Evaluation Optimal Prediction Performance of MLMs on High-volatile Financial Market Data

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***Abstract*—The present study evaluates the prediction performance of the multi-machine learning models (MLMs) on high-volatile financial markets data sets since 2007 to 2020. The linear and nonlinear empirical data sets are comprised on stock price returns of Karachi stock exchange (KSE) 100-Index of Pakistan and currencies exchange rates of Pakistani Rupees (PKR) against five major currencies (USD, Euro, GBP, CHF & JPY). In the present study, the support vector regression (SVR), random forest (RF), and machine learning-linear regression model (ML-LRM) are under-evaluated for comparative prediction performance. Moreover, the findings demonstrated that the SVR comparatively gives optimal prediction performance on group1. Similarly, the RF relatively gives the best prediction performance on group2. The findings of study concludes that the algorithm of RF is most appropriate for nonlinear approximation/evaluation and the algorithm of SVR is most useful for high-frequency time-series data estimation. The present study is contributed by exploring comparative enthusiastic/optimistic machine learning model on multi-nature data sets. This empirical study would be helpful for finance and machine-learning pupils, data analysts and researchers, especially for those who are deploying machine-learning approaches for financial analysis.**

Keywords*—Support vector regression; random forest; machine learning-linear regression model; optimal prediction performance; currencies exchange rates; stock price returns

I. Introduction

Since several decades, a lot of researchers and data analysts have been applying traditional econometric models (TEM) for hypothetical testing and financial-nonfinancial market evaluation. But there have some constraints with TEM as nonlinear approximation, future prediction developments of the markets and data prediction accuracy. On the other hand, nowadays, the supervised and unsupervised machine learning approaches have quite famous to precisely evaluate the different nature of big data. So, the analysis effectiveness is directly associated with the prediction accuracy the model.

The machine learning approaches are successfully employed into different domains with respect to their applications. But it is usually used for speech recognition, image processing, wind-speed frequency scaling, network filtering and financial markets prediction [1-4]. Furthermore, the evaluation of stock market and forex market returns with machine learning approaches are very hot topic nowadays. Moreover, the financial-nonfinancial future markets predictions are very helpful for those who are willing for financing in the market and for hedgers to hedge their financial assets [5, 6]. The machine learning algorithms (MLAs) have capability to analyze the linear-nonlinear data [7]. For example, the forex market is very dynamical market due to globalization. In prior era, the researchers and data analysts were used TEM to examine the forex market returns. But since last decade, the researchers and data experts have been rapidly diversifying from TEM to machine learning approaches for financial market prediction [8-10]. In fact, the MLMs are most powerful and very effective approaches to predict the high-volatile and nonlinear data financial data [11, 12]. So, the key purpose of present study is to evaluate the prediction performance of underlying machine learning models on different nature financial data sets, such as the group1 comprised on stock price returns of KSE 100-index of Pakistan which is illustrated in Fig. 1.

Fig. 1 indicates that the stock prince returns of KSE 100-index is very dynamic financial market. This diagram is comprised on original data, rolling mean and average which collectively demonstrates the good returns (positive returns), bad returns (negative returns) and no returns (zero returns). The group2 contains on the PKR exchange rates against five major currencies (USD, Euro, GBP, CNY & JPY) which is illustrated in Fg. 2.

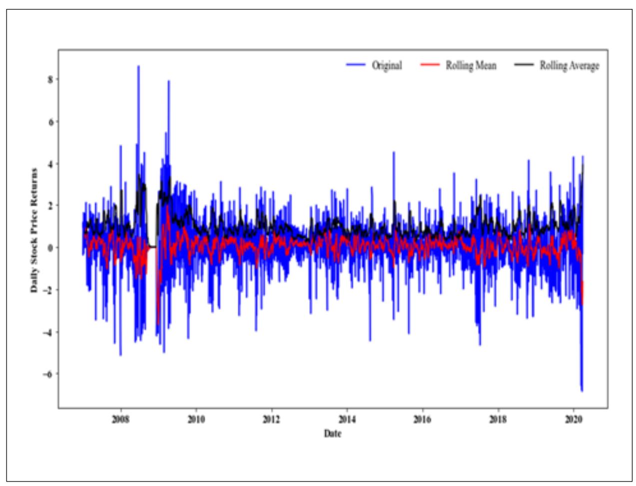

Fig. 1. Daily Stock Price Returns of KSE 100-index.

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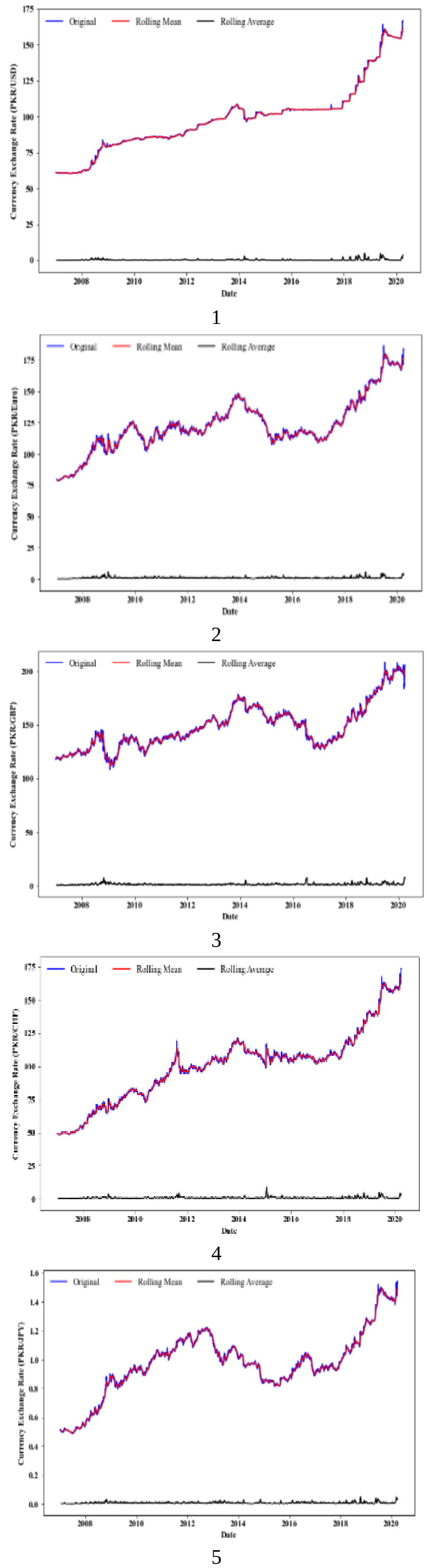


Fig. 2. PKR Exchange Rates against Five Major Currencies.

Fig. 2 demonstrated that the PKR exchange rates against entire currencies have been steadily increasing over the period, which indicating the domestic currency (PKR) has been depreciating since 2007 to till 2020. Furthermore, these both empirical data sets will be evaluated by SVR, RF and ML-LRM. These empirical machine learning models are commonly used for classification and regression problems. But the present study will be executed the prediction performance of entire machine learning models on nonlinear and high-frequency data sets which quite effective for researchers and data analysts.

The remaining sections of study comprised as: the Section 2 will be contained on most similar literature on the stock markets and the forex markets which executed by MLMs. The Section 3 will be contained on data collection process, data preparation and mathematical interpretation and application of the models. Similarly, the Section 4 will be contained on results and discussion and forecast optimal prediction model. Finally, the Section 5 will be contained on conclusion-based sound evidence, limitation of the study and significant future developments of the study.

II. Similar Studies

Since the last decade, the researchers and data analysts have been rapidly diversified from TEM to flexible and experimental machine learning approaches for optimal prediction. In the modern era, the MLAs are typically used to determine the returns of dynamical stock markets. To predict the next day price index of the Taiwan index feature, [13] have deployed hybrid SVR with SOFT (self-organized feature map) approach by filter-based feature selection to improve the prediction accuracy of the model and mitigate the cost of training time. The findings of this study demonstrates that the hybrid SVR improves the training time and prediction accuracy. Another study has employed SVR for prediction stock prices on daily and up to the minute. The findings of this study shows that the SVR has absolute predictive power, whenever applicate the new strategy of model periodically [14]. The hybrid prophet-SVR model is outperformed than relatively other approaches by using time series demand with seasonality in stock index [15]. [16] have applied the machine learning based RF to examine the future predictions of stock prices of key listed firms. Moreover, [17] have been executed the trend of the Thai-stock market by deploying the SVR, multi-layer perception (MLP), and partial least square classifier models (PLSCM). The scholars have concluded that the Thai-stock market is rapidly growing while the investors are absolutely acquaintance about market dynamics. Similarly, some studies have evaluated the factors of stock prices returns via the reinforcement learning approach [18]. A lot of other studies have executed the real impact of prices by using mixed methodologies. Moreover, the Long-Short Term Memory (LSTM) is an artificial recurrent neural network (RNN) architecture which works on feedforward standards. Especially, it employed for outliers' detection problem in given big data set by fixing threshold, hence, this approach is very useful to investigate the dynamical stock market [19-21]. But the present study will execute the stock price returns of KSE 100-index of Pakistan and subsequent evaluate the optimal prediction performance model.

Furthermore, the forex market is quite significant for those who want to be financing into the international market for economic privileges. Because the currency exchange rates may bring probabilistic effects on economic value of their imperative assets. For currency risk management, a researcher community has been predicted the future currency exchange rates on voluntarily currency selection by using MLMs. For instance, The stochastic volatility model with jumps to SVR in order to account for sudden big changes in exchange rate volatility [22]. So the experimental studies demonstrate that the empirical new model has the ability to improve the forecast accuracy. The author in [23] had predicted the exchange rates of major currencies of developed counties. This study deployed the mixed methodologies as the deep neural networks, MLMs and econometric approaches to predict the currencies exchange rates. Besides, this study concludes that the currencies exchange rates of developing countries are more volatilized than developed countries. So, the traditional models may not properly investigate to the nonlinear approximation. According to econometric assumption, the empirical data should be in linear format for econometric modelling. But the empirical data lost their originality whenever it transformed from nonlinear to linear scale through the natural logarithm or another approach. But the MLMs have ability to evaluate every kind of data. Therefore, the usage of MLAs have been precipitously increasing over the period for optimal prediction to nonlinear approximation. The author in [24] has analyzed the couple of currencies exchange rates (USD/CHF, USD/CAD and USD/JPY) along with the shuffled frog leaping algorithm (SFLA). Moreover, a lot of other scholars executed MLMs prediction performance along with different currencies exchange rates data. Another study executed the currency exchange rate is a certain cause of domestic inflation by using the Dorn-busch approach. Besides, they also investigated that the USA housing prices raised 7% with excluded currency ERs. But in the last decade, the USA housing prices 40% grown-up by variation into local currency exchange rates [25]. After intensely viewed to the comprehensive literature, we summarized that the MLMs are excessively used to predict the stock market and forex market returns.

III. Empirical Data and Research Methodology

A. Data Collection and Preparation for Analysis

The empirical data set of the present study is divided into two certain groups. The group1 is contained on the stock price returns of KSE 100-index of Pakistan. In addition, the group1 data is dragged from the official website of the KSE of Pakistan (https://www.psx.com.pk/). This study measures the price returns from given stock prices as follow: Lumley [26].

$$R(t_{0,}t_1) = \left(\frac{(P_{t_1} - P_{t_0})}{P_{t_0}}\right) * 100 \qquad (1)$$

In Equation 1, the stock price returns are executed as the P_{t_0} is daily stock prices at the time t_0 subtract from the stock price P_{t_1} at time t_1 and divided by P_{t_0} and multiplied by 100, whereas the P_{t_1} denotes to current stock prices and P_{t_0} denotes to the previous stock price of the stock market. As Fig. 1 is showing the stock price returns are high-volatile while this study follows [27-29] for normalizing the empirical data set.

$$y = ln\left(r + \sqrt{r^2 + 1}\right) \qquad (2)$$

Moreover, the group2 is contained on PKR exchange rate against five major currencies (USD, EUR, GBP, CHF, JPY). The thirteen-year daily currencies exchange rates data set dragged by the official website of the central bank of Pakistan (http://www.sbp.org.pk/). The Fig. 2 discretely exhibits the volatility of currency exchange rates against each given currency.

B. Research Methodology

The certain methodologies play an important role in the empirical studies to execute the hypothetical examination. But before to mathematical interpretation of the models, we must take keenly overview the whole process of performance evaluation of the models. Fig. 3 showed that the primarily both kinds of raw data sets are uploaded into the data repository of jupyter notebook and subsequently refine the data and scaled the data and become in specific format to optimize the machine learning algorithm. Furthermore, the scaled data set would split into train and test, whenever 80% will use for training purpose and rest of data will use for testing purpose. Furthermore, we shall train the model and evaluate the prediction performance of training model with average loss function. This study would execute the prediction performance of the models, if the train predicted error $\xi_t < \xi_e$ expected error otherwise update the training data set.

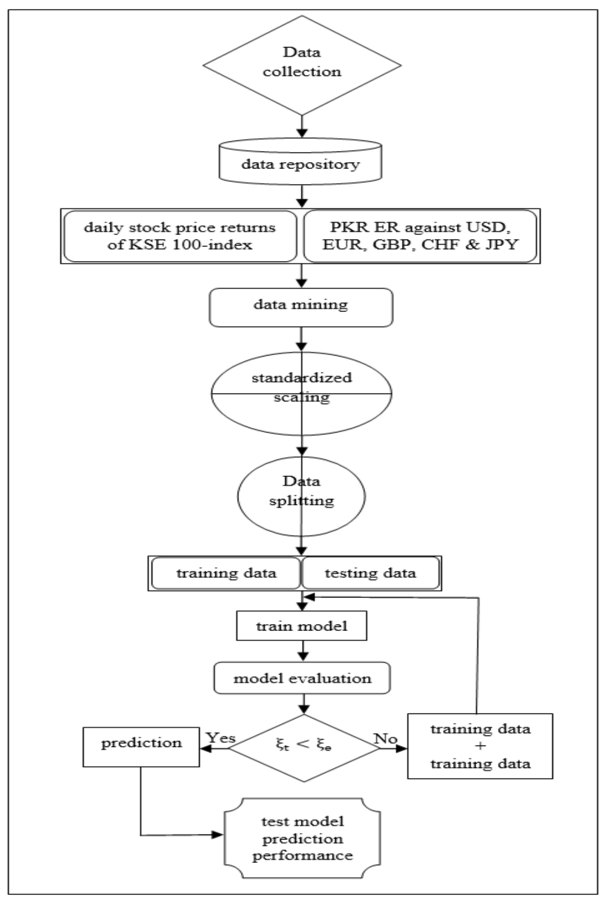


Fig. 3. Flowchart of Models' Prediction Process.

1) Support vector regression: The support vector regression model is popular as supervised learning approach which used for sort regression analysis [30, 31]. The support vector machine (SVM) was primarily built for structural risk measurement, but subsequent the researchers and data analysts had customized it for regression purposes, especially for time-series data. The SVM has the ability to measure linear and nonlinear approximation. The authors in [32] have employed the support vector machine (SVM) for the statistical problem. For the execution of the model prediction performance, the present study follows [33, 34].

In Fig. 4, $x_i \in \mathbb{R}_n$ is an input function whereas $i-th$ is $n-th$ number of x as $i = 1, 2, 3, \cdots, n.$ and $y_i = \in \mathbb{R}_n$ is an output function where $i-th$ is $n-th$ number of y as $i = 1, 2, 3, \cdots, n.$ where $k-th$ is x vector at $n-th$number of vectors which associated with specific weights $\overline{\alpha}$ at $m-th$ number of $k-th$ vectors and summation b bias. For instance, we have a time-series data set where $z = (x_i y_i), 1 \leq i \leq N.$ The core idea dragged by [35]. Let suppose $\overline{\alpha}_m = W^t$, the problem may solve as follows:

$$\int(x_i) = \mathrm{W^t}\varphi(x_\mathrm{i}) + \mathrm{b} \tag{3}$$

In equation 3, the w^t represents to specific weight at $n-th$ number of x vector and b denoted to biases. Moreover, x is considered as input vector taken by φ into a higher dimensional space. The model performance can be improved by optimization the weights and bias of the model as below:

$$\underset{(w, b, \varepsilon_1, \varepsilon_2)}{min} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\varepsilon_1^i, \varepsilon_2^i) \tag{4}$$

In equation 4, the C is makes swapping between two models' simplicity and generalization ability. If $Y_I - W^T(\phi(x)) - b \leq \xi + \varepsilon_1^i$ and $W^T(\phi(x)) + b - y_i \leq \xi + \varepsilon_1^i$, the error position is determined by slack variables as ξ & ε_i. We can map high volatile and nonlinear data set from the original vector space by using the kernel approach. However, this is a pretty way to drag the SVR model as below:

$$y_i = \int(x_i)\sum_{i=1}^{n}((\alpha_1\alpha_m)\, K(x_i, x_n)) + b \tag{5}$$

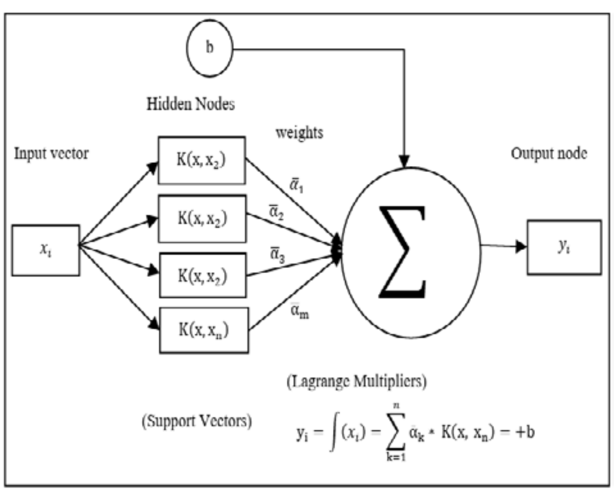


Fig. 4. Structure of Support Vector Regression.

Whereas.

Here α_1 α_2 both are represented to langrage variables multiplier. The below equation indicates that the extensive utilization of kernel by Gaussian Function concerning the size of σ^2:

$$Z(x_i x_k) = exp\left(\left(-\|x_i - x_n\|^2(2\sigma^2)\right)\right) \tag{6}$$

2) Random forest: The RF is an ensemble approach which keeps the capability of performing as both regression and classification problems. In addition, it can handle binary and multi-classification problems. Moreover, the present study uses bootstrap aggregation for absolute random selection as follows [36]. For instance, when the explained variable is a continuous variable and θ is getting random vector then it promotes to decision trees of RF for regression purpose. Moreover, the x and y are random vectors and training data set taken systematically. Besides, $h_i(x)$ is a single decision tree from multi decision trees where $k-th$ denote the number of decision trees for prediction $h(x, \theta_i)$, where the $k-th$ number of outputs by $i-th$ random vectors as $i = 1, 2, 3, \cdots, k$ as follows [37].

$$H(x) = \frac{1}{k}\sum_{i=1}^{k} h_i(x) \tag{7}$$

In equation 7, the $H(x)$ demonstrates the output of combined RF regression models. Moreover, in the training data set $k-th$ shows the number of values represented in the model.

$$H(x) = \underset{Y}{argmax} \sum_{i=1}^{k} I(h_i(x) = Y) \tag{8}$$

Whereas I*() is an appropriate linear function of the model and Y denotes an outcome. Similarly, $h_i(x)$ and $h_k(x)$ are training data sets that collection of X, Y vectors.

$$\int(x, y) \equiv \hat{P}_k\, I(h_k(x) = Y) - max_{j \neq y}\, \hat{P}_k\, I(h_K(x) = j \tag{9}$$

For example, A is the outcome from classifier $h_k(x$ from random vectors that can be optimum ensemble as $\hat{p}(A)$ = proportion of classifiers $h_k(1 \leq k \leq K,$ whenever event A occurs. In addition, the analysts acknowledge that they optimize the model prediction performance by making more generalizations to stochastic error (e).

$$Pe^* = P_{x,y}(\int(x, y) < 0 \tag{10}$$

According to the theorem, the stochastic problem can be determined as below equation whenever the number of decision trees may increase.

$$Pe^* \xrightarrow[K-\infty]{} P_{x,y}\left[P_{\ominus}(h(x, \ominus) = y)\, max_{j \neq y}\, P_{\ominus}(h(x, \ominus) = j) < 0\right] \tag{11}$$

In equation 11, the $P_{x,y}$ denotes problem in x, y random vectors and $k-th$ denotes the total number of decision trees in the model. In addition, if the decision trees grow up the generalization of PE will tend to upper bond. Hence, the RF algorithm has worthy convergence and can prevent over-fitting [38, 39].

3) Machine learning-linear regression model: The regression approach is very useful for linearity approximation. Although the traditional approaches have been employing for execution the high-frequency and nonlinear data sets, but traditional approaches (linear regression) cannot properly investigate the nonlinear data sets [12]. However, the present study is applicating the ML-LRM Fig. 5 for best prediction performance. For instance, x_i is input parameter where $i-th$ is $n-th$number of input parameters as i = $1,\cdots,2,\cdots,3,\cdots n$ and every input parameter takes specific weight which denotes by w_i with $i=1,2,3,\cdots,n$ at $n-th$ number of weights. At the time of training model, the weight multiplied with input parameters and summation biases weights. Moreover, the nth denotes the number of values of the training model. Primarily, we train our model on training data set and test the model output y_i by using the testing data set and execute the prediction performance of the model.

In mapping function Φ makes typical function with x input parameter as $\Phi: X \rightarrow \mathbb{R}^N$. A linear function of hypothetical set: weight and bias are associated with mapping function as $\mathbf{x} \rightarrow \mathbf{w}\,.\,\Phi(x) + b: w \in R^N, b \in \mathbb{R}$. Moreover, the exclusive weight leads to risk minimization and optimization of the typical model.

$$\underset{w,b}{min}\, F(w,b)\frac{1}{m}\sum_{i=1}^{m}(w.\boldsymbol{\Phi}(x_i)+b-\ y_i)^2 \tag{12}$$

$$F(W)=\frac{1}{m}\|X^T\,W-Y\|^2 \tag{13}$$

$$X=\begin{bmatrix}\boldsymbol{\Phi}(\boldsymbol{x_1}) & \dots & \boldsymbol{\Phi}(\boldsymbol{x_m})\\ 1 & \dots & 1\end{bmatrix}\in\mathbb{R}^{(N+1)\times m} \tag{14}$$

So,

$$X^T=\begin{bmatrix}\boldsymbol{\Phi}(x_1)^T & 1\\ \vdots & -\\ \boldsymbol{\Phi}(x_m)^T & 1\end{bmatrix}\ W=\begin{bmatrix}\omega_1\\ \vdots\\ \omega_N\\ b\end{bmatrix}\ Y=\begin{bmatrix}y_1\\ \vdots\\ y_m\end{bmatrix} \tag{15}$$

Additionally, the convex and differentiable functions executed as:

$$\nabla F(W)=\frac{2}{m}X(X^T\,W-Y) \tag{16}$$

$$\nabla F(W)=0 \Leftrightarrow X\left(X^{'}\,W-Y\right)=0 \Leftrightarrow XX^{'}\,W=XY \tag{17}$$

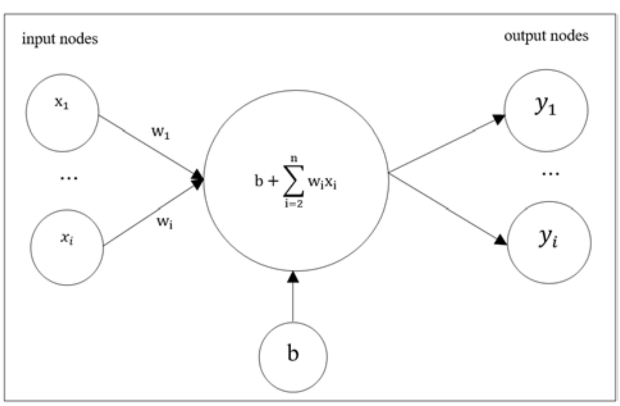


Fig. 5. Structure of ML-LRM.

Equation 17 is explained that if the w = 0, then the hypothesis set would also be zero / no fraction between input-output parameters of the model.

IV. Results and Discussion

Table I summarizes the significant information of both group data. The group1 is contained on daily stock price returns of KSE 100-index of Pakistan and group2 is contained on PKR currency exchange rate against five major currencies of the world. The above statistics demonstrated that the total number of values are 3187 and 3464 in group1 and group2, respectively. Moreover, in group1, the mean and standard deviations are 0.04 and 1.19, respectively, indicating that the group1 data set is highly deviated over the period. In group2, the mean of currencies exchange rates is 97.06, 121.7, 146.9, 98.4 and 0.96, and the standard deviation of currencies exchange rates is 23.4, 21.3, 20.9, 26.9 and 0.22, respectively. According to group 2 statistics, the PKR has been depreciated since 2007 to 2020. Furthermore, the other descriptive statistics are illustrated in the above table as like minimum, maximum, etc.

Table II executes the augmented dickey fuller (ADF) approach to investigate whether the particular parameters have unit-root (non-stationary) or not (stationary) at specific critical level. Although the machine learning algorithms have capability to analyze the nonlinear approximation, but with respect to econometric assumptions, the empirical data should be to stationary (normal distributed) before to diagnosed. So in Table II, the statistics demonstrated that the t-value > critical value at 1%, 5% & 10% confidence intervel at 1st difference. However, the unit root is not existed in the significant model.

TABLE I. Descriptive Statistics

statistics	**KSE 100-Index**	**Currency Exchange Rates**				
	Price Return	***PKR/USD***	***PKR/Euro***	***PKR/GBP***	***PKR/CHF***	***PKR/JPY***
count	3187	3464	3464	3464	3464	3464
mean	0.04	97.0	121.7	146.9	98.4	0.96
std	1.19	23.4	21.3	20.9	26.9	0.22
min	-6.85	60.3	78.4	108.2	48.3	0.48
0.25	-0.48	83.7	111.6	132.5	78.9	0.85
0.5	0.04	98.06	118.4	141.4	103.6	0.96
0.75	0.63	104.8	131.2	159.1	109.9	1.08
max	8.60	166.7	186.5	208.4	173.9	1.54

TABLE II. Augmented Dickey-Fuller (ADF) Test

Parameters	**ADF**	**Critical Values**		
		1%	***5%***	***10%***
Price Returns	-47.339*	-3.432	-2.8622	-2.567
PKR/USD	-52.361*	-3.432	-2.8621	-2.567
PKR/Euro	-57.412*	-3.432	-2.8621	-2.567
PKR/GBP	-56.698*	-3.432	-2.8621	-2.567
PKR/CHF	-56.854*	-3.432	-2.8621	-2.567
PKR/JPY	-57.382*	-3.432	-2.8621	-2.567

Note: * indicates no unit-root exist in the model at 1st differecne

TABLE III. PREDICTION PERFORMANCE OF MLMS WITH MAE

parameters	SVR	RF	ML-LRM
price returns	0.819**	0.978	0.823
PKR-ER against five major currencies	2.718	0.1338**	6.487
	4.774	0.519**	10.967
	5.340	0.622**	9.7980
	3.044	0.424**	8.6620
	0.048	0.003**	0.1440

Note: In Table III, ** indicate comparative best prediction performance model on certain data group.

TABLE IV. PREDICTION PERFORMANCE OF MLMS WITH MSE

parameters	SVR	RF	ML-LRM
price returns	1.545**	2.036	1.559
PKR-ER against five major currencies	13.542	0.158**	73.6090
	38.536	0.570**	173.561
	48.862	0.790**	184.280
	18.531	0.423**	108.558
	0.0030	3.203**	0.02600

Note: In Table IV, ** indicate comparative best prediction performance model on certain data group.

TABLE V. PREDICTION PERFORMANCE OF MLMS WITH RMSE

parameters	SVR	RF	ML-LRM
price returns	1.243**	1.427	1.247
PKR-ER against five major currencies	3.679	0.397**	8.579
	6.207	0.755**	13.174
	6.990	0.889**	13.574
	4.304	0.650**	10.412
	0.056	0.005**	0.1690

Note: In Table V, ** indicate comparative best prediction performance model on certain data group.

Tables III, IV and V execute the prediction performance of MLMs on different nature of data sets. In 1st experiment, the present study used daily stock price returns of KSE 100-index to evaluate the prediction performances of MLMs through mean absolute error (MAE), mean Squared error (MSE) and root mean squared error (RMSE). Consequently, the output shows that the SVR gives relatively optimal prediction performance than RF and ML-LRM on group1 data set; hence, the MAE, MSE and RMSE of SVR is less than RF and ML-LRM. But the ML-LRM is giving best prediction than RF on the corresponding data group. So, on the 1st experiment, the absolute prediction performance is summarized as SVR > ML-LRM > RF. Furthermore, in 2nd experiment, we used group2 data regarding currencies exchange rates for the prediction performance of MLMs. In addition, the loss of RF < SVR < ML-LRM while the RF is giving optimal prediction performance than SVR and ML-LRM. In addition, the SVR gives best prediction than ML-LRM at the same experiment. In 2nd experiment, the prediction performance of MLMs is categorically assembled as RF > SVR > ML-RM. In fact, the empirical data set is nonlinear nature in 2nd experiment and linear regression algorithm is operating in ML-LRM while relatively the ML-LRM doesn't properly investigate the data. On the other hand, the RF is typically used for classification and regression problems. So the RF algorithm is best recognizing the typical data set, even though the data is nonlinear. However, the RF is comparatively given the optimal prediction performance in 2nd experiment.

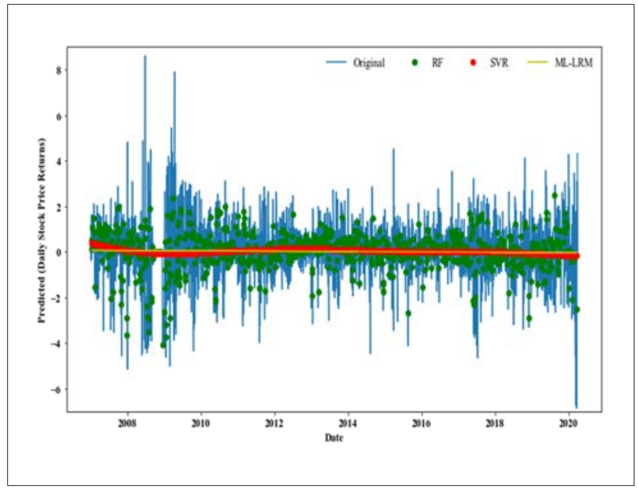
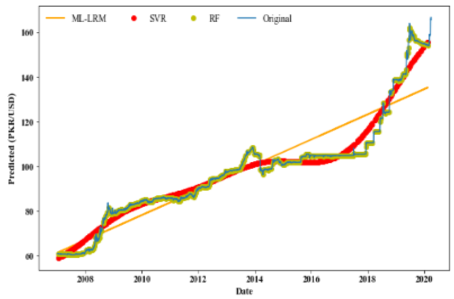


Fig. 6. Graphically Evaluation of Prediction Performance of MLMs on Group1.

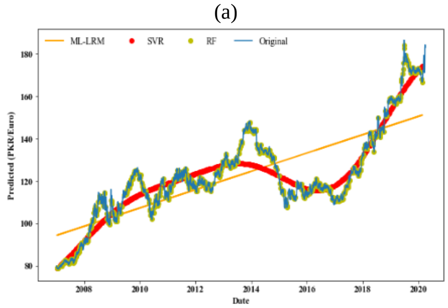
Fig. 6 executes the graphical prediction performance of SVR, RF and ML-LRM at group1. The output demonstrated the SVR model is given optimal prediction than RF and ML-LRM, hence, the red line is very closed to true line. But the RF predicted plots are slightly away from true line. Similarly, the ML-LRM prediction line is comparatively less close to true line. So, the whole prediction performance of MLMs from Fig. 6 executes as follows: SVR > ML-RM > RF. Thus, the SVR can comparatively best predict than RF and ML-LRM on a high-volatile time series data set. Some previous studies are supporting to findings of current study as: [40] determined the comparative prediction performance between SVR and ensemble empirical mode decomposition (EEMD) through Singular Spectrum Analysis (SSA) on Shanghai stock price index. Moreover, this study correspondingly examining the market tendency, market fluidity, economic topographies of the market. The output shows that the SVR can relatively best predict to the fluidity of forex market and stock market than EEMD. So, this is sound evidence about the SVR can gives more efficient and accurate prediction than generic TEM and MLMs on high-frequency data which supported to findings of current study.

The Fig. 7 executes the graphical prediction performances of five empirical models on group2. Each model has relatively summarized the prediction performance of SVR, RF and ML-LRM. In addition, the output of every model is categorically presented along with specific color as follows: SVR with dark-red, RF with yellow-green, ML-LRM with dark-orange and original input data with light-blue color. The model 7(a) in our 2nd experiment exhibits the prediction performance of MLMs by taking the PKR exchange rate against USD on the y-axis and the number of time steps on the x-axis. Consequently, the RF is giving relatively best prediction than SVR and ML-LRM while yellow green line is extremely closed to the true line. In model 7(b), again the RF is relatively giving the best prediction while the yellow green line is very closed to light blue line. Similarly, the output of models c, d & e is accompanied as previous two models. With respect to our

2nd experiment, the findings concluded the RF can comparatively best predict to the nonlinear approximation than SVR and ML-LRM. The findings of 2nd experiment is supported by [41].



(a)



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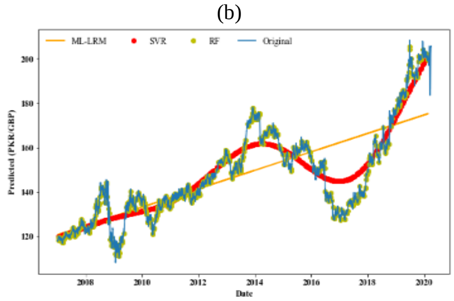

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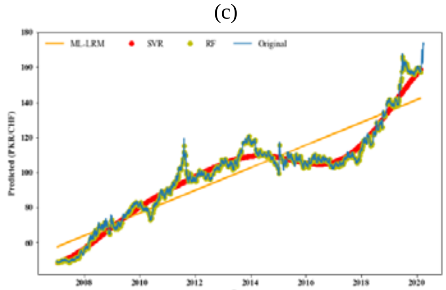

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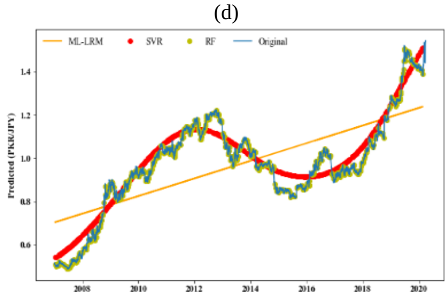

(e)

Fig. 7. Graphically Evaluation of Prediction Performance of MLMs on Group2.

V. CONCLUSION

The stock market and forex market both are highly dynamical financial markets. The usage of machine learning approaches are rapidly growing in financial markets for economical analysis. Therefore, the key purpose of the present study is to investigate the best predictor machine learning model by giving different nature of high frequency financial data sets. So, the empirical findings demonstrated that the SVR and RF have ability to optimistic prediction on high-volatile and nonlinear data sets respectively. In fact, the SVR is a supervised learning approach which works on the principle of support vector machine (SVM) to solve the classification and regression problems. Hence, the SVR is very useful approach for complex and high volatile data. On the other hand, the RF is usually used for classification problems. However, the RF has given best prediction on nonlinear approximation. Moreover, this study had targeted only forex market and stock market of a country, hence, the study may more robuster by using panel financial market data. Further research directions are using hybrid deep neural networks with filter-based feature selection to improve the prediction accuracy and reduce the cost of training time and compare the performance with RF and SVR by using more complex financial data.

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REFERENCES

[1] Z.S. Zhang, Ervin Radiological images and machine learning: trends, perspectives, and prospects, Computers in biology medicine 108 (2019) 354-370.

[2] A. Kuchi, M.T. Hoque, M. Abdelguerfi, M.C. Flanagin, Machine learning applications in detecting sand boils from images, Array 3(2019) 100012.

[3] J.S. Almeida, P.P. Rebouças Filho, T. Carneiro, W. Wei, R. Damaševičius, R. Maskeliūnas, V.H.C. de Albuquerque, Detecting Parkinson’s disease with sustained phonation and speech signals using machine learning techniques, Pattern Recognition Letters 125 (2019) 55-62.

[4] Z.-T. Liu, M. Wu, W.-H. Cao, J.-W. Mao, J.-P. Xu, G.-Z. Tan, Speech emotion recognition based on feature selection and extreme learning machine decision tree, Neurocomputing, 273 (2018) 271-280.

[5] J. Calabuig, H. Falciani, E.A. Sánchez-Pérez, Dreaming machine learning: Lipschitz extensions for reinforcement learning on financial markets, Neurocomputing, 398 (2020) 172-184.

[6] B.M. Henrique, V.A. Sobreiro, H. Kimura, Literature review: Machine learning techniques applied to financial market prediction, Expert Systems with Applications, 124 (2019) 226-251.

[7] L. Chen, Z. Qiao, M. Wang, C. Wang, R. Du, H.E. Stanley, Which artificial intelligence algorithm better predicts the Chinese stock market?, IEEE Access, 6 (2018) 48625-48633.

[8] B.J. de Almeida, R.F. Neves, N. Horta, Combining Support Vector Machine with Genetic Algorithms to optimize investments in Forex markets with high leverage, Applied Soft Computing, 64 (2018) 596-613.

[9] J. Carapuço, R. Neves, N. Horta, Reinforcement learning applied to Forex trading, Applied Soft Computing, 73 (2018) 783-794.

[10] A.V. Contreras, A. Llanes, A. Pérez-Bernabeu, S. Navarro, H. Pérez-Sánchez, J.J. López-Espín, J.M. Cecilia, Theory, ENMX: An elastic network model to predict the FOREX market evolution, Simulation Modelling Practice, 86 (2018) 1-10.

[11] R. Chowdhury, M. Mahdy, T.N. Alam, G.D. Al Quaderi, M.A. Rahman, Predicting the stock price of frontier markets using machine learning and modified Black–Scholes Option pricing model, Physica A: Statistical Mechanics its Applications, 555 (2020) 124444.

[12] H. Maqsood, I. Mehmood, M. Maqsood, M. Yasir, S. Afzal, F. Aadil, M.M. Selim, K. Muhammad, A local and global event sentiment based efficient stock exchange forecasting using deep learning, International Journal of Information Management, 50 (2020) 432-451.

[13] C.-L. Huang, C.-Y. Tsai, A hybrid SOFM-SVR with a filter-based feature selection for stock market forecasting, J Expert Systems with applications 36 (2009) 1529-1539.

[14] B.M. Henrique, V.A. Sobreiro, H. Kimura, Stock price prediction using support vector regression on daily and up to the minute prices, The Journal of finance data science 4(2018) 183-201.

[15] L. Guo, W. Fang, Q. Zhao, X. Wang, The hybrid PROPHET-SVR approach for forecasting product time series demand with seasonality, J Computers Industrial Engineering 161 (2021) 107598.

[16] M. Vijh, D. Chandola, V.A. Tikkiwal, A. Kumar, Stock closing price prediction using machine learning techniques, Procedia Computer Science 167 (2020) 599-606.

[17] P. Werawithayaset, S. Tritilanunt, Stock Closing Price Prediction Using Machine Learning, 2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE), IEEE, 2019, pp. 1-8.

[18] R. Philip, Estimating permanent price impact via machine learning, Journal of Econometrics, 215 (2020) 414-449.

[19] A. Yadav, C. Jha, A. Sharan, Optimizing LSTM for time series prediction in Indian stock market, Procedia Computer Science, 167 (2020) 2091-2100.

[20] Y. Zhang, G. Chu, D. Shen, The Role of Investor Attention in Predicting Stock Prices: The Long Short-term Memory Networks Perspective, Finance Research Letters, DOI (2020) 101484.

[21] A. Moghar, M. Hamiche, Stock Market Prediction Using LSTM Recurrent Neural Network, Procedia Computer Science, 170 (2020) 1168-1173.

[22] P. Wang, Pricing currency options with support vector regression and stochastic volatility model with jumps, Expert Systems with Applications 38 (2011) 1-7.

[23] W. Chen, H. Xu, L. Jia, Y. Gao, Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants, International Journal of Forecasting, DOI (2020).

[24] R. Dash, An improved shuffled frog leaping algorithm based evolutionary framework for currency exchange rate prediction, Physica A: Statistical Mechanics and its Applications, 486 (2017) 782-796.

[25] Z. McGurk, US real estate inflation prediction: Exchange rates and net foreign assets, The Quarterly Review of Economics and Finance, 75 (2020) 53-66.

[26] T. Lumley, Survey analysis in R, the 'survey'package). Guía de usuario disponible en: http://faculty. washington. edu/tlumley/survey, DOI (2010).

[27] J. Aizenman, A. Powell, Volatility and financial intermediation, Journal of International Money and Finance, 22 (2003) 657-679.

[28] P. Aghion, S.N. Durlauf, Handbook of economic growth, Elsevier2005.

[29] M. Busse, C. Hefeker, Political risk, institutions and foreign direct investment, European journal of political economy, 23 (2007) 397-415.

[30] V. Vapnik, S.E. Golowich, A.J. Smola, Support vector method for function approximation, regression estimation and signal processing, Advances in neural information processing systems, 1997, pp. 281-287.

[31] T. Wuest, D. Weimer, C. Irgens, K.-D. Thoben, Machine learning in manufacturing: advantages, challenges, and applications, Production & Manufacturing Research, 4 (2016) 23-45.

[32] C. Cortes, V. Vapnik, Support-vector networks, Machine learning, 20 (1995) 273-297.

[33] W. Fenghua, X. Jihong, H. Zhifang, G. Xu, Stock price prediction based on SSA and SVM, Procedia Computer Science, 31 (2014) 625-631.

[34] D. Wang, Y. Zhao, Using News to Predict Investor Sentiment: Based on SVM Model, Procedia Computer Science, 174 (2020) 191-199.

[35] P. Anand, R. Rastogi, S. Chandra, A class of new Support Vector Regression models, Applied Soft Computing, DOI (2020) 106446.

[36] W. Alsuraihi, E. Al-hazmi, K. Bawazeer, H. Alghamdi, Machine Learning Algorithms for Diamond Price Prediction, Proceedings of the 2020 2nd International Conference on Image, Video and Signal Processing, 2020, pp. 150-154.

[37] V. Vapnik, S.E. Golowich, A. Smola, Support vector method for function approximation, regression estimation, and signal processing, Advances in neural information processing systems, DOI (1997) 281-287.

[38] S. Pan, S. Zhou, Evaluation Research of Credit Risk on P2P Lending based on Random Forest and Visual Graph Model, Journal of Visual Communication and Image Representation, DOI (2019) 102680.

[39] L. Breiman, Random forests, Machine learning, 45 (2001) 5-32.

[40] V. Zavgorodniy, P. Lukyanov, S. Nazarov, 2nd International Conference on Information Technology and Quantitative Management, ITQM, DOI (2014).

[41] C. Ciner, Do industry returns predict the stock market? A reprise using the random forest, The Quarterly Review of Economics and Finance, 72 (2019) 152-158.