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Comparative Predictive Performance of Support Vector Machines across Global Stock Indices

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Abstract: Given the complexity and non-linearity of stock market data, stock market prediction still remains an intriguing and challenging task. Previously, very few studies have attempted to compare the performance of data mining techniques in diverse markets. Current study adds to the understanding regarding the comparative performance of data mining technique, in terms of accuracy and profitability across seven major stock indices. For prediction purpose, technical analysis has been employed on selected indicators based on daily values of indices spanning a period of 12 years. We created 196 data sets spanning different time periods for model building such as 1 year, 2 years, 3 years, 4 years, 6 years and 12 years for selected seven stock indices. Predictive models have been built using Support Vector Machines (SVMs) with multi-directional dependent variables. Findings of the study indicate that SVM exhibit significantly different accuracy across the global stock indices. Further, highest hit ratio has been obtained for SVM model of FTSE data and highest return has been achieved by SVM model of IBOVESPA data.

Keywords: Stock Market Forecasting, Data Mining Techniques, Support Vector Machines.

I. INTRODUCTION

Stock market is a place where public listed company's shares are traded. The variations of stock market depend on variations of numerous indicators representing the agriculture, industry and service sector. Therefore, stock market returns are affected by various factors in these sectors. Stock markets generates enormous amount of complex and non-linear data. One of the most challenging tasks in modern finance is to find an efficient way to analyze stock market data so as to provide investors useful information for investment decisions. The purpose of prediction is to reduce uncertainty associated with investment decision making. There are multifarious methods available to deal with such an enormous amount of data. But, due to inherent limitations of traditional forecasting techniques in building a model to predict the future values accurately, data mining techniques took prominent place in the domain of stock market prediction. The major drawbacks to traditional methods are: incorrect number of variables, incorrect forecasting model and incorrect values of coefficients of these parameters. These issues can be solved using data mining techniques. In data mining, model is built iteratively till the extraction of unknown patterns and relationships in the data which are almost inconceivable by human imagination.

Data mining techniques can effectively deal with the nonlinearity of the stock market and allow search for hidden patterns, in large volumes of data (Weiss and Indurkhya, 1998). Global integration of stock markets is on the rise, but uniqueness of economies and stock markets cannot be ignored. It makes an interesting research domain to explore the performance of data mining techniques across the global stock markets. Different stock markets bear distinct characteristics on account of stage of native economic development, market dynamics, regulations and nature of market operators. Comparative performance of data mining techniques in such integrated/ diverse settings reveals the ability of these techniques to perform in convergent/ divergent manner across the globe. Exploration of previous studies suggests that little attention has been paid to the said domain. Therefore, the current study adds to the understanding regarding the variations in performance of data mining techniques across the global stock indices. Present paper aims to compare the performance of Support Vector Machines across global stock markets.

II. Background of the Study

Data mining has established itself as a theoretically sound alternative to traditional statistical models in stock market study. Data mining technique is a science and technology of exploring data in order to discover previously unknown patterns and is a part of the overall process of Knowledge Discovery in Databases (KDD). Data mining is a powerful tool for information extraction from large volumes of data (Nag *et al* 2015). These techniques have become an increasingly important research area (Fayyad *et al*. 1996, Weiss and Indurkhya 1998; Shapiro and Frawley 1991, Chen *et al* 2006).

Researchers have also deployed successful applications of data mining in diverse domains including customer relationship management (Rygielski 2002), credit card use (Kumar and Ravi 2008), MIG welding process (Lahoti and Pratihar 2017), bankruptcy prediction (Paramjeet and Ravi 2011, Ramu and Ravi 2009), bacteriology for bacterial identification (Rahman *et al* 2011), detecting blog spam (Yang and Kwok 2017), software fault prediction (Erturk and Sezer 2016), machining parameter optimisation (Ahmad *et al* 2014), demand forecasting (Tigas *et al* 2013), emotional speech analysis (Tuckova and Sramka 2012), fault diagnosis and condition monitoring (Muralidharan and Sugumaran 2016, Saimurugan and Ramachandran 2014) and software engineering (Taylor *et al* 2010). These techniques can be of immense help for better targeting and acquiring new customers, electricity market price spike forecast, sales prediction for different kinds of commodities, business failure detection, financial reports analysis etc. Therefore, data mining techniques have rapidly found applications in diverse fields including stock markets.

Although, there is a plethora of data mining techniques employed for stock market predictions, but SVM (Lahmiri 2011, Hou et al 2013) is definitely among the most popular choices. SVMs adopt the Structural Risk Minimisation Principle which leads to better generalization than conventional techniques with the possibility of wide range of kernel functions. Various researchers establishing the superiority of SVM are there (Cao and Tay 2001, Kim 2003, Huang et al 2005, Kumar and Thenmozhi 2006).

Technical analysis was used for stock market predictions. Technical analysis is based on the rationale that history will repeat itself and that the correlation between price and volume reveals market behavior (Atsalakis and Valavanis 2009). Technical indicators have been used to explore the dynamics of stock price movement by analyzing the past trend of stock prices which include moving average, exponential moving average, bias, MACD, stochastic %K, stochastic %D, OBV (On Balance Volume), momentum, William's % R, ROC (Price rate-of-change), A/D Oscillator, Disparity 5days, Disparity 10days, OSCP (Price Oscillator), CCI (Commodity Channel Index), RSI (Relative strength index) and other measures (Kim 2006, Kim 2003, Cao and Tay 2001).

The purpose of forecasting in stock trading is not only to produce more accurate forecasts but also more profitable forecasts. For an investor, the purpose to forecast is to earn profit. Therefore, the accuracy measures should be translated into profitability for deciding the best prediction model. For this purpose, outcomes of a prediction model are used to build trading strategies. Relatively fewer studies have translated model outcomes into profitability measures (Altay and Satman 2005, Atsalakis and Valavanis 2009, Hargreaves and Hao 2013, Hsieh et al 2011, Hong et al 2007, Schumaker and Chen 2009, Teixeira and Oliveira 2010, Zhai et al 2007, Zhang et al 2007).

Testing the performance of Support Vector Machines across countries is a relatively newer research domain (Chen et al 2006). Outcome of the study will shed the light on utility of Support Vector Machines for predictive modeling in stock exchanges across the globe.

III. METHODS

The present manuscript explores the performance of Support Vector Machines across the global stock indices. Selection of stock indices, data collection and procedures adopted for carrying out the study are given in this section.

Based on Morgan Stanley Capital International (MSCI) market classification, we selected seven countries across the globe (Anonymous, 2016). We selected three developed markets (United States, United Kingdom and Japan) and four emerging markets (China, Brazil, India and South Africa). These selected seven countries account for 55.20 percent of world's GDP as per International Monetary Fund, 2018. Further, we selected indices from largest stock exchanges of these countries on the basis of turnover of financial derivative segment. We selected Dow Jones Industrial Average (DJIA) from New York Stock Exchange of United States, FTSE 100 (labeled as FTSE) from London Stock Exchange Group of United Kingdom, Nikkei 225 (labeled as NIKKEI) from Japan Exchange Group-Tokyo of Japan, SSE 50 (labeled as SSE) from Shanghai Stock Exchange of China, iBovespa (labeled as IBOVESPA) from BM&F Bovespa of Brazil, Nifty 50 (NIFTY) from National Stock Exchange of India and JALSH from JSE Limited (Johannesburg) of South Africa. We recorded daily closing, opening, high and low values of these seven stock indices are recorded for the period of twelve years starting from 1st April, 2005 to 31th March, 2017.

To forecast the direction of daily change in the value of stock index, we used 12 technical indicators as input variables. These indicators include Stochastic %K, Stochastic %D, Stochastic slow %D, Momentum, ROC (rate of change), LW %R (Larry William's %R), A/D Oscillator (accumulation/distribution oscillator), Disparity 5-days, Disparity 10-days, OSCP (Price Oscillator), CCI (Commodity Channel Index) and RSI (Relative Strength Index) (Versace *et al* 2004, Altay and Satman 2005, Huang et al 2008, Kim 2003, Kim 2006, Zhai *et al* 2007, Atsalakis and Valavanis 2009). These indicators are elaborated in Table 1.

Table 1: Selected technical indicators and their description

Input variables	Description	Formula
Stochastic %K	An oscillator that measures the relative position of the closing price within a past high-low range (Kaufman 2013)	$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100$ Where Ct is closing price, LLt is lowest low and HHt is highest high in t days.
Stochastic %D	Moving average of %K (Kaufman 2013)	$\frac{\sum_{i=0}^{n-1} \%K_{t-1}}{n}$
Stochastic slow %D	Moving average of %D (Kaufman 2013)	$\frac{\sum_{i=0}^{n-1} \%D_{t-1}}{n}$
Momentum	It measures the amount that a price has changed over a given time span. (Chang et al 1996)	$C_t - C_{t-n}$ Where n=10, Ct is closing price today

n−1

ROC (rate of change)	It measures the difference between the current price and the price n days ago (Murphy 1986)	$\frac{C_t}{C_{t-n}} \times 100$
LW %R (Larry William's %R)	It is a momentum indicator that measures overbought/oversold levels (Achelis 1995).	$\frac{H_n - C_t}{H_n - L_n} \times 100$
A/D Oscillator ((accumulation/distribution oscillator)	It is a momentum indicator that associates changes in price (Chang et al 1996)	$\frac{H_t - C_{t-1}}{H_t - L_t} \times 100$
Disparity 5-days	It measures the relative position of the closing price to a 5-day moving average (Choi 1995)	$\frac{C_t}{MA_5} \times 100$ Where MA5 is 5-day moving average
Disparity 10-days	It measures the relative position of the closing price to a 10-day moving average (Choi 1995)	$\frac{C_t}{MA_{10}} \times 100$ Where MA10 is 10-day moving average
OSCP (Price Oscillator)	It displays the difference between two moving averages of a security's price (Achelis 1995)	$\frac{MA_5 - MA_{10}}{MA_5}$
CCI (Commodity Channel Index)	It is a measure of the deviation of the current price from the previous *n* days (Kaufman 2013)	$\frac{H_t + L_t + C_t - ADP_{t-1}}{0.015 \times AvgDev_{t-1}}$ Where, $ADP_t = \frac{\sum_{i=t-n+1}^{t}(H_i+L_i+C_i)}{n}$. $AvgDev_t = \frac{\sum_{i=t-n+1}^{t}\lvert H_i+L_i+C_i-ADP_{t-1})}{n}$
RSI (Relative Strength Index)	It is a momentum oscillator that measures the speed and change of price movements ranges from 0 to 100 (Kaufman 2013)	$100-\frac{100}{1+RS}$, where $RS=\frac{AU}{AD}$ AU = total of the upwards price changes during the past 14 days, AD = the total of the downwards price changes (used as positive numbers) during the past 14 days

For the purpose of experimentation, we created data sets spanning variable time length. We created 196 data sets with 28 data sets for each stock index. These 28 data sets are of 1 year (12 data sets), 2 years (6 data sets), 3 years (4 data sets), 4 years (3 data sets), 6 years (2 data sets) and 12 years (1 data set). For each data set, we use 80% records for training the model and the remaining 20% for testing the model.

For the purpose of model building, we considered multidirectional dependent variables. Multi-directional included three possible outcomes *i.e.* increase, neutral and decrease. For assigning various value changes to these categories, values of index returns were arranged in increasing order. Values of return near zero were analyzed to cover up for the transaction cost. Based on analysis of various stock index returns, three categories of outcomes were classified as follows:

Increase: Top 45 percent values

Decrease: Bottom 45 percent values

Neutral: Remaining 10 percent values

Based on test set, daily directional outcomes were predicted. Further, a trading strategy was evolved to calculate returns. Trading strategy involved 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 BUY position is taken and maintained till opposite outcome (increase) is obtained. We treated 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 of all indices. The study considers the transaction cost of 0.05%.

In this study, we used Support Vector Machines for predicting the selected indices.

Support Vector Machines: Support Vector Machine (SVM) is a supervised statistical learning technique (Vapnik 1998) based on Structural Risk Minimization (SRM) principle and is an approximation implementation of the method of SRM with a good generalization capability. This technique came up as a promising alternative to NN in terms of accuracy. They are less prone to overfitting than other methods. Even when the dimensionality of the data is high, SVM with a small number of support vectors can have good generalization (Han *et al* 2012). Kernel functions play a vital role in pattern recognition through SVM.

There are various kernels for generating the inner products to construct machines with different types of nonlinear decision surfaces in the input space (Kumar and Thenmozi, 2006). There are many possible kernel functions like Gaussian, Linear, Polynomial, Radial basis and Sigmoidal functions. The choice of kernel function is a critical decision for prediction efficiency. In most cases support vector machine gives better results when radial basis function (RBF) kernel is used (Arasu *et al* 2014). For the current study, RBF kernel is selected for training the model.

RBF kernel:

K(x, y) = e^-(gamma * <x-y, x-y>),

where gamma is the constant of RBF.

John Platt's sequential minimal optimization algorithm was implemented using Weka software. The levels for various parameters considered in current study i.e. Complexity parameter (c), ε parameter, Tolerance parameter and Gamma of kernel function are 1, 1.0E-12, 0.001 and 0.01 respectively.

Wilcoxon Signed Rank Test: Frank Wilcoxon proposed Wilcoxon signed rank test in 1945 (Wilcoxon 1945). It is a non-parametric statistical test to compare two related samples or repeated measurements on a single sample to assess whether their population mean differs (Rosner *et al* 2006). It is also known as paired difference test. This test is applied to find the significant difference in hit ratio and returns across the models of all indices.

Let D_i be the difference between two paired random variables, assuming the difference be mutually independent, Di, i = 1, 2, … N derives from a continuous distribution F which is symmetric about a median ϴ.

$$D_i = Y_i - X_i, \text{ i= 1 to N}$$

Further, N_0 and M are denoted for number of zero and the number of non-zero differences in the sample respectively.

$$N = N_0 + M$$

Wilcoxon Signed Rank test statistic is the linear rank statistic $R_+ = \sum_{i=1}^{N}(R_I V_i)$ where Vi = $1_{Di>0}$ is the indicator for the sign of the difference and R_i is the rank of $|D_i|$, i=1,2……,N. Therefore, Wilcoxon Signed Rank test statistic represents the sum of the positive signed ranks build in terms of the sum of negative signed ranks, R− or the difference of both R = (R+) – (R−).

Let w_{α} be critical values for the exact distribution of R+. Reject the null hypothesis at the α level of significance if R+ ≥ $w_{\alpha/2}$ or R+ ≤ $R_{+} = 1 + \frac{N(N+1)}{2} - w_{\alpha/2}$.

Large-sample approximation uses asymptotic normal distribution of R+. Under the null hypothesis,

$$E_0(R_+) = \frac{N(N+1)}{4}$$

$$Var_0(R_+) = \frac{N(N+1)(2N+1)}{4}$$

Standardized version of R_+ is asymptotically:

$$R_+^* = \frac{R_+ - E_0(R_+)}{Var_0(R_+)^{1/2}} \quad \square\ N(0,1)$$

Reject null hypotheses if $|R_+^*| \geq Z_{1-\alpha/2}$ (Rey and Neuhauser, 2014).

IV. Results

The results of summary statistics of Hit Ratio, raw return and transaction cost adjusted return, Mean Absolute Error and Root Mean Square Error for SVM Models of all indices are described in the following section. Results of pairwise comparison for various indices are also presented in the following section.

Summary statistics of Hit Ratio: Multi-directional SVM models

Table 2 summarizes the index wise descriptive statistics of Hit Ratio for SVM models of selected indices. SVM model of FTSE data achieved highest mean Hit Ratio of 80.372 followed by model for DJIA and JALSH data with mean value of 77.557 and 76.802 respectively. SVM model for NIFTY data obtained the minimum Hit Ratio *i.e.* 63.893. Table 45 also reveals that SVM model of SSE data has obtained the highest value of standard deviation *i.e.* 13.395 followed by models for NIKKEI and NIFTY data with standard deviation values of 12.154 and 11.880 respectively. SVM model of DJIA data obtained the lowest value of standard deviation *i.e.* 9.906. Further, it can be seen from the Table 45 that SVM model of JALSH data was found to obtain the highest value of range *i.e.* 55.367 followed by models of NIKKEI and SSE data with values of range of 51.020 and 49.120 respectively. ANN model of FTSE data obtained the minimum value of range *i.e.* 38.450.

Table 2: Summary statistics of Hit Ratio

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	77.557	80.372	76.335	76.802	63.893	67.374	68.893
Standard Error	1.872	1.876	2.105	2.104	2.245	2.297	2.531
Median	79.474	84.000	79.735	77.500	64.373	69.388	72.541
Standard Deviation	9.906	9.926	11.138	11.133	11.880	12.154	13.395
Sample Variance	98.132	98.532	124.047	123.933	141.145	147.719	179.426
Kurtosis	-0.013	1.150	-1.166	4.564	0.244	0.810	0.287
Skewness	-0.652	-1.337	-0.407	-1.504	-0.193	-0.837	-1.079
Range	39.069	38.450	39.722	55.367	47.396	51.020	49.120
Minimum	54.000	52.941	53.061	38.000	39.583	34.694	37.500
Maximum	93.069	91.391	92.784	93.367	86.979	85.714	86.620

Hit Ratio based comparison of Index Pairs

Table 3 represents that there was a significant difference between Hit Ratio of different indices based on SVM models for 13 out of 21 index pairs. Hit Ratio of SVM model for FTSE was found to be significantly different from Hit Ratio of SVM models for NIFTY, NIKKEI and SSE data at 0.01 percent level of significance.

Table 3: Hit Ratio based comparison of Index Pairs

Pairs	Mean Difference	Std Error	*S*- value (*p*- value)
FTSE vs DJIA	0.028	0.016	64.5 (0.1022)
IBOVESPA vs DJIA	-0.012	0.018	-22 (0.6252)
IBOVESPA vs FTSE	-0.040	0.024	-51 (0.2527)
JALSH vs DJIA	-0.008	0.021	-5 (0.907)
JALSH vs FTSE	-0.036	0.014	-107.5 (0.0071)
JALSH vs IBOVESPA	0.005	0.024	10 (0.8153)
NIFTY vs DJIA	-0.137	0.025	-176 (<0.0001)
NIFTY vs FTSE	-0.165	0.018	-199 (<0.0001)
NIFTY vs IBOVESPA	-0.124	0.026	-158.5 (<0.0001)
NIFTY vs JALSH	-0.129	0.016	-193 (<0.0001)
NIKKEI vs DJIA	-0.102	0.022	-160 (<0.0001)
NIKKEI vs FTSE	-0.130	0.021	-183 (<0.0001)
NIKKEI vs IBOVESPA	-0.090	0.024	-143 (0.0004)
NIKKEI vs JALSH	-0.094	0.024	-142 (0.0004)
NIKKEI vs NIFTY	0.035	0.022	56 (0.2079)
SSE vs DJIA	-0.087	0.022	-150 (0.0002)
SSE vs FTSE	-0.115	0.023	-174 (<0.0001)
SSE vs IBOVESPA	-0.074	0.031	-94.5 (0.0286)
SSE vs JALSH	-0.079	0.027	-137 (0.0008)
SSE vs NIFTY	0.050	0.029	79 (0.0712)
SSE vs NIKKEI	0.015	0.031	51 (0.2527)

(Positive mean difference indicates that mean value of Hit Ratio of former is greater than mean Hit Ratio of latter index and negative mean difference indicates that mean value of Hit Ratio of former is lesser than mean Hit Ratio of latter index.)

Further, Hit Ratio of FTSE model was significantly different from Hit Ratio of JALSH model at 1 percent level of significance. Hit Ratio for SVM model for FTSE was not significantly different from IBOVESPA and DJIA. Further, the Table 3 reveals that Hit Ratio for SVM model for DJIA data observed to be significantly different from Hit Ratio of SVM models for NIFTY and NIKKEI data at 0.01 percent level of significance. Hit Ratio for SVM models for DJIA was also significantly different from SSE at 1 percent level of significance and Hit Ratio for SVM models for DJIA was not significantly different from IBOVESPA and JALSH. Hit Ratio for IBOVESPA model was significantly different from Hit Ratio of SVM models of NIFTY at 0.01 percent level of significance. Hit Ratio of IBOVESPA model was significantly different from Hit Ratio of SVM model for NIKKEI at 1 percent level of significance. Hit Ratio of IBOVESPA model was significantly different from Hit Ratio of SVM model for SSE at 5 percent level of significance. Hit Ratio of models of JALSH and IBOVESPA was not significantly different from each other. Hit Ratio of SVM model for JALSH was found to be significantly different from Hit Ratio of NIFTY at 0.01 percent level of significance. Hit Ratio of SVM model of JASLH was significantly different from NIKKEI and JALSH at 1 percent level of significance. Further, Hit Ratio for NIFTY model was not significantly different from Hit Ratio of NIKKEI and SSE. Also, Hit Ratio for NIFTY model was not significantly different from Hit Ratio of SSE model.

Summary statistics of Raw Return

Table 4 summarizes the index wise descriptive statistics of raw returns for SVM models of selected indices. SVM model of IBOVESPA was found to have highest returns *i.e.* 132.981 followed by SVM models of NIKKEI and SSE data with mean values 107.140 and 106.565 respectively. Minimum return was observed for SVM model of DJIA *i.e.* 83.449. Table 4 also reveals that SVM model of IBOVESPA obtained the highest value of standard deviation *i.e.* 78.313 followed by models for SSE and NIFTY with standard deviation values of 76.262 and 70.531 respectively. SVM model of FTSE obtained the lowest value of standard deviation *i.e.* 44.144. Further, SVM model of SSE was found to obtain the highest value of range *i.e.* 266.897 followed by models of DJIA and JALSH with values of range of 247.034 and 246.866 respectively. ANN model of FTSE obtained the minimum value of range *i.e.* 197.183. IBOVESPA performed best among all indices in terms of Hit Ratio and returns.

Table 4: Summary statistics of Raw Return

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	83.449	89.876	132.981	95.319	86.026	107.140	106.565
Standard Error	10.172	8.342	14.800	11.208	13.329	11.529	14.412
Median	70.980	80.690	119.643	80.278	69.165	104.049	102.533
Standard Deviation	53.823	44.144	78.313	59.308	70.531	61.004	76.262
Sample Variance	2896.877	1948.692	6132.963	3517.416	4974.584	3721.428	5815.855
Kurtosis	4.584	1.349	0.240	1.368	2.623	0.923	-0.498
Skewness	2.081	1.049	0.588	1.138	1.500	0.842	0.564
Range	247.034	197.183	320.319	246.866	314.494	244.580	266.897
Minimum	7.004	13.474	-2.392	0.000	-19.567	4.688	0.000
Maximum	254.039	210.657	317.927	246.866	294.927	249.268	266.897

Raw Returns based comparison of Index Pairs

The comparison of raw returns of all index pairs using SVM model, where dependent variable is multi-directional, is presented in Table 5. It can be seen from Table 5 that there was a significant difference between raw returns of different indices based on SVM models for 11 out of 21 index pairs. Raw return of SVM model for FTSE was found to be significantly different from raw return of SVM models for IBOVESPA at 1 percent level of significance.

Table 5: Raw Returns based comparison of Index Pairs

Pairs	Mean Difference	Std Error	*S*- value (*p*- value)
FTSE vs DJIA	10.497	5.090	91 (0.0063)
IBOVESPA vs DJIA	50.120	10.905	123 (<0.0001)
IBOVESPA vs FTSE	39.623	10.346	110 (0.0005)
JALSH vs DJIA	17.757	4.947	108 (0.0007)
JALSH vs FTSE	7.260	4.371	49 (0.166)
JALSH vs IBOVESPA	-32.363	9.673	-98 (0.0028)
NIFTY vs DJIA	5.287	8.795	57 (0.105)
NIFTY vs FTSE	-5.209	11.341	-19 (0.598)
NIFTY vs IBOVESPA	-44.833	12.635	-109 (0.0006)
NIFTY vs JALSH	-12.469	10.936	-35 (0.328)
NIKKEI vs DJIA	20.627	7.503	87 (0.0096)
NIKKEI vs FTSE	10.131	8.803	53 (0.133)
NIKKEI vs IBOVESPA	-29.493	13.707	-73 (0.0338)
NIKKEI vs JALSH	2.870	10.956	11 (0.761)
NIKKEI vs NIFTY	15.340	10.658	44 (0.216)
SSE vs DJIA	33.974	12.212	93 (0.0051)
SSE vs FTSE	23.477	12.219	69 (0.0461)
SSE vs IBOVESPA	-16.146	15.123	-32 (0.372)
SSE vs JALSH	16.217	13.131	50 (0.157)
SSE vs NIFTY	28.687	11.667	70 (0.0428)
SSE vs NIKKEI	13.347	12.332	32 (0.372)

(Positive mean difference indicates that mean value of raw returns of former is greater than mean raw returns of latter index and negative mean difference indicates that mean value of raw returns of former is lesser than mean raw returns of latter index.)

Raw return of FTSE model was significantly different from raw return of DJIA model at 1 percent level of significance on the basis of Wilcoxon signed test. Further, raw return of FTSE model was not significantly different from raw return of models of JALSH and NIFTY. Table 5 reveals that raw return for SVM model for DJIA observed to be significantly different from raw return of IBOVESPA model at 0.01 percent level of significance. Also, raw return of DJIA model was significantly different from NIKKEI, SSE and JALSH at 1 percent level of significance. Raw return of DJIA was not significantly different from NIFTY. Raw return for IBOVESPA model was significantly different from raw return of SVM models of NIFTY and JALSH at 1 percent level of significance. Raw return of IBOVESPA model was significantly different from raw return of SVM model of NIKKEI at 5 percent level of significance. Raw returns of IBOVESPA and SSE were not significantly different from each other. Raw return of SVM model for NIKKEI was not significantly different from raw return of JALSH, NIFTY and SSE. Also, raw return for SSE model was significantly different from raw return of NIFTY at 5 percent level of significance. Raw returns of models of SSE and JALSH were not significantly different from each other.

Summary statistics of Transaction Cost adjusted Returns

Table 6 summarizes the index wise descriptive statistics of transaction cost adjusted returns for SVM models of selected indices for multidirectional dependent variable.

Table 6: Summary statistics of Transaction Cost adjusted Returns

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	83.425	89.852	132.959	95.297	86.008	107.120	106.545
Standard Error	10.171	8.342	14.799	11.208	13.328	11.528	14.411
Median	70.950	80.661	119.621	80.253	69.141	104.020	102.519
Standard Deviation	53.820	44.140	78.308	59.305	70.527	60.998	76.257
Sample Variance	2896.587	1948.353	6132.212	3517.067	4974.045	3720.791	5815.164
Kurtosis	4.585	1.349	0.240	1.368	2.624	0.923	-0.498
Skewness	2.081	1.049	0.588	1.138	1.500	0.842	0.564
Range	247.014	197.158	320.299	246.843	314.471	244.560	266.879
Minimum	6.994	13.472	-2.397	0.000	-19.570	4.685	0.000
Maximum	254.009	210.630	317.902	246.843	294.901	249.245	266.879

It can be seen from Table 6 that SVM model of IBOVESPA has found to have highest transaction cost adjusted returns *i.e.* 132.959 followed by SVM model of NIKKEI and SSE with mean value 107.120 and 106.545 respectively. Minimum return has been observed for SVM model of DJIA *i.e.* 83.425. Table 6 also reveals that SVM model of IBOVESPA has obtained the highest value of standard deviation *i.e.* 78.308 followed by models for SSE and NIFTY with standard deviation values of 76.257 and 70.527 respectively. SVM model of FTSE obtained the lowest value of standard deviation *i.e.* 44.140. SVM model of IBOVESPA was found to obtain the highest value of range *i.e.* 320.299 followed by models of NIFTY and SSE with values of range of 314.471 and 266.879 respectively. ANN model of FTSE obtained the minimum value of range *i.e.* 197.158.

Transaction Cost adjusted Returns based comparison of Index Pairs

The comparison of transaction cost adjusted returns of all index pairs using SVM model, where dependent variable is multi-directional, is presented in Table 7. It can be seen from Table 7 that there was a significant difference between returns of different indices based on SVM models for 11 out of 21 index pairs. Return of SVM model for FTSE was found to be significantly different from return of SVM models for IBOVESPA at 1 percent level of significance. Return of FTSE model was significantly different from return of DJIA model at 1 percent level of significance. Further, return of FTSE model was not significantly different from return of JALSH and NIFTY. Return for SVM model for DJIA was observed to be significantly different from return of IBOVESPA model at 0.01 percent level of significance. Also, return of DJIA model was significantly different from returns of models of NIKKEI, SSE and JALSH at 1 percent level of significance. Return of DJIA model was not significantly different from NIFTY model return. Returns for IBOVESPA model was significantly different from return of SVM models of NIFTY and JALSH data at 1 percent level of significance. Return of IBOVESPA model was significantly different from return of SVM model of NIKKEI at 5 percent level of significance. Returns of IBOVESPA and SSE were not significantly different from each other. Return of SVM model for NIKKEI was not significantly different from return of JALSH, NIFTY and SSE models. Also, return for SSE model was significantly different from return of NIFTY at 5 percent level of significance. Returns of SSE and JALSH were not significantly different from each other.

Table 7:Transaction Cost adjusted Returns based comparison of Index Pairs

Pairs	Mean Difference	Std Error	*S*- value (*p*- value)
FTSE vs DJIA	10.495	5.089	91 (0.0063)
IBOVESPA vs DJIA	50.123	10.904	123 (<0.0001)
IBOVESPA vs FTSE	39.627	10.345	110 (0.0005)
JALSH vs DJIA	17.757	4.947	108 (0.0007)
JALSH vs FTSE	7.261	4.371	49 (0.1661)
JALSH vs IBOVESPA	-32.366	9.671	-98 (0.0028)
NIFTY vs DJIA	5.293	8.795	57 (0.1045)
NIFTY vs FTSE	-5.203	11.341	-19 (0.598)
NIFTY vs IBOVESPA	-44.830	12.634	-109 (0.0006)
NIFTY vs JALSH	-12.464	10.935	-35 (0.3277)
NIKKEI vs DJIA	20.631	7.503	87 (0.0096)
NIKKEI vs FTSE	10.136	8.802	53 (0.1327)
NIKKEI vs IBOVESPA	-29.491	13.705	-73 (0.0338)
NIKKEI vs JALSH	2.874	10.955	11 (0.7606)
NIKKEI vs NIFTY	15.339	10.658	44 (0.2156)
SSE vs DJIA	33.977	12.212	93 (0.0051)
SSE vs FTSE	23.481	12.219	69 (0.0461)
SSE vs IBOVESPA	-16.146	15.122	-32 (0.3700017)
SSE vs JALSH	16.220	13.131	50 (0.1500073)
SSE vs NIFTY	28.684	11.667	70 (0.0428)
SSE vs NIKKEI	13.345	12.331	32 (0.3717)

(Positive mean difference indicates that mean value of transaction cost adjusted returns of former is greater than mean transaction cost adjusted returns of latter index and negative mean difference indicates that mean value of transaction cost adjusted returns of former is lesser than mean transaction cost adjusted returns of latter index.)

Summary statistics of Mean Absolute Error

Table 8 summarizes the index wise descriptive statistics of Mean Absolute Error for SVM models of selected indices for multidirectional dependent variable. It can be seen from Table 8 that SVM model of NIFTY obtained highest mean value of Mean Absolute Error *i.e.* 0.351 followed by SVM model of NIKKEI and SSE data with mean values of 0.316 and 0.314 respectively. SVM model of FTSE observed to have minimum Mean Absolute Error *i.e.* 0.288. SVM model of NIFTY obtained highest value of standard deviation *i.e.* 0.041 followed by models for NIKKEI and SSE with standard deviation value of 0.041 and 0.034 respectively. SVM model of FTSE obtained the lowest value of standard deviation *i.e.* 0.027. Further, SVM model of NIFTY was found to obtain the highest value of range *i.e.* 0.161 followed by models of JALSH and NIKKEI with values of range of 0.151 and 0.150 respectively. ANN model of FTSE data obtained the minimum value of range *i.e.* 0.120.

Table 8: Summary Statistics of Mean Absolute Error

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.294	0.288	0.298	0.295	0.351	0.316	0.314
Standard Error	0.005	0.005	0.005	0.006	0.008	0.007	0.006
Median	0.291	0.284	0.296	0.294	0.349	0.312	0.309
Standard Deviation	0.028	0.027	0.028	0.032	0.041	0.035	0.034
Sample Variance	0.001	0.001	0.001	0.001	0.002	0.001	0.001
Kurtosis	0.845	1.752	-1.366	2.427	-0.135	0.632	-0.084
Skewness	0.604	1.142	0.037	1.089	-0.061	0.615	0.767

Range	0.127	0.120	0.097	0.151	0.161	0.150	0.129
Minimum	0.242	0.250	0.247	0.244	0.265	0.259	0.257
Maximum	0.369	0.370	0.345	0.396	0.426	0.408	0.386

Mean Absolute Error based comparison of Index Pairs: Multi-directional SVM Models

The comparison of Mean Absolute Error of all index pairs using SVM model, where dependent variable is multi-directional, is presented in Table 9. There was a significant difference between Mean Absolute Error of different indices based on SVM models for 14 out of 21 index pairs. Mean Absolute Error of FTSE model was significantly different from Mean Absolute Error of models of NIFTY, NIKKEI and SSE at 0.01 percent level of significance. Mean Absolute Error for SVM model of FTSE was not significantly different from JALSH, IBOVESPA and DJIA. Mean Absolute Error for SVM model for DJIA observed to be significantly different from Mean Absolute Error of SVM models for NIFTY at 0.01 percent level of significance. Mean Absolute Error for SVM models for DJIA was also significantly different from NIKKEI and SSE data at 1 percent level of significance. DJIA model Mean Absolute Error was not significantly different from models of IBOVESPA and JALSH.

Table 9: Mean Absolute Error based comparison of Index Pairs

Pairs	Mean Difference	Std Error	*S*- value (*p*- value)
FTSE vs DJIA	-0.0057	0.0052	-35.5 (0.4039)
IBOVESPA vs DJIA	0.0037	0.0049	37.5 (0.4029)
IBOVESPA vs FTSE	0.0094	0.0064	60 (0.1763)
JALSH vs DJIA	0.0007	0.0062	-8 (0.8593)
JALSH vs FTSE	0.0065	0.0042	61.5 (0.1202)
JALSH vs IBOVESPA	-0.0029	0.0060	-32 (0.4524)
NIFTY vs DJIA	0.0573	0.0090	185 (<0.0001)
NIFTY vs FTSE	0.0630	0.0060	202 (<0.0001)
NIFTY vs IBOVESPA	0.0536	0.0082	183 (<0.0001)
NIFTY vs JALSH	0.0566	0.0057	201 (<0.0001)
NIKKEI vs DJIA	0.0222	0.0063	132 (0.0013)
NIKKEI vs FTSE	0.0280	0.0057	167.5 (<0.0001)
NIKKEI vs IBOVESPA	0.0186	0.0066	109 (0.0103)
NIKKEI vs JALSH	0.0215	0.0071	114 (0.0069)
NIKKEI vs NIFTY	-0.0351	0.0075	-157 (<0.0001)
SSE vs DJIA	0.0201	0.0065	122 (0.0035)
SSE vs FTSE	0.0259	0.0056	162.5 (<0.0001)
SSE vs IBOVESPA	0.0165	0.0076	86 (0.0481)
SSE vs JALSH	0.0194	0.0070	128.5 (0.0019)
SSE vs NIFTY	-0.0372	0.0083	-146 (0.0003)
SSE vs NIKKEI	-0.0021	0.0079	-19.5 (0.6651)

(Positive mean difference indicates that mean value of Mean Absolute Error of former is greater than Mean Absolute Error of latter index and negative mean difference indicates that mean value of Mean Absolute Error of former is lesser than Mean Absolute Error of latter index.)

Mean Absolute Error for IBOVESPA model was significantly different from Mean Absolute Error of SVM models of NIFTY at 0.01 percent level of significance. Also, Mean Absolute Error of IBOVESPA was significantly different from SSE at 5 percent level of significance. Mean Absolute Error of IBOVESPA model was not significantly different from Mean Absolute Error of SVM model for JALSH. Mean Absolute Error of SVM model for JALSH was found to be significantly different from Mean Absolute Error of NIFTY at 0.01 percent level of significance. Mean Absolute Error of SVM model of JASLH was significantly different from NIKKEI and JALSH at 1 percent level of significance. Further, Mean Absolute Error for NIFTY model was significantly different from Mean Absolute Error of NIKKEI model at 0.001 percent level of significance. Also, Mean Absolute Error for SSE model was significantly different from Mean Absolute Error of NIFTY model at 1 percent level of significance. MAE of SVM models of SSE and NIKKEI were not significantly different from each other.

Summary Statistics of Root Mean Square Error

Table 10 summarizes the index wise descriptive statistics of Root Mean Square Error for SVM models of selected indices for multidirectional dependent variable. SVM model of NIFTY obtained the highest mean value of Root Mean Square Error *i.e.* 0.448 followed by SVM model of NIKKEI and SSE with mean values of 0.408 and 0.405 respectively. SVM model of FTSE was observed to have minimum Root Mean Square Error *i.e.* 0.373. SVM model of NIFTY obtained the highest value of standard deviation *i.e.* 0.047 followed by models for NIKKEI and SSE with standard deviation values of 0.042 and 0.041 respectively. SVM model of FTSE obtained the lowest value of standard deviation *i.e.* 0.035. Further, SVM model of JALSH was found to obtain the highest value of range *i.e.* 0.187 followed by models of NIFTY and NIKKEI data with values of range of 0.185 and 0.178 respectively. SVM model of IBOVESPA obtained the minimum value of range *i.e.* 0.128.

Table 10: Summary statistics of Root Mean Square Error

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.380	0.373	0.385	0.381	0.448	0.408	0.405
Standard Error	0.007	0.007	0.007	0.008	0.009	0.008	0.008
Median	0.377	0.369	0.384	0.382	0.449	0.405	0.401
Standard Deviation	0.036	0.035	0.037	0.040	0.047	0.042	0.041
Sample Variance	0.001	0.001	0.001	0.002	0.002	0.002	0.002
Kurtosis	0.475	0.968	-1.303	1.308	0.164	0.206	-0.218
Skewness	0.291	0.862	-0.066	0.685	-0.357	0.312	0.572
Range	0.163	0.152	0.128	0.187	0.185	0.178	0.158
Minimum	0.306	0.320	0.315	0.310	0.342	0.332	0.329
Maximum	0.470	0.471	0.443	0.497	0.527	0.510	0.487

Root Mean Square Error based comparison of Index Pairs: Multi-directional SVM Models

The comparison of Root Mean Square Error of all index pairs using SVM model, where dependent variable is multi-directional, is presented in Table 11. There was a significant difference between Root Mean Square Error of different indices based on SVM models for 13 out of 21 index pairs. Root Mean Square Error of FTSE model was significantly different from Root Mean Square Error of models of NIFTY, NIKKEI and SSE at 0.01 percent level of significance. Root Mean Square Error for SVM model of FTSE was not significantly different from JALSH, IBOVESPA and DJIA.

Table 11: Root Mean Square Error based comparison of Index Pairs: Multi-directional SVM Models

Pairs	Mean Difference	Std Error	*S*- value (*p*- value)
FTSE vs DJIA	-0.0075	0.0067	-37 (0.3841)
IBOVESPA vs DJIA	0.0047	0.0063	34 (0.4488)
IBOVESPA vs FTSE	0.0122	0.0083	60 (0.1763)
JALSH vs DJIA	0.0005	0.0077	-8 (0.8593)
JALSH vs FTSE	0.0081	0.0051	59.5 (0.1333)
JALSH vs IBOVESPA	-0.0042	0.0076	-32 (0.4524)
NIFTY vs DJIA	0.0681	0.0102	185 (<0.0001)
NIFTY vs FTSE	0.0756	0.0068	202 (<0.0001)
NIFTY vs IBOVESPA	0.0634	0.0094	184 (<0.0001)
NIFTY vs JALSH	0.0676	0.0064	201 (<0.0001)
NIKKEI vs DJIA	0.0276	0.0076	132 (0.0013)
NIKKEI vs FTSE	0.0351	0.0071	167 (<0.0001)
NIKKEI vs IBOVESPA	0.0229	0.0080	111 (0.0088)
NIKKEI vs JALSH	0.0271	0.0085	116 (0.0058)
NIKKEI vs NIFTY	-0.0405	0.0086	-155.5 (<0.0001)
SSE vs DJIA	0.0252	0.0080	121 (0.0038)
SSE vs FTSE	0.0327	0.0068	164 (<0.0001)
SSE vs IBOVESPA	0.0205	0.0094	83 (0.0572)
SSE vs JALSH	0.0247	0.0083	128.5 (0.0019)
SSE vs NIFTY	-0.0429	0.0095	-146 (0.0003)

SSE vs NIKKEI	-0.0024	0.0096	-21 (0.6411)

(Positive mean difference indicates that mean value of Root Mean Square Error of former is greater than mean Root Mean Square Error of latter index and negative mean difference indicates that mean value of Root Mean Square Error of former is lesser than mean Root Mean Square Error of latter index.)

Further, the Table 11 reveals that Root Mean Square Error for SVM model for DJIA has observed to be significantly different from Root Mean Square Error of SVM models for NIFTY at 0.01 percent level of significance. Root Mean Square Error for SVM models for DJIA has also been significantly different from NIKKEI and SSE at 1 percent level of significance. DJIA model Root Mean Square Error was not significantly different from models of IBOVESPA and JALSH. Root Mean Square Error for IBOVESPA model was significantly different from Root Mean Square Error of SVM models of NIFTY at 0.01 percent level of significance. Also, Root Mean Square Error of IBOVESPA was significantly different from SSE at 1 percent level of significance. Root Mean Square Error of IBOVESPA model was not significantly different from Root Mean Square Error of SVM model for JALSH. Root Mean Square Error of SVM model for JALSH was found to be significantly different from Root Mean Square Error of NIFTY at 0.01 percent level of significance. Root Mean Square Error of SVM model of JASLH was significantly different from NIKKEI and JALSH at 1 percent level of significance. Further, Root Mean Square Error for NIFTY model was significantly different from Root Mean Square Error of NIKKEI model at 0.01 percent level of significance. Also, Root Mean Square Error for SSE model was significantly different from Root Mean Square Error of NIFTY model at 1 percent level of significance. Root Mean Square Error of SVM models of SSE and NIKKEI were not significantly different from each other.

V. Discussions

The findings of the study indicate that Support Vector Machines exhibits significantly different performance across selected stock indices. On the basis of hit ratio, significant differences across 12 pairs are there out of total 21 pairs. On the other hand, for returns significant differences are there only for 9 pairs out of 21 pairs. This clearly indicates a difference in performance of support vector machines across different countries. These differences may be on account of reasons such as structure of the market, level of maturity, market stability, risk factor, volatility of market, political stability (Ahmad et al 2016, Morck et al 1999, Flannery and Protopapadakis 2002). These differences may be on account of reasons such as level of maturity, structure of the market,risk factor, market stability, political stability, volatility of market etc (Ahmad et al 2016, Morck et al 1999, Flannery and Protopapadakis 2002).

VI. Conclusion

Findings of the study indicate that SVM exhibit significantly different accuracy across the global stock indices. Further, highest hit ratio has been obtained for SVM model of FTSE data and lowest hit ratio has been obtained for model of NIFTY data. Highest return has been achieved by SVM model of IBOVESPA data and lowest returns has been obtained by model of DJIA data. Also, Mean Absolute Error and Root Mean Square Error of models built using SVM were highest for NIFTY model and lowest for FTSE model.

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