Predicting Daily Returns of Global Stocks Indices: Neural Networks vs Support Vector Machines

Abstract

Uniqueness in economies and stock markets has given rise to an interesting domain of exploring data mining techniques across global indices. Previously, very few studies have attempted to compare the performance of data mining techniques in diverse markets. The current study adds to the understanding regarding the variations in performance of data mining techniques across the global stock indices. We compared the performance of Neural Networks and Support Vector Machines using accuracy measures Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) across seven major stock markets. 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. Based on prediction models built using Neural Networks and Support Vector Machines, the findings of the study indicate there is a significant difference, both for MAE and RMSE, across the selected global indices. Also, Mean Absolute Error and Root Mean Square Error of models built using NN were greater than Mean Absolute Error and Root Mean Square Error of models built using SVM.

Keywords: Stock Market Forecasting, Neural Networks, Support Vector Machines.

1.0 Introduction

Capital is an important means of production and stock market plays a crucial role in mobilizing capital for various business activities including food processing, textiles, fertilizers and pesticides etc. Stock market plays a significant role in the economic growth of the country to a great extent. 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.

A large body of research on application of data mining to stock market has been produced. Data mining techniques can effectively deal with the nonlinearity of the stock market and allows a search for valuable information, in large volumes of data (Weiss and Indurkhya, 1998). For making profitable

trades, investors are highly interested in forecasting the future trend of stock market indices and stock prices. Further, uniqueness in economies and stock markets has given rise to an interesting domain of exploring data mining techniques across global indices. 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 data mining techniques across global stock markets by using the popular techniques such as Neural Networks and Support Vector Machines. Comparisons are also drawn between ANN and SVM in terms of MAE and RMSE of predicted values of daily returns.

2.0 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).

Applications of data mining techniques encompasses wide variety of domains including credit card use (Kumar and Ravi 2008), customer relationship management (Rygielski 2002), bankruptcy prediction (Paramjeet and Ravi 2011, Ramu and Ravi 2009), bacteriology for bacterial identification (Rahman *et al* 2011), MIG welding process (Lahoti and Pratihar 2017), detecting blog spam (Yang and Kwok 2017), fault diagnosis and condition monitoring (Muralidharan and Sugumaran 2016, Saimurugan and Ramachandran 2014), 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) and software engineering (Taylor *et al* 2010). Data mining techniques have been used in a wide range of stock market prediction applications. This range includes stock price forecasting, stock index forecasting and forecasting stock prices with the help of external factors (Bollen *et al* 2010, Kuo *et al* 2001, Michael et al 2005, Mittal and Goel 2012, Shriwas and Sharma 2014, Thawornwong and Enke 2004).

The preference of Neural networks is quite evidence in the literature due to its the accuracy in terms of direction of prediction (Mizuno et al 1998, Majumder and Hussian 2010, Vojinovic et al 2001, Tjung et al 2010, Hammad et al 2007, Altay and Satman 2005). On the other hand, SVM has also been preferred by many researchers (Cao and Tay 2001, Kim 2003, Huang et al 2005, Kumar and Thenmozhi 2006).

Testing the performance NN and SVM across global stock indices is a relatively newer research domain (Chen et al 2006). Outcome of the study will shed the light on utility of NN and SVM for predictive modeling in stock indices across the globe.

3.0 Methods

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

3.1 Sampling and Data Collection

On the basis of Morgan Stanley Capital International (MSCI) market classification, we selected seven countries across the globe for the study (Anonymous, 2016) which includes three developed markets (United States, United Kingdom and Japan) and four emerging markets (China, Brazil, India and

South Africa). Further, we selected indices from largest stock exchanges of these countries on the basis of turnover of financial derivative segment. Description of the selected indices is provided in Table1.

Table1: List of selected stock indices

Selected Stock Index (Selected Stock Exchange: Country)	Notation used in the study
Dow Jones Industrial Average (New York Stock Exchange: United States)	DJIA
FTSE 100 (London Stock Exchange Group: United Kingdom)	FTSE
Nikkei 225 (Japan Exchange Group-Tokyo: Japan)	NIKKEI
SSE 50 (Shanghai Stock Exchange: China)	SSE
iBovespa (BM&F Bovespa: Brazil)	IBOVESPA
Nifty 50 (National Stock Exchange: India)	NIFTY
JALSH (JSE Limited (Johannesburg): South Africa)	JALSH

Closing, Opening, High and Low values of selected stock indices were recorded for the period of twelve years starting from 1st April, 2005 to 31th March, 2017.

3.2 Data Transformation

The existence of continuous, noisy and complex data may pose a challenging task to extract information from the raw data (Liu and Setiono 1996). Therefore, data is transformed to improve the predictive power of the techniques (Asadi et al 2012, Kim 2003, Kim 2006). We used 12 technical indicators (Kim 2003, Kim 2006) for predicting direction of stock indices. These indicators include Stochastic %K, Stochastic %D, Stochastic Slow %D, Momentum, rate of change (ROC), Larry Willaim's %R (LW %R), A/D Oscillator (Accumulation/Distribution), Disparity 5-days, Disparity 10-days, OSCP(Price Oscillator), CCI (Commodity Channel Index) and RSI (Relative Strength Index). These indicators are elaborated in Table 2.

Table 2: Selected technical indicators and their description

Input variables	Description	Formula
[a] Stochastic %K	Relative position measure based on range of closing price	$$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100$$ Where Ct is closing price, LLt is lowest low and HHt is highest high in t days.
[a] Stochastic %D	Moving average of %K	$$\frac{\sum_{i=0}^{n-1} \%K_{t-1}}{n}$$

[a] Stochastic slow %D	Moving average of %D	$$\frac{\sum_{i=0}^{n-1} \%D_{t-1}}{n}$$
[b] Momentum	It measures the amount that a price has changed over a given time span	$$C_t - C_{t-n}$$ Where n=10, Ct is closing price today
[c] ROC (rate of change)	It measures the difference between the current price and the price n days ago	$$\frac{C_t}{C_{t-n}} \times 100$$
[d] LW %R (Larry William's %R)	It is a momentum indicator that measures overbought/oversold levels	$$\frac{H_n - C_t}{H_n - L_n} \times 100$$
[b] A/D Oscillator ((accumulation/distribution oscillator)	It is a momentum indicator that associates changes in price	$$\frac{H_t - C_{t-1}}{H_t - L_t} \times 100$$
[e] Disparity 5-days	It measures the relative position of the closing price to a 5-day moving average	$$\frac{C_t}{MA_5} \times 100$$ Where MA5 is 5-day moving average
[e] Disparity 10-days	It measures the relative position of the closing price to a 10-day moving average	$$\frac{C_t}{MA_{10}} \times 100$$ Where MA10 is 10-day moving average
[d] OSCP (Price Oscillator)	It displays the difference between two moving averages of a security's price	$$\frac{MA_5 - MA_{10}}{MA_5}$$
[a] CCI (Commodity Channel Index)	It is a measure of the deviation of the current price from the previous n days	$$\frac{H_t + L_t + C_t - ADP_{t-1}}{0.015 \times AvgDev_{t-1}}$$ Where, $ADP_t = \frac{\sum_{i=t-n+1}^{t}(H_i+L_i+C_i)}{n}$. $AvgDev_t = \frac{\sum_{i=t-n+1}^{t}|H_i+L_i+C_i-ADP_{t-1})}{n}$
[a] RSI (Relative Strength Index)	It is a momentum oscillator that measures the speed and change of price movements ranges from 0 to 100	$100 - \frac{100}{1+RS}$, 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

([a] Kaufman 2013, [b] Chang et al 1996, [c] Murphy 1986, [d] Achelis 1995, [e] Choi et al 1995)

We created data sets spanning different time periods for model building such as 1 year, 2 years, 3 years, 4 years, 6 years and 12 years. Therefore, we made 28 data sets for each index. The data sets were created for all seven indices. In all 196 data sets have been analyzed. In order to validate the performance of data mining techniques, each data set is divided into 80% of training set and the remaining 20% were used for testing the model.

We evaluated the performance of models built using data mining techniques using Mean Absolute Error and Root Mean Square Error. For the purpose of model building, we considered "return" as a dependent variable. Daily closing values were transformed into daily returns using the following formula:

$$\text{Daily Returns} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where P_t is Current closing price and P_{t-1} is Previous day closing price

3.3 Data Analysis

In this study, we used two data mining techniques namely Neural Networks and Support Vector Machines for predicting the selected indices.

Neural Networks: Neural Networks (NN) are signal processing systems or artificially created systems which are inspired by biological nervous system (Preethi and Santhi 2012). NN has powerful pattern classification and recognition capabilities due to their nonlinear nonparametric adaptive-learning properties. Stock market prediction is one of the major application domains of neural networks. The main advantage of neural networks is that they can estimate any nonlinear function to a random degree of accuracy with a suitable number of hidden units (Kim and Shih 2007).

In current study, we employed multilayer perceptron classifier that uses backpropagation to classify instances. The levels of learning rate (lr), momentum constant (mc) and number of epochs to train through were 0.3, 0.2 and 500 respectively.

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.

As the current study attempts to compare performance of NN and SVM across global stock indices, model specifications for a given technique are kept uniform so as to avoid any biases on account of model optimization in different settings.

3.4 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

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

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:

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

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

Framework of methodology used for conducting the study is presented as fig 1.

Input

Closing values, High values, Low values, Opening values

Indices values i.e. DJIA, FTSE, IBOVESPA, JALSH, NIFTY, NIKKEI, SSE

Data Transformation

Stochastic K, Stochastic D, Stochastic Slow D, Momentum, ROC, LW%R, A/D Oscillator, Disparity 5-days, Disparity 10-days, OSCP, CCI, RSI

Data Sets

S1-S12 (12 data sets of 1 year each), B1-B6 (6 data sets of 2 years), T1-T4 (4 data sets of 3 years), Q1 –Q3 (3 data sets of 4 years), H1-H2 (2 data sets of 6 years) and D= 1 data set of 12 years

NN (Multilayer Perceptron)

SVM (RBF Kernel)

Data Mining Techniques

MAE

RMSE

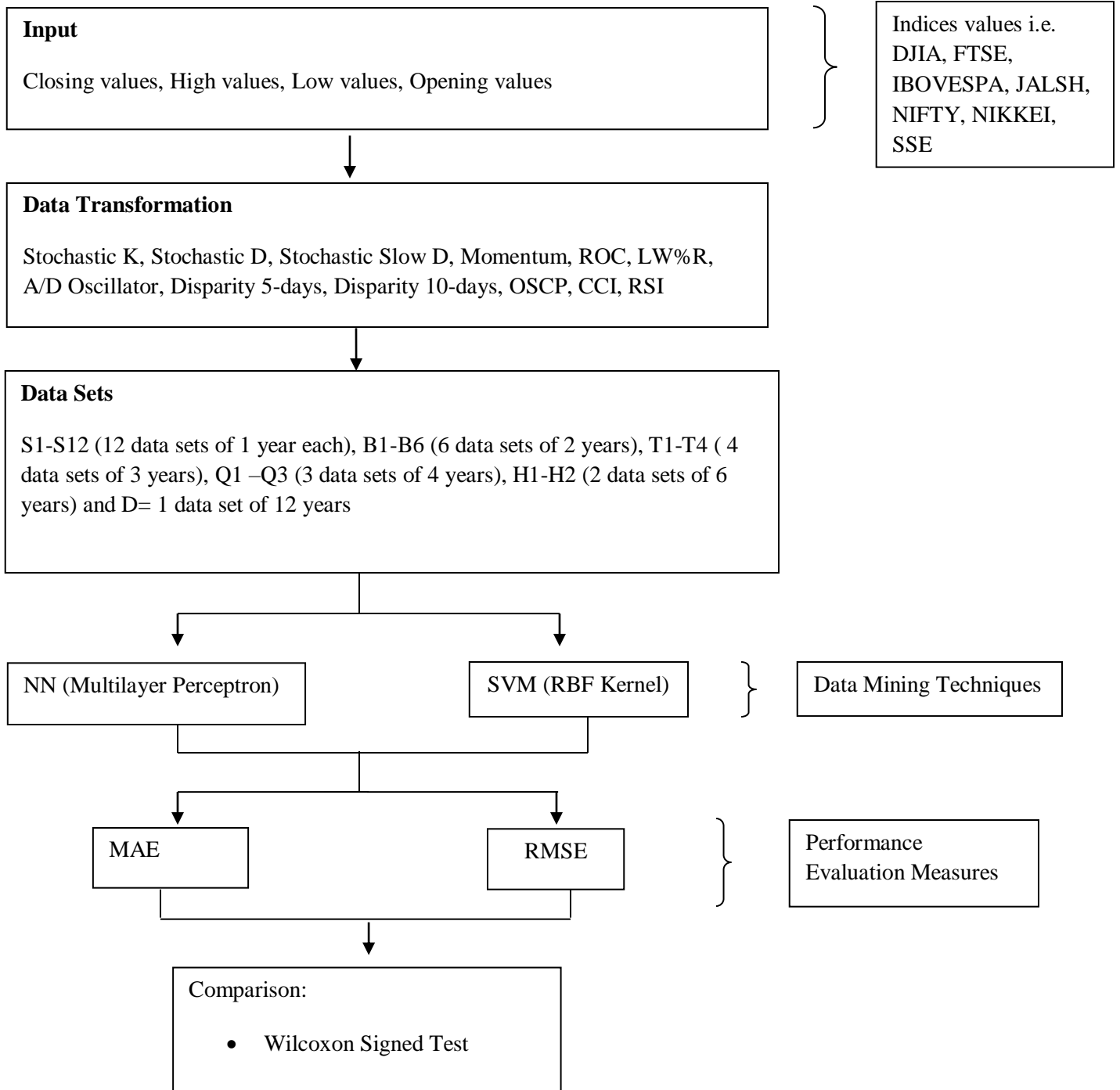Performance Evaluation Measures

Comparison:

- Wilcoxon Signed Test

Fig 1: Process followed under methodology

4.0 Results

Table 3 summarizes the index wise descriptive statistics of mean absolute error for NN models of selected indices for return as a dependent variable. NN model of NIKKEI and SSE data has obtained highest mean values of mean absolute error i.e. 0.006 followed by NN model of IBOVESPA and NIFTY data with mean values of 0.005 and 0.004 respectively. NN model of FTSE and DJIA data have obtained minimum mean absolute error i.e. 0.003. Table 3 also reveals that NN models of all indices except JALSH has obtained the highest value of standard deviation i.e. 0.002. Further, NN model of NIFTY and SSE data have found to obtain the highest value of range i.e.0.009. NN model of JALSH data has obtained the minimum value of range i.e. 0.005.

Table 3: Summary statistics of Mean Absolute Error (NN models)

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.003	0.003	0.005	0.003	0.004	0.006	0.006
Standard Error	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.003	0.003	0.004	0.003	0.004	0.005	0.006
Standard Deviation	0.002	0.002	0.002	0.001	0.002	0.002	0.002
Sample Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kurtosis	5.339	1.945	1.626	0.977	2.700	0.231	-0.926
Skewness	2.283	1.441	1.468	1.350	1.436	1.045	0.210
Range	0.008	0.006	0.008	0.005	0.009	0.008	0.009
Minimum	0.001	0.001	0.002	0.002	0.002	0.003	0.002
Maximum	0.009	0.008	0.011	0.007	0.011	0.011	0.011

Table 4 summarized index wise root mean square error for model built using NN, calculated with respect to return as an output variable. NN model of NIKKEI data has attained highest mean value of root mean square error i.e. 0.009 followed by NN model SSE and IBOVESPA data with mean values of 0.008 and 0.007 respectively. NN models of FTSE and DJIA data have observed to have minimum root mean square error i.e. 0.004. Table 4 also reveals that NN models of IBOVESPA data has obtained the highest value of standard deviation i.e. 0.005 and models of FTSE and JALSH data have obtained lowest values of standard deviation i.e.0.002. Further, NN model of IBOVESPA data has found to obtain the highest value of range i.e. 0.024. NN model of JALSH data has obtained the minimum value of range i.e. 0.008.

Table 5 summarizes the index wise descriptive statistics of mean absolute error for SVM models of selected indices. SVM models of NIKKEI and SSE have obtained highest mean values of mean absolute error i.e. 0.005 followed by SVM models of IBOVESPA and NIFTY with mean value of 0.004. SVM model of JALSH, FTSE and DJIA have observed to have minimum mean absolute error i.e. 0.003. SVM models of all indices has obtained same value of standard deviation i.e. 0.002.

Table 4: Summary statistics of Root Mean Square Error: NN Models

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.004	0.004	0.007	0.005	0.006	0.009	0.008
Standard Error	0.001	0.000	0.001	0.000	0.001	0.001	0.001
Median	0.003	0.003	0.005	0.004	0.005	0.007	0.008
Standard Deviation	0.003	0.002	0.005	0.002	0.003	0.004	0.003
Sample Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kurtosis	6.103	4.866	8.014	2.187	1.105	-0.971	-1.261
Skewness	2.507	1.996	2.724	1.596	1.254	0.728	0.043
Range	0.012	0.011	0.024	0.008	0.012	0.013	0.011
Minimum	0.001	0.002	0.003	0.003	0.003	0.004	0.002
Maximum	0.013	0.013	0.027	0.010	0.015	0.017	0.013

Further, SVM model of DJIA has found to obtain the highest value of range i.e.0.011. SVM model of JALSH has obtained the minimum value of range i.e. 0.007.

Table 5: Summary statistics of Mean Absolute Error: SVM Models

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.003	0.003	0.004	0.003	0.004	0.005	0.005
Standard Error	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.002	0.002	0.003	0.003	0.003	0.004	0.005
Standard Deviation	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Sample Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kurtosis	6.807	4.845	6.786	4.897	2.872	1.201	-0.886
Skewness	2.626	2.193	2.453	2.191	1.784	1.395	0.351
Range	0.011	0.009	0.010	0.007	0.009	0.008	0.009
Minimum	0.001	0.001	0.002	0.002	0.002	0.003	0.002
Maximum	0.012	0.011	0.012	0.009	0.011	0.011	0.010

Table 6 summarizes index wise root mean square error for model built using SVM. SVM model of SSE has attained highest mean value of root mean square error i.e. 0.008 followed by SVM model of NIKKEI with mean value 0.007 and NIFTY with mean value 0.006. SVM models of JALSH, FTSE and DJIA have observed to have minimum root mean square error i.e. 0.004. SVM models of DJIA, IBOVESPA, NIFTY, NIKKEI and SSE has obtained the highest value of standard deviation i.e. 0.004 and models of FTSE and JALSH have obtained lowest values of standard deviation i.e.0.003. Further, SVM model of IBOVESPA has found to obtain the highest value of range i.e.0.018. SVM model of JALSH has obtained the minimum value of range i.e. 0.011.

Table 6: Summary statistics of Root Mean Square Error: SVM Models

Parameter/Index	DJIA	FTSE	IBOVESPA	JALSH	NIFTY	NIKKEI	SSE
Mean	0.004	0.004	0.006	0.004	0.006	0.007	0.008
Standard Error	0.001	0.001	0.001	0.000	0.001	0.001	0.001
Median	0.003	0.003	0.004	0.004	0.004	0.007	0.007
Standard Deviation	0.004	0.003	0.004	0.003	0.004	0.004	0.004
Sample Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kurtosis	7.678	5.154	6.871	4.477	2.604	1.498	-1.190
Skewness	2.769	2.275	2.413	2.151	1.796	1.294	0.298
Range	0.016	0.014	0.018	0.011	0.013	0.014	0.012
Minimum	0.001	0.002	0.003	0.002	0.002	0.003	0.002
Maximum	0.018	0.016	0.021	0.013	0.016	0.018	0.014

We compared various indices in pairs so as to ascertain comparative performance of predictive models across different indices. For making the comparison of MAE and RMSE, of all possible pairs of indices, we applied Wilcoxon Signed Rank test, a non-parametric test.

The comparison of Mean Absolute Error and Root Mean Square Error of all index pairs using NN model, where dependent variable is return, is presented in Table 7. There was a significant difference between Mean Absolute Error of different indices based on NN models for 18 out of 21 index pairs. Maximum mean difference of 0.003 is observed for NIKKEI-FTSE, NIKKEI-DJIA, SSE-DJIA, SSE-FTSE and SSE-JALSH. Minimum mean difference of -0.001 is observed for JALSH-IBOVESPA. There is no significant difference between the MAE of FTSE-DJIA, NIFTY-IBOVESPA and SSE-NIKKEI.

Further, that there was a significant difference between Root Mean Square Error of different indices based on ANN models for 17 out of 21 index pairs. Maximum mean difference of 0.00458 is observed for NIKKEI-DJIA. Minimum mean difference of 0.00013 is observed for FTSE-DJIA.

The comparison of Mean Absolute Error and Root Mean Square Error of all index pairs using SVM model, where dependent variable is return, is presented in Table 8. There was a significant difference between Mean Absolute Error of different indices based on SVM models for 17 out of 21 index pairs. Maximum mean difference of 0.00244 is observed for SSE-DJIA and SSE-FTSE. Minimum mean difference of -0.0001 is observed for NIFTY-IBOVESPA. Further, there was a significant difference between Root Mean Square Error of different indices based on ANN models for 17 out of 21 index pairs. Maximum mean difference of 0.00346 is observed for SSE-DJIA. Minimum mean difference of 0.00012 is observed for JALSH-FTSE.

Table 9 summarizes difference in accuracy measures i.e. Mean Absolute Error and Root Mean Square Error of models built using Neural Networks and Support Vector Machines. Mean absolute error as well as root mean square error were more in case of NN compared to SVM.

Table 7: MAE and RMSE based comparison of Index pairs: ANN Models

Pairs	MAE		RMSE	
	Mean Difference (Std Error)	*S*- value (*p*-value)	**Mean Difference (Std Error)**	*S*- value (*p*- value)
FTSE vs DJIA	0.000 (0.000)	21.5 (0.6327)	0.00013 (0.00027)	36 (0.422)
IBOVESPA vs DJIA	**0.002 (0.000)**	**184.5 (<.0001)**	**0.00273 (0.00082)**	**194 (<.0001)**
IBOVESPA vs FTSE	**0.002 (0.000)**	**175 (<.0001)**	**0.0026 (0.00085)**	**173 (<.0001)**
JALSH vs DJIA	**0.001 (0.000)**	**96 (0.0179)**	**0.0006 (0.00032)**	**98.5 (0.0219)**
JALSH vs FTSE	**0.001 (0.000)**	**115 (0.0063)**	0.00048 (0.00027)	82.5 (0.0586)
JALSH vs IBOVESPA	**-0.001 (0.000)**	**-125.5 (0.0012)**	**-0.0021 (0.00089)**	**-139.5 (0.0006)**
NIFTY vs DJIA	**0.001 (0.000)**	**158 (<.0001)**	**0.00197 (0.00053)**	**158 (<.0001)**
NIFTY vs FTSE	**0.001 (0.000)**	**171 (<.0001)**	**0.00185 (0.00047)**	**154.5 (<.0001)**
NIFTY vs IBOVESPA	0.000 (0.000)	-26.5 (0.5341)	-0.0008 (0.00091)	-19 (0.6565)
NIFTY vs JALSH	**0.001 (0.000)**	**93 (0.0313)**	**0.00137 (0.00045)**	**111.5 (0.0084)**
NIKKEI vs DJIA	**0.003 (0.000)**	**202 (<.0001)**	**0.00458 (0.00074)**	**202 (<.0001)**
NIKKEI vs FTSE	**0.003 (0.000)**	**202 (<.0001)**	**0.00445 (0.00072)**	**201.5 (<.0001)**
NIKKEI vs IBOVESPA	**0.001 (0.000)**	**119 (0.0045)**	**0.00185 (0.00117)**	**107.5 (0.0115)**
NIKKEI vs JALSH	**0.002 (0.000)**	**194.5 (<.0001)**	**0.00398 (0.00074)**	**192 (<.0001)**
NIKKEI vs NIFTY	**0.001 (0.000)**	**135 (0.0009)**	**0.00261 (0.00089)**	**124.5 (0.0027)**
SSE vs DJIA	**0.003 (0.000)**	**189 (<.0001)**	**0.00385 (0.00064)**	**172 (<.0001)**
SSE vs FTSE	**0.003 (0.000)**	**202 (<.0001)**	**0.00373 (0.00055)**	**198.5 (<.0001)**
SSE vs IBOVESPA	**0.001 (0.000)**	**117.5 (0.0051)**	**0.00113 (0.00107)**	**88 (0.0316)**
SSE vs JALSH	**0.003 (0.000)**	**184.5 (<.0001)**	**0.00325 (0.00057)**	**172.5 (<.0001)**
SSE vs NIFTY	**0.002 (0.000)**	**145 (<.0001)**	**0.00188 (0.00059)**	**111.5 (0.0084)**
SSE vs NIKKEI	0.000 (0.001)	28.5 ((0.5261)	-0.0007 (0.00098)	-20 (0.6571)

(Text in bold represents significant difference in index pairs)

Table 8: MAE and RMSE based comparison of Index pairs: SVM Models

Pairs	MAE		RMSE	
	Mean Difference (Std Error)	*S*- value (*p*- value)	Mean Difference (Std Error)	*S*- value (*p*- value)
FTSE vs DJIA	-1.00E-06 (0.00017)	7.5 (0.8603)	0.00016 (0.00023)	51.5 (0.2464)
IBOVESPA vs DJIA	**0.00103 (0.00022)**	**160.5 (<.0001)**	**0.00184 (0.00038)**	**164 (<.0001)**
IBOVESPA vs FTSE	**0.00104 (0.00014)**	**187 (<.0001)**	**0.00169 (0.00032)**	**198 (<.0001)**
JALSH vs DJIA	0.00026 (0.00023)	56.5 (0.0853)	**0.00028 (0.00034)**	**90 (0.0274)**
JALSH vs FTSE	**0.00027 (0.00015)**	**93 (0.0310)**	0.00012 (0.00022)	45 (0.2872)
JALSH vs IBOVESPA	**-0.0008 (0.00017)**	**-163.5 (<.0001)**	**-0.00160 (0.00041)**	**-168 (<.0001)**
NIFTY vs DJIA	**0.00098 (0.00035)**	**116 (0.0032)**	**0.00137 (0.00051)**	**128 (0.0020)**
NIFTY vs FTSE	**0.00099 (0.00022)**	**157.5 (<.0001)**	**0.00121 (0.00035)**	**120 (0.0010)**
NIFTY vs IBOVESPA	-0.0001 (0.00028)	-23 (0.5687)	-0.00050 (0.00050)	-45 (0.2878)
NIFTY vs JALSH	**0.00071 (0.00027)**	**86 (0.0359)**	**0.00109 (0.00038)**	**107 (0.0074)**
NIKKEI vs DJIA	**0.00196 (0.00028)**	**196 (<.0001)**	**0.00302 (0.00050)**	**179.5 (<.0001)**
NIKKEI vs FTSE	**0.00196 (0.00022)**	**201 (<.0001)**	**0.00286 (0.00043)**	**202 (<.0001)**
NIKKEI vs IBOVESPA	**0.00093 (0.00025)**	**121.5 (0.0008)**	**0.00118 (0.00053)**	**84 (0.0410)**
NIKKEI vs JALSH	**0.00169 (0.00022)**	**201 (<.0001)**	**0.00274 (0.00044)**	**186 (<.0001)**
NIKKEI vs NIFTY	**0.00098 (0.00028)**	**125 (0.0013)**	**0.00165 (0.00050)**	**126.5 (0.0023)**
SSE vs DJIA	**0.00244 (0.00042)**	**166 (<.0001)**	**0.00346 (0.00067)**	**156 (<.0001)**
SSE vs FTSE	**0.00244 (0.00038)**	**197 (<.0001)**	**0.00331 (0.00061)**	**176 (<.0001)**
SSE vs IBOVESPA	**0.0014 (0.00037)**	**131 (0.0006)**	**0.00162 (0.00071)**	**104 (0.0149)**
SSE vs JALSH	**0.00217 (0.00038)**	**181.5 (<.0001)**	**0.00319 (0.00060)**	**1820 (<.0001)**
SSE vs NIFTY	**0.00146 (0.00039)**	**129.5 (0.0017)**	**0.00209 (0.00065)**	**109 (0.0062)**
SSE vs NIKKEI	0.00048 (0.00045)	24 (0.5938)	0.00045 (0.00084)	7(0.8767)

(Text in bold represents significant difference in index pairs)

Table 9: Difference in results of ANN and SVM

SVM-NN (Output variable)	SVM	NN	Mean Difference	Std Error	Correlation	Test Statistic S (p-value)
MAE (Return)	0.0039	0.0042	-0.0003	0.0001	0.886	-2690 (0.0001)
RMSE (Return)	0.0056	0.0060	-0.0004	0.0002	0.838	-1883.5 (0.0100)

5.0 Discussion

The findings of the study indicate that data mining techniques exhibits significantly different performance across selected stock indices. For NN, significant differences are observed in 18 pairs out of total 21 pairs on basis of MAE. Pair-wise comparison based on RMSE exhibit significant difference in 17 pairs out of 21 pairs of stock indices. For SVM, almost similar variation across indices is observable. On the basis of MAE, significant differences across 17 pairs are there out of total 21 pairs. On the other hand, for RMSE significant differences are there for 17 pairs out of 21 pairs. This clearly indicates a difference in performance of data mining techniques 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, Flannery and Protopapadakis 2002). Findings of the study also indicate that SVM perform fair better than NN both in terms of Mean Absolute Error and Root Mean Square Error. The superiority of SVM in terms of error measures is supported by various studies (Kim 2003, Sheta et al 2015 Grosan et al 2005)

6.0 Conclusion

Findings of the study indicate that NN and SVM exhibit significantly different accuracy across the global stock indices. Also, Mean Absolute Error and Root Mean Square Error of models built using NN were greater than Mean Absolute Error and Root Mean Square Error of models built using SVM.

7.0 References

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