TARGET VECTOR

Stock Security	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	-17.23	-50.25	-42.77	51.93	-3.34	1
HDFC	-57.38	7.58	-12.31	-11.76	-13.85	1
HINDUNILVR	26.00	-33.43	-43.58	-29.75	-6.28	1
ICICIBANK	15.80	-78.63	19.28	32.86	-10.90	3
INFY	-15.80	-22.84	-9.43	1.80	-25.62	1
ITC	-32.71	-44.05	-47.42	45.10	51.22	2
ONGC	-72.85	-71.28	-38.46	11.28	109.04	2
RELIANCE	-36.82	4.23	-40.61	0.45	-18.65	2
SBIN	32.97	30.13	6.41	-16.33	13.07	4
TCS	48.35	-2.42	5.89	-57.72	3.12	3
Total	4	3	3	6	4	20

s=10, m = 5, ξ is prediction (%), μ= prediction (%), λ is 0, Φ=20, SPR=0.40

Model validation in terms of percentage prediction (Table 6) against random data percentage prediction (Table 8) is illustrated in Table 10. The SPR value 0.62 shows that model percentage prediction effectively outperforms against random data percentage prediction.

TABLE 10 THE PREDICTION (%) OF THE MODEL > THE PREDICTION (%) OF RANDOM DATA

Stock Security	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	1	1	1	0	0	3
HDFC	1	0	0	1	1	3
HINDUNILVR	1	1	1	1	1	5
ICICIBANK	1	1	0	1	1	4
INFY	0	1	0	0	0	1
ITC	1	0	1	0	0	2
ONGC	1	1	1	0	0	3
RELIANCE	1	1	1	0	1	4
SBIN	0	1	1	1	1	4
TCS	0	1	0	1	0	2
Total	7	8	6	5	5	31

s=10, m = 5, ξ & μ= Model prediction (%) > random data prediction (%), λ is 0, Φ=31, SPR=0.62

The model validation in terms of percentage ROR (Table 7) against random data percentage ROR (Table 9) is illustrated in Table 11. The SPR value 0.70 from Table 11 shows that the model percentage ROR effectively outperform against random data percentage ROR.

TABLE 11: THE ROR (%) OF THE MODEL > THE ROR (%) OF RANDOM DATA

Stock Security	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	1	1	1	0	0	3
HDFC	1	0	1	1	1	4
HINDUNILVR	1	1	1	1	1	5
ICICIBANK	1	1	1	1	1	5
INFY	1	1	0	0	0	2
ITC	1	1	1	0	1	4
ONGC	1	1	1	0	0	3
RELIANCE	1	1	1	0	1	4
SBIN	0	0	1	1	1	3
TCS	0	1	0	1	0	2
Total	8	8	8	5	6	35

s=10, m = 5, ξ & μ= Model ROR (%) > random data ROR (%), λ is 0, Φ=35, SPR=0.70

The percentage ROR of the selected stock security shows in Table 12 for Testing data sample duration. The percentage ROR of the model compared against percentage ROR of respective stock security is illustrated in Table 13. The result shows that the model output in terms of percentage ROR outperforms to respective index.

TABLE 12 THE ROR OF STOCK SECURITY IN TESTING DATA DURATION

Stock Security	Time Period	ROR (%)
COALINDIA	19-May-2015 To 30-May-2017	-26.39
HDFC	19-May-2015 To 30-May-2017	27.32
HINDUNILVR	21-May-2015 To 30-May-2017	24.09
ICICIBANK	21-May-2015 To 30-May-2017	2.50
INFY	19-May-2015 To 30-May-2017	-1.48
ITC	20-Mar-2015 To 30-Mar-2017	29.52
ONGC	21-May-2015 To 30-May-2017	-15.81
RELIANCE	21-May-2015 To 30-May-2017	51.59
SBIN	19-May-2015 To 30-May-2017	0.14
TCS	19-May-2015 To 30-May-2017	1.53
Total	19-May-2015 To 30-May-2017	7

TABLE 13 THE ROR (%) OF MODEL > THE ROR (%) OF RESPECTIVE STOCK

Stock Security	CASE1	CASE2	CASE3	CASE4	CASE5	Total
COALINDIA	1	1	1	0	1	4
HDFC	0	0	0	1	0	1
HINDUNILVR	1	0	1	0	1	3
ICICIBANK	1	1	1	1	1	5
INFY	1	1	0	0	0	2
ITC	0	0	0	0	1	1
ONGC	1	1	1	1	1	5
RELIANCE	1	1	1	0	1	4
SBIN	1	1	1	1	1	5
TCS	0	1	0	1	0	2
Total	7	7	6	5	7	32

s=10, m = 5, ξ & μ= Model ROR (%) > Stock ROR (%), λ is 0, Φ=32, SPR=0.64

Table 13 shows that the percentage ROR of the model remarkable outperforms with respect to the percentage ROR of stock. The Reliance stock gave 51% return during Testing dataset duration which was highest among all other stock. The proposed model outperforms Reliance stock in four CASEs out of five CASEs (see Table 13). The model highest percentage ROR 125% found in CASE3 for Reliance stock.

VII. CONCLUSION

The proposed model effectively predicts the direction of stock price even in noisy and random time series. The experiments results show that neural network has the ability to solve the non-linear problem. The proposed SPR helps researchers for validate their model and measured their model's overall performance into one common measurement unit where another comparison model not available. The result obtains from the experiment is remarkable, till there is scope to improve the model performance using various ways such as; database distribution, input selection, architecture parameters etc.This research study also provides future scope for other researchers to measures their model performance, test model with other neural network architecture and evaluate their model performance.

VIII. ACKNOWLEDGEMENT

Authors would like to thank all the researchers for providing comprehensive literature for this paper.

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