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Proceedings of the International Conference on Conference on Business, Management and Finance
Vol. 1, Issue. 1, 2024, pp. 11-22
DOI: https://doi.org/10.33422/icbmf.v1i1.399

ISSN: 3030-0959 online

Translating Directional Accuracy into Profitability: Machine Learning Based Predictive Models for Global Stock Indices

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Abstract

Understanding the linkage between directional accuracy and return remains a negligibly explored domain in the context of stock market prediction. Maximum studies in the given domain are based on mathematical accuracy measures and directional accuracy measures. Merely the efficiency of directional prediction may not suffice, as the magnitude of directional change also assumes importance in stock markets. Without any doubt, profitability measures reign supreme in the case of the stock market. The current study attempts to investigate the association between Accuracy rate and returns for data sets based on seven stock indices across the globe. The outcome of the study relies on machine learning: ANN (Artificial Neural Networks) and SVM (Support Vector Machine) based predictive models, built using 196 data sets of variable duration. The results of the current research reveal a strong positive correlation between accuracy rate and returns. Moreover, significant variations in the extent of the relationship are also observed. Quantile regression models indicate a relatively stronger relationship between accuracy rate and return at the lower range of returns. Findings of the study carry value for academicians, researchers, and practitioners in the field of machine learning and stock market predictions.

Keywords: Directional accuracy, Profitability measures, Machine learning, Support Vector Machines (SVM), Artificial Neural Network (ANN)

1. Introduction

Predictive modeling has assumed fundamental importance for investment in stock markets. It is basically a repetitive process. Supervised machine learning techniques, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), supported by advanced computational resources yield, a wide variety of models. Accuracy measures play a crucial role in the choice of predictive models. Contemporary accuracy measures used for predictive modeling are largely influenced by the streams of engineering and science. The choice of accuracy measure is instrumental in the performance and utility of the predictive models. Accuracy rate is one of the most popular accuracy measures in the field of predictive modeling to assess accuracy, also known as Hit Ratio. The preference for Accuracy rate as a measure to assess the accuracy of predictive models is quite common in the literature. The Accuracy rate is the percentage of correctly predicted instances to total instances. Both direction and magnitude assume importance in the context of stock markets. The applicability of supervised machine learning techniques in stock markets is more concerned with profitability as compared to mere directional accuracy. Profitability has also become an important financial subject, which has garnered significant attention from researchers over the past few years. Given the relationship between historical information and future stock returns (Fama, 1991), profitability is also predictable (Hargreaves & Hao, 2013; Ferson & Harvey, 1993). Many parameters of profitability are available which include rate of return, net gain in assets, excess stock return, accumulated profits and Sharpe Ratio. The most appropriate accuracy measure would be returns derived from predictive models (Thawornwong & Enke, 2004; Fama, 1970, Fama, 1991).

It makes an interesting study to explore the linkage between accuracy measures and returns. Linking model accuracy and return remains a relatively lesser explored domain in Machine Learning-based forecasting. The present paper aims to explore the relationship between Accuracy rate and returns derived from predictive models pertaining to global stock indices.

2. Background

Accuracy measures play a crucial role in optimizing the efficiency of various models. As machine learning techniques originated in the physical sciences and engineering disciplines, performance measures are quite popular in the domain. There are various accuracy measures available, such as absolute forecasting errors, percentage errors, symmetric errors, measures based on relative errors, and scaled and relative measures, but directional accuracy measures assume higher importance in stock market prediction (Majumder & Hussain, 2010). Accuracy rate, a directional measure, has been preferred by various researchers for predicting the accuracy of models (Kim & Han, 2000; Kim, 2003; Choudhary & Garg, 2008; Cao & Tay, 2003; Altay & Satman, 2005; Chun & Park, 2005; Gestel et al., 2001; Huang et al., 2005; Roh, 2007; Siekmann et al., 1999; Kara et al., 2011; Ou & Wang, 2009; Yu et al., 2009; Kumar & Thenmozhi, 2006; Kim, 2006; Mizuno et al., 1998; Yao & Poh, 1995; Wunsch et al., 1998).

Stock return is also becoming a popular measure for evaluation pertaining to predictive modeling. Various instances of its usage in stock market forecast studies are also available (Thawornwong & Enke, 2004, Teixeira et al., 2010, Hsieh et al., 2011). Although in a small way, investigation of related literature reveals the consideration of transaction cost-adjusted returns (Hsieh et al., 2011, Teixeira & Oliveira 2010, Chen et al., 2003, Trippi & Desieno, 1991, Vanstone et al., 2010). As the count of trades impacts the net profitability, the actual profits generated through predictive models can only be ascertained by considering transaction costs. Previously, only a handful of studies have attempted to link directional accuracy and profitability measures such as returns (Yao & Tan, 2000). Merely, goodness of fit does not ensure profitability, and the efficiency of neural networks can be improved using profitability-based accuracy measures (Yao & Tan, 2000). The present study is a pioneering attempt to link accuracy rate and returns. Further, the investigation of the relationship across global stock indices has the potential to provide useful insights for researchers and investors.

3. Methodology

In the current study, seven largest indices belonging to seven different countries across the globe were considered. U.S., Japan, and the U.K. (developed countries) and Brazil, India, China, and South Africa (emerging countries) were the counties chosen as per the MSCI market classification (Anonymous, 2016). These countries account for 55.20 percent of the world's GDP, as per the International Monetary Fund (2018). Based on turnover in the financial derivatives segment, Dow Jones Industrial Average (DJIA) from the New York Stock Exchange of the United States, FTSE 100 (labelled as FTSE) from the London Stock Exchange Group of the United Kingdom, Nikkei 225 (labelled as NIKKEI) from the Japan Exchange Group-Tokyo of Japan, SSE 50 (labelled as SSE) from the Shanghai Stock Exchange of China, iBovespa (labelled as IBOVESPA) from BM&F Bovespa of Brazil, Nifty 50 (NIFTY) from the National Stock Exchange of India, and JALSH from JSE Limited (Johannesburg) of South Africa were selected. For a comprehensive analysis, daily values of open, close, high, and low prices of selected indices over a period of 12 years, spanning from April 1, 2005, to March 31, 2017.

The collected raw data was further transformed into technical indicators. Transforming raw data into technical indicators is a necessary step. Technical indicators basically provide structured patterns and trends in data by filtering out the noise that might not be apparent in raw data. By incorporating these indicators as input features, machine learning techniques can enhance their predictive power. These input features are stochastic oscillators (stochastic%K, stochastic%D, and stochastic slow%D), momentum indicators, AD (accumulation/distribution) momentum oscillators, Larry William % range, price oscillators (OSCP), disparity indicators (price rate of change (ROC, 5-day disparity index, 10-day disparity index), relative strength index (RSI), and commodity channel index (CCI) (Kim, 2003; Kim, 2006; Kwon & Moon, 2007).

To conduct the analysis, different datasets with varying time spans were generated. In total, 196 data sets were generated, i.e., 28 for each selected stock index. These data sets include 12 sets of 1 year each, 6 sets of 2 years each, 4 sets of 3 years each, 2 sets of 6 years each, and 1 set of 12 years. Two machine learning techniques, i.e., ANN and SVM, were used to build the predictive models where bidirectional outcomes were considered as dependent features. Changes in daily close price value were transformed into bidirectional outcomes, i.e., "increase" (positive daily return) and "decrease" (negative daily return). The data was trained using 80% of values for all 196 data sets, and 20% was used for model testing.

3.1 *ANN (Artificial Neural Networks)*

For predictive modeling, the ANN technique was firstly employed. A key feature of ANN lies in its capacity to predict any non-linear functions to varying degrees of accuracy determined by the count of hidden units (Zhang & Jiang, 2007; Kim & Shin, 2007). In this study, a multilayer perceptron was considered, with the backpropagation algorithm supervised learning, for instance, classification. A backpropagation algorithm uses supervised learning to train the model. Output for the "j" unit is represented by the following function:

$$Oj = G(\sum_{i=1}^{m} w_{ij}y_i - \Theta_j) \quad (1)$$

Where, G= Sigmoid function, w_{ij} = weight on connection from i*th* unit, y_i = output value of ith unit in previous layer, m= number of units in previous layer and Θ_j= threshold. The experiment was carried out with default values of hidden layer i.e., "a" and all nodes in this network were sigmoid. The level of hidden layer i.e., "a" = (attributes + classes) / 2. There are 14 attributes (12 technical indicators, Direction, Calculated return values) and 2 classes for model building.

Sigmoid function: $f(x; a) = \frac{1}{1+e^{-ax}}, -\infty < x < \infty$ (2)

The number of epochs, momentum constant (mc) and learning rate (lr) values were set at 500, 0.2 and 0.3 respectively.

3.2 SVM (Support Vector Machines)

The RBF kernel (Radial Basis Function) was used as the kernel function of SVM due to its capability and easy implementation (Huang et al. 2010). In SVM, a hyperplane is constructed as a decision surface such that positive and negative distance margins are maximized (Kara et al. 2011, Xu et al. 2009). Let the minimum margin be q. The points that are at *q* distance from the hyperplane are known as support vectors. For a binary classification training set, with input vectors $x_i \epsilon R^d$ (i = 1, 2,..., N) and corresponding labels $y_i \epsilon \{+1, -1\}$ (i = 1, 2,..., N), where both +1 and -1 indicate both classes. SVM helps to construct a classifier or a decision function from sample sets that has a lower probability of misclassifying the test set. It maps out the input vectors into high-dimensional feature space (xi) ϵ H and constructs an Optimal Separating Hyperplane (OSH) that maximizes margin (Xu et al. 2009). The classifier is determined by the following decision function (Kara et al. 2011):

$$f(x) = sgn(\sum_{i=1}^{N} y_i \, \alpha_i \, . K(x, y) + b \quad (3)$$

Maximize, $\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j . y_i y_j . K(x, y)$ (4)

Subject to $0 \leq \alpha_i \leq$ c (5)

Where $\sum_{i=1}^{N} \alpha_i y_i = 0$ (6)

The implementation of SMO- Sequential Minimal Optimization (by John Platt) algorithm was carried out using Weka software. The parameter values for the current study, including Complexity parameter (c), Gamma of the kernel, Tolerance parameter and ε parameter, were set at 1, 0.01, 0.001and 10^{-12}respectively.

3.3 Trading strategy

Based on the test set, daily directional outcomes were predicted. Further, a trading strategy was evolved to calculate returns. A trading strategy involves opting to BUY the stock if an increase in stock price/ index value is predicted in the directional prediction. A position so taken is held till an opposite directional prediction (decrease) is encountered. On receiving the opposite directional outcome (i.e., from increase to decrease) the position is squared off by selling. Similarly, on getting the directional prediction as 'decrease' a SELL position is taken and maintained till the opposite outcome (increase) is obtained. We treated the cycle of BUY-SELL as one trade. We did not consider short selling of stocks while calculating the returns. We calculated separate returns for all trades, which were then aggregated to calculate the average return for all selected indices. The study considers a transaction cost of 0.05%.

If direction changes to Increase $\longrightarrow$ Buy Signal

If direction changes to Decrease $\longrightarrow$ Sell Signal

Otherwise $\longrightarrow$ Hold

Let I_0 be an initial investment, return per trading cycle:

$$T(r) = \sum_{i=1}^{n} I_{t-x}\left[\left(1 + r_{t-(x-1)}\right)\left(1 + r_{t-(x-2)}\right) \dots\dots\dots\dots .(1 + r_{t-2})(1 + r_{t-1})(1 + r_t)\right] \quad (7)$$

Where, $r_t = \frac{CP_t - CP_{t-1}}{CP_{t-1}}$, CP_t is today's closing price, CP_{t-1} is closing price of previous day, x= length of trading cycle, t = time line.

Therefore, $T(r) = \sum_{i=1}^{n} T(r)_i$ (8)

Return after deducting transaction cost, Total return, T(R) =

$$\sum_{i=1}^{n}[T(r)_i - T(r)_i * 0.0005] \quad (9)$$

Annual Return= $\frac{T(R) \times \Pi_i}{252}$ (10)

where, Π_i= Duration of test set in days, Number of working days per year= 252

Values of Π_i for all sets are given below:

S = 50 (1year dats sets), B = 100 (2 years data sets), T = 150 (3 years data sets), Q = 200 (4 years data sets), H = 300 (6 years datasets), D = 600 (12 years dataset).

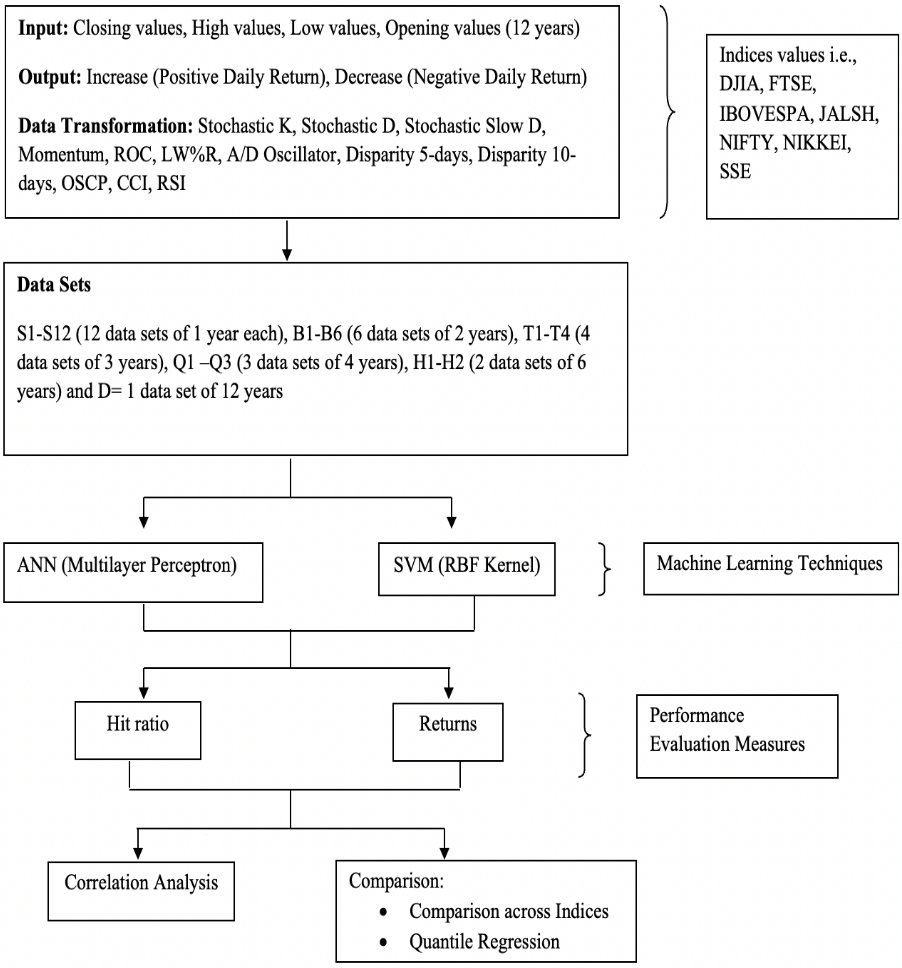
All experiments are performed using Weka 3.8 (Waikato Environment for Knowledge Analysis) and SAS 9.3.

3.4 Quantile Regression

Quantile regression is a statistical technique that estimates and provides inferences about conditional quantile functions. It has become an alternative approach to the traditional method of conditional mean estimation. Quantile regression models the relationship between predictor variables and specific percentiles (or quantiles) of the dependent variable. It specifies changes in the quantiles of the response. Koenker and Basset introduced the quantile regression model (Koenker & Basset, 1978).

The influence of predictor variables on return, i.e., the response variable, is not constant but rather varies across the responses. In the current study, we attempt to examine the impact of predictor variables on high and low values of returns. The models, based on quantile regression, are built for 0.25, 0.5, and 0.75 quantiles, where the response variable is return, and the predictor variables are accuracy rate, techniques, indices, and data sets. The methodology framework implemented in the study is presented as Fig 1.

Fig1: Methodology framework



4. Findings

For investigating the translation of the accuracy rate into returns, we use correlation analysis. Table 1 shows that a significant positive correlation is observed between accuracy rate and return for each stock index. The highest correlation coefficient (0.67) is found for NIKKEI, while the lowest correlation coefficient (0.2856) is noticed for FTSE. A relatively stronger correlation is there between Accuracy rate and returns for NIKKEI (p<0.0001), JALSH (p<0.0001), NIFTY (p=0.0001) and IBOVESPA (p=0.0001). Whereas, relatively weaker correlations between Accuracy rate and return are observed for FTSE (p=0.0328), DJIA (p=0.0015) and SSE (p=0.0015). The correlation between Accuracy rate and return is maximum in the case of NIKKEI models and minimum for FTSE models.

Table1: Index Wise Correlation Between Accuracy Rate and Returns

Index	**Correlation (*p*-value)**
DJIA (n=56)	0.4146 (0.0015)
FTSE (n=56)	0.2856 (0.0328)
IBOVESPA (n=56)	0.4886 (0.0001)
JALSH (n=56)	0.5801 (<0.0001)
NIFTY (n=56)	0.5655 (0.0001)
NIKKEI (n=56)	0.6700 (<0.0001)
SSE (n=56)	0.4208 (0.0015)

Table2 presents the results for difference in degree of correlation between Accuracy rate and returns for all indices.

Table2: Comparison of Degree of Correlation Coefficient for Various Pairs

Indices	SSE	NIKKEI	JALSH	IBOVESPA	FTSE	DJIA	NIFTY
SSE	-	**-1.847 (0.032*)**	-1.091 (0.138)	-0.437 (0.331)	0.789 (0.215)	0.038	-0.981 (0.163)
NIKKEI	-	-	0.763 (0.223)	1.423 (0.077)	**0.266 (0.004**)**	**1.903 (0.029*)**	0.874 (0.191)
JALSH	-	-	-	0.661 (0.254)	**1.899 (0.029*)**	1.140 (0.127)	-0.112 (0.455)
IBOVESPA	-	-	-	-	1.238 (0.108)	0.479 (0.316)	0.549 (0.291)
FTSE	-	-	-	-	-	-0.759 (0.224)	**1.787 (0.037*)**
DJIA	-	-	-	-	-	-	1.028 (0.152)
NIFTY	-	-	-	-	-	-	-

(Negative Z-value indicates that index appearing in column is having higher value of correlation coefficient as compared to index appearing in row, Positive Z-value indicates that exchange appearing in column is having lower value of correlation coefficient as compared to index appearing in row) (Value in parentheses represents *p*-value)

Table 2 shows that all correlation coefficients are positive and significant. A Z-test was used for comparing the correlation coefficients. Table 2 indicates that there is a significant difference in the correlation coefficient for five pairs out of possible 21 pairs. These five pairs include NIKKEI-DJIA (p = 0.029), JALSH-FTSE (p = 0.029), SSE-NIKKEI (p = -1.847), FTSE-NIFTY (p = 0.037), and NIKKEI-FTSE (p = 0.004). No significant difference exists for the remaining sixteen pairs. The difference in correlation coefficient between Accuracy rate and return, for ANN based models and SVM based models was further investigated. Table 3 shows that the correlation coefficient for SVM models is 0.4647 ($p<0.0001$) and the same is 0.1705 ($p=0.0169$) for ANN models. There is a significant difference between the correlation coefficient, between Accuracy rate and returns, of ANN models and SVM models at the 0.1% level of significance.

Table3: Technique wise correlation between Accuracy rate and returns

Technique	Correlation Coefficient (*p*-value)	*Z*-value	*p*-value
SVM (n=194)	0.4647 (<0.0001)	3.244	0.001
ANN (n=196)	0.17050169)		

Data sets, indices and techniques are used as control variables for quantile regression analysis. Table 4 reports summary statistics of the variables used in the model.

Table 4: Summary Statistics

Variable	Q1	Median	Q3	Mean	Standard Deviation	MAD
Accuracy rate	0.796	0.871	0.955	0.856	0.115	0.115
Return	69.452	96.385	140.300	113.400	66.367	47.721

Table 5 shows the summary of the quantile regression model. The model presents the estimated effects of the variable at different quantiles, i.e. 0.25, 0.5 and 0.75. Coefficients of Accuracy rate decrease from quantile 0.25 to quantile 0.75. This implies that there is variation in the influence of Accuracy rate on returns across the quantiles. All three values of the Accuracy rate at different quantiles are positive and significantly different at 0.01% level of significance. Further, the varying effects of data sets and stock indices are also present across different quantiles.

Table 5: Model Summary

Parameters	Estimate (Standard error)		
	Q=0.25	**Q=0.5**	**Q=0.75**
Intercept	-92.534*** (18.654)	-59.711** (17.129)	-31.665 (21.209)
Accuracy rate	202.352*** (22.112)	197.966*** (19.515)	181.000*** (23.426)
D1	22.180* (8.782)	20.861** (6.199)	15.516 (14.369)
H1	22.369* (9.399)	17.695** (5.329)	16.163 (11.645)
H2	19.373* (9.049)	18.876** (6.795)	27.323 (15.010)
Q1	150.731*** (13.732)	148.058*** (9.969)	157.926*** (13.421)
Q2	9.779 (11.625)	7.170 (5.872)	1.096 (11.075)
Q3	4.669 (12.512)	8.796 (7.553)	7.648 (10.255)
T1	54.477*** (13.131)	68.412*** (9.334)	81.646*** (19.513)
T2	18.906 (10.758)	20.918** (5.809)	15.195 (8.168)
T3	8.863 (12.538)	-5.138 (8.016)	13.844 (11.312)
T4	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
B1	1.686 (13.318)	20.942 (15.817)	37.711 (52.116)
B2	147.271*** (22.472)	163.016*** (12.219)	170.118*** (18.046)

Parameters	**Estimate (Standard error)**		
	Q=0.25	**Q=0.5**	**Q=0.75**
B3	10.403 (12.571)	9.918 (6.044)	6.105 (10.991)
B4	-0.383 (9.111)	-2.709 (8.200)	4.396 (24.562)
B5	16.617 (11.143)	19.548* (8.646)	19.377 (42.023)
B6	-5.869 (14.668)	0.352 (8.070)	3.628 (19.234)
S1	2.631 (12.218)	16.106 (14.675)	24.805 (15.470)
S2	-9.609 (17.156)	14.302 (11.931)	28.213 (21.807)
S3	73.855** (22.757)	75.651*** (18.049)	110.512*** (16.090)
S4	114.278*** (13.162)	117.758*** (8.178)	115.674*** (12.146)
S5	-19.031 (16.388)	-5.147 (11.280)	4.222 (10.788)
S6	0.822 (11.493)	10.390 (9.352)	11.370 (9.042)
S7	-0.773 (15.521)	22.971 (12.678)	11.515 (13.832)
S8	-12.699 (17.764)	-1.605 (15.900)	16.668 (20.730)
S9	2.181 (11.811)	1.347 (7.838)	-1.576 (12.660)
S10	4.304 (14.383)	11.144 (9.884)	15.811 (17.227)
S11	61.618*** (13.605)	86.919*** (13.673)	86.676*** (20.402)
S12	-17.827 (11.483)	-8.497 (9.481)	-9.895 (12.094)
FTSE	-29.845*** (7.366)	-56.051*** (5.148)	-61.639*** (5.783)
IBOVESPA	6.578 (10.509)	0.370 (7.126)	2.175 (6.873)
DJIA	-35.509*** (6.656)	-54.109*** (4.304)	-58.804*** (5.681)
NIKKEI	20.064** (6.378)	-4.584 (5.199)	-7.837 (6.059)
JALSH	-13.991* (6.919)	-36.260*** (4.250)	-45.838*** (5.228)
NIFTY	-13.168 (7.027)	-35.623*** (5.258)	-33.056*** (7.359)
SSE	0 (0)	0 (0)	0 (0)
ANN	-4.599 (2.741)	-4.335 (2.454)	-4.091 (2.698)
SVM	0 (0)	0 (0)	0 (0)
Test Results	**Chi-Square=239.9394, *df*=70, p<0.0001**		

*significant at 5 percent, ** significant at 1 percent, *** significant at 0.01 percent

(Standard errors are presented in parentheses)

5. Discussion and Conclusion

The basic purpose of forecasting in stock trading is not only to produce more accurate forecasts but also more profitable forecasts. Given the nature of stock market predictions, it has become necessary to move from simple mathematical model accuracy to model profitability. On account of the influence and guidance of physical sciences and engineering in the context of machine learning techniques, the majority of the previous studies ignored profitability-based assessment of models (Altay & Satman, 2005, Choudhry & Garg, 2008, Gestel et al., 2001, Chun & Park, 2005, Siekmann et al., 1999, Kara et al., 2011, Ou & Wang, 2009, Yu et al., 2009, Kim, 2006, Kim, 2003, Kim & Han 2000). The evaluation of predictive models is a crucial dimension in context of stock market prediction. Directional accuracy measures are rated higher as compared to mathematical accuracy measures. The mere efficiency of directional prediction may not suffice, as the extent of directional change also assumes importance in stock markets. Understanding the linkage between directional accuracy and return remains a barely explored domain in the given context. Several insights can be gleaned from the current study. Firstly, Accuracy rate and returns have a strong positive correlation for all the indices. But there is a significant variation between the correlation coefficients of five index pairs. This indicates that although Accuracy rate and return exhibit a unidirectional relationship, the strength of the relationship varies across different indices. This proves that there is a significant variation in the translation of Accuracy rates into profitability across global stock indices. This variation is also evident for models built on the basis of ANN and SVM. Accuracy rate is merely an indicator of directional accuracy, but in the case of stock predictions, both magnitude and directional accuracy matter. Therefore, there exists a relevant necessity to move towards more appropriate performance measures such as profits, returns, Sharpe ratio, intensity of trading, etc.

Moreover, outcome of quantile regression shows that the impact of Accuracy rate on returns decreases with quantiles. At lower ranges of returns, a strong relationship exists between Accuracy rate and return. Conversely, for higher ranges of returns, a weak relationship exists between both Accuracy rate and returns. This phenomenon may be present on account of higher volatility and trading opportunities in emerging markets as compared to mature and developed markets. Therefore, the findings of the study conclusively prove that a positive relation exists between Accuracy rate and returns. At the same time, variations in the relationship between Accuracy rate and return is quite evident across global stock indices as well as machine learning techniques. For improved decision making, it is required to evaluate machine learning based forecast models on basis of profitability-based performance measures rather than solely on directional accuracy measures.

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