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Foreign Exchange Rates Prediction using Fuzzy Based Support Vector Regression

Mr. Satyanarayana Reddy Beeram[1*], Mr. Lakshmikanth Paleti [2], Mr. Sambasiva Rao Aaradhyuala[3], Mr. Mahesh Reddy Gogula[4], Mr. Narasimha Rao Yamarthi[5]

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Abstract: Foreign exchange value prediction models are playing a vital role in financial decision making and global business trading. Forecasting the foreign exchange values with high accuracy, became a prominent research topic for both academic and economic research scholars. Due to the complexity and chaotic nature of foreign exchange dataset values, minimizing the range of prediction errors became another prominent research challenge in this area. Although many former researchers designed various time series prediction models, they were suffering from the prediction accuracy and prediction errors. In this paper, we proposed a Fuzzy based Support Vector Regression (F-SVR) model to address the former research limitations by incorporating the fuzzy logic with SVR. Fuzzy membership functions are used in this model to assign the time coefficients along with the data points, to get more control on training and prediction process of SVR. Experiments conducted on USD-INR dataset using the proposed F-SVR model with various kernel functions proven that the F-SVR with radial basis kernel function recorded the high prediction accuracy and less prediction error range than the traditional SVR kernels.

Keywords*: *Support Vector Machines; Fuzzy Logic; F-SVR; Foreign exchange value forecasting; USD-INR data set.

1. Introduction

The global trading among the countries is happening through the global foreign currency market estimated currency pair values or foreign exchange rates (i.e., USD-INR, EUR-USD and USD-JPY etc.) [1]. At global market these foreign exchange rates (FOREX) are updated periodically based on numerous factors like financial trends, financial expectations, transaction volumes, demand-supply graphs, and the other relevant activities. Due to the high volume of transactions, any small variance in the currency exchange rates leads to either a huge profit or loss. As the exchange rate became a key decision-making factor in financial aspects, forecasting the exchange rate is an ever-green research concept for the research scholars.

Former research [2][3] and [4] outlined that, forecasting the FOREX rates is a complex non-linear stochastic process, which is proven by substantial evidences of their research works. By using the computational intelligence mechanisms (i.e., SVM, ANN's, Random walks etc.), former research scholars [3], [5], [6] and [7] worked on the nonlinear time series datasets to predict the current and future values based on the past information. Mohd. Alamili [8] specified the need of coordinating the fundamental analysis and computational intelligence, while analyzing the chaotic time series to obtain the more accurate results with less error percentage. His research study conducted the experiments on EUR/USD dataset using the SVR and ANN mechanisms. In order to forecast the foreign exchange values, most of the aforementioned research works [3], [5], [9] and [8] were widely adopted the popular prediction models like Support Vector Regression (SVR) and Artificial Neural Networks (ANN's). In these research works SVR outperformed ANNs, in terms of accuracy, reliability, error rate and complexity.

Although the SVR is proven as a standard regression model [10] and [11], it is still suffering from the considerable performance limitations while forecasting the time-series data values with less prediction accuracy and high prediction error range. According to the Research analysis on SVR [8], [12], [13] and [14], few reasons to the limitations are: SVR is not considering the time value impact during the time series predictions and SVR is assuming that the contribution of all prediction variables of a dataset is same and uniform.

In order to address the limitations of SVR during the time series dataset values prediction, this paper proposed a fuzzy based support vector regression (F-SVR) model. To expand the scope of time series predictions with F-SVR,

[1]Associate Professor, Department of Computer Science and Engineering KKR&KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh India*
[2]Associate Professor, Department of CSBS, RVR & JC College of Engineering, Guntur, Andhra Pradesh, India
[3]Assistant Professor, Department of IT, RVR & JC College of Engineering, Guntur, Andhra Pradesh, India.
[4]Assistant Professor, Department of Computer Science and Engineering, KITS Engineering College, Guntur, India
[5]Professor, School of Computer Science and Engineering, VIT-AP University, India
[1]Corresponding Author Email: snreddy.beeram@gmail.com*

the time coefficients are assigned with each data point of predictor variables. Fuzzy membership function assigns these time coefficients with each input pairs, to improve the regularization and to get the better control on training and prediction sets using multiple free parameters. These fuzzy coefficients are later substituted into SVR formulations, to achieve the high accuracy and less prediction error ranges. To evaluate the performance of the proposed F_SVR model, a real time USD-INR dataset with three years of exchange value records is used in this study (for more information on dataset see in secton-3.1). The F-SVR prototype is designed with python and is used to execute the experiments on USD-INR dataset, using various kernel functions. Experimental analysis demonstrated the F-SVR achieved high prediction accuracy and low prediction error range. In this study, the prediction accuracy is measured by the MSE, RMSE and NRMSE metrics, whereas the prediction error ranges are measured by the custom metrics like MPPE (Max Positive Prediction Error range) and MNPE (Max negative Prediction Error range). Exceeded positive (+ve) or negative (-ve) variance of predicted values, leads to loss of reliability on prediction mechanisms. Due to this reason, we compared the experimental results of various kernels with MPPE and MNPE custom metrics also.

2. Literature Review

SVM is a supervised learning model of machine learning domain. SVM is mainly used for data classification and regression activities, with the help of the SVM training algorithms like Sequential Minimal Optimization (SMO) and Coordinate Descent (CoD). The basic foundation laid for the SVMs in 1957 by Frank Rosenblantt [15], who introduced the “Perceptron Model” for visual patterns classification with the help of efficient learning models. Later Vapnik et al [16] and [17], continued the design of efficient learning mechanisms (i.e., VC theory for statistical learning) and finally introduced the SVM, which is enriched with kernel set and soft margins to classify the linear and non-linear data.

To deal with the multi-dimensional real-value data (Rd), Drucker et al., [18] proposed the dimensionality independent non-linear data regression model as Support Vector Regression (SVR). Since beginning the SVMs are proven as better classification and regression models, in dealing with the ‘n’ dimensional datasets, especially with the discrete time series (i.e., stock market data, foreign exchange data, weather report data etc.), which are linearly non-separable. Although SVM classification and SVM regression both works for different end targets, internally they both follow the same pattern in processing. The SVM is mainly used for identifying an optimal hyper-plane for better classification of the given data values. In other hand the SVR concentrates on learning an optimal function f(x) from training set to predict the future value as output with at most ε deviation. Generally, the SVM classification model is available in C-SVM and nu-SVM forms, at the same time the SVR also available in epsilon insensitive SVM (ε-SVM) and nu-SVM forms. The ε-SVM assures the prediction value (Ϋ) with max ε deviation, but unable to control the size of support vectors participating in optimization, which leads to consumption of more resources. In contrary to ε-SVM, the nu-SVM is able to control the size of support vectors in optimization, but unable to set a max deviation value ε, which leaves the prediction model with uncertain deviation range. While forecasting the foreign exchange values, the results accuracy and max deviation assurance are the prominent requirement, hence most of the financial forecasting models use to prefer the ε-SVM model as the compatible flavor of SVM.

For example, a given training data set Ɗ with η dimensions and the data points presented as $\{(\varkappa_1, \gamma_1),(\varkappa_2, \gamma_2) \ldots (\varkappa_m, \gamma_m)\}$,where each predictor variable $\varkappa_i \in \boldsymbol{x}$ and $\boldsymbol{x} \subseteq R^n$, similarly the criterion variable $\gamma_1 \in \mathbf{y}$ and $\mathbf{y} \subseteq R$. At this level, the goal is to find the best optimal function $f(x)$: $(R^n \rightarrow R)$, to forecast the test set $\bar{\mathbf{y}}$ values with high probability.

In case of the simple linear regression model for predicting the criterion $\boldsymbol{y}$ value with an optimal function f, in which the $\boldsymbol{b}$ is an intercept of $\boldsymbol{y}$ and $\boldsymbol{m}$ is the slope is represented as shown in equation 1:

$$f(\varkappa) = y = m.\varkappa + b \tag{1}$$

In order to calculate the prediction accuracy, the standard error of estimate σ_{est} with the sum of squared deviations $(y - \bar{y})^2$ is defined as shown in equation 2:

$$\sigma_{est} = \sqrt{\frac{\Sigma(y-\bar{y})^2}{N}} \tag{2}$$

While dealing with the η-dimensional datasets, the multi-regression linear model with the coefficients $\boldsymbol{w}$ and the dimensional variables $(\varkappa_1, \varkappa_2 \ldots \varkappa_p)$ are implemented as shown in equation 3:

$$f(\varkappa_1, \varkappa_2 \ldots \varkappa_p) = w_1.\varkappa_1 + w_2.\varkappa_2 \ldots + w_p.\varkappa_p \tag{3}$$

In multi-regression linear model, the performance of equation 3 is calculated with the help of Mean Squared Error (MSE), where $\bar{y}_i = (w_1.\varkappa_1 + w_2.\varkappa_2 \ldots + w_p.\varkappa_p)$ is represented as shown in equation 4.

$$MSE = \left(\frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{2N}\right) \tag{4}$$

While analyzing the chaotic time series and predicting the future values, many research scholars [3], [9], [8] and [19] observed that the SVM recorded high accuracy, when compared to the other prediction models like ANN [20] and Random Walks. Tyree and Long (1995) et al [6], compared the Random Walk model predicted exchange values against the ANN's. For this they have chosen the USD-DEM dataset, to execute the scheduled Uni-variant and multi-Variant prediction operations. From these simulations, they noticed that the random walks are recorded high accuracy and lowest error rate than ANN's. Nanthakumaran and Tilakaratne et al (2017) [9], evaluated the performance of Support Vector Regression (SVR) model and Artificial Neural Networks (ANN's), in forecasting the foreign exchange values, using the EUR/LKR and JPY/LKR datasets. In this comparison SVR recoded high directional accuracy and MSE over ANN's. Alamili M [8] conducted the experimental analysis and comparison between ANNs and SVMs, with the help of two FOREX datasets (i.e., EUR/USD dataset and Mackey-Glass data set). By insisting various combinations of ϒ, C and ω values, Alamili proven that the SV Regression achieved the high hit rate and less margin errors compared to ANNs. Rajesh et al., (2019) [21] conducted the experiments on stock trend predictions with SVM, Random Forest and KNN classifiers, in combination with heat map and ensemble learning methods, to achieve the high accuracy in stock predictions. Krishna et al., (2019) [22] proposed the ARIMA and ANN models for the future gold price forecasting. Experiments on standard gold dataset had proven that, the Feed Forward Neural Network (FFNK) shown the high accuracy (in terms of MAE and RMSE) than the ARIMA model. But in case of sale value prediction experiments by Imambi et al., [23] have shown that, the ARIMA model forecasted the future sale values efficiently.

3. Fuzzy Reliance Support Vector Regression

3.1. Dataset Characterization

In order to evaluate the performance of F-SVR, in forecasting the foreign exchange values, we have selected the past 3 years of USD-INR dataset (i.e., from 2018 - 21) from the reliable web resources1. After downloading the dataset, it was thoroughly analyzed to recognize the patterns and relations existed among the data set values. To easily understand the nature of dataset and correlations among values, it is represented in a graph manner as shown in Figure 1. This analysis on dataset revealed a few considerable facts about the data values are: i) although the dataset values are chaotic in nature, but they follow the rhythmic ups and downs continuously ii) Exchange value dataset values are not strictly random, which means the side by side data point variations are not greater than their mean square value iii) As dataset values are deterministically non-linear, the forecasting process become notoriously too complex and sensitive operation iv) At any particular date point the exchange value predictions are more dependent on its recent past values than the total history values.

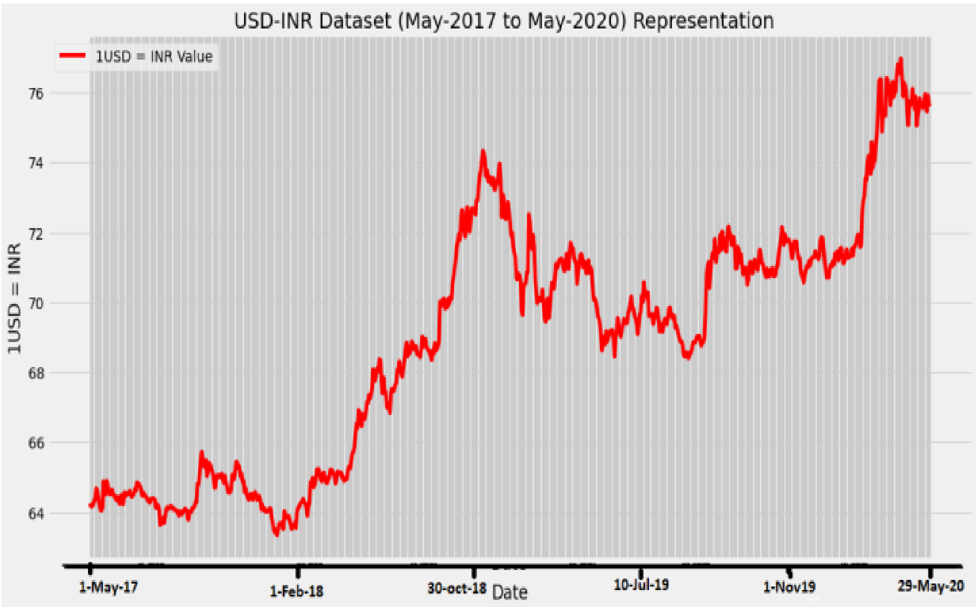

Fig 1. Graphical representation of USD-INR dataset

3.2.Support Vector Regression (SVR)

From the USD-INR dataset graphical representation (Figure 1), we noticed that the exchange values are fluctuated from date to date, in a linearly inseparable model. Due to this reason, just finding the best fit hyper plane with linear regression is not possible and it cannot give the accurate prediction results. This is the considerable research gap we identified in forecasting the linearly inseparable foreign exchange values, which can be bridged using the gradient-descent [24] model cost functions of SVR. Although the SVM and SVR follows the same methodology, in SVM the hyper plane is used for classification, where as in SVR the hyper plane is used for forecasting the continuous future values. Unlike the linear regression model with minimized error rate functions, the SVR assures the approximation of error rate, which is tolerance to a certain threshold ($\mathcal{E}$) value at any given time. Because of this, it is termed as the Epsilon Insensitive Support Vector Regression ($\mathcal{E}$-SVR [25]) with $L2$ loss function. Using the predictor (x) and criterion (y) variables, $\mathcal{E}$-SVR defines a function $f(x)$, which results the$\bar{y}$from$y$,in subject to$(y - \bar{y}) \leq \mathcal{E}$**.** This guaranteed error range helps the FOREX investors and traders in calculating the max risk associated with their trading.

To forecast the future values of the training dataset Ɗ, using a non-linear SVR function $f(x)$, is formulated by Vapniket al. [17] as shown in equation 5:

$$f(x) = y = W^T . \Phi\ (\varkappa_i) + b \qquad (5)$$

When compared the linear regression relation equation 1 against the non-linear regression equation 5, the non-linear regression model is especially designed to transform the linearly inseparable data to the high dimensional feature space $\Phi\ (\varkappa_i)$, using the training data weight vector W^T and the scalar b values as aforementioned. Generally, the SVR [18] is used to find the compatible hyper plane with aware of $\mathcal{E}$-insensitive loss function, to minimize the error range. To achieve this, the function $f(x)$ is transformed to find the optimal hyper plane, to minimize the error rate between predictor variables (y) and criterion variables ($\bar{y}$) (with most $\mathcal{E}$-deviation), for the whole training data $T$is defined as shown in equation 6.

$$(min)\ \frac{1}{2} W^T W \qquad (6)$$

subject to: $\quad (y_i - W^T . \Phi\ (\varkappa_i) - b) \leq \mathcal{E}$

$$\mathcal{E}\ \geq (b + W^T . \Phi\ (\varkappa_i) - y_i)\ \ where\ \mathcal{E}\ \geq 0$$

While doing the regression with linearly inseparable data, the value of W should be minimized to a possible level to keep the function flat. At this time a set of mis-classification values may be raised due to the limitations in considering the data range for training. Soft margin is the boundary selection model, which plays a vital role in SVR by allowing the limited range of errors if required. The distance from the hyper plane to any misclassification point is represented with (slack variable ξ) and to control the soft margin, a regularization constant variable C is added as presented in equation 7:

$$(min) \frac{1}{2} W^T W +\ \mathrm{C}\ \sum_{\boldsymbol{i=1}}^{\boldsymbol{m}} (\xi_i^+ + \xi_i^-) \qquad (7)$$

subject to:

$$(y_i - W^T . \Phi\ (\varkappa_i) - b) \leq\ \mathcal{E} +\ \xi_i^+$$

$$\mathcal{E} + \xi_i^-\ \ \geq (b + W^T . \Phi\ (\varkappa_i) - y_i)\ \ \ where\ \xi_i^-, \xi_i^+, \mathrm{C} \geq 0$$

The increased value of Cdecreases the misclassifications count that leads to over-fitting problem and the decreased value of C increases the misclassifications count that leads to under-fitting problem. With the help of the regularization parameter C**,** the criterion (y**)** variable values, which greater than the threshold value ($\mathcal{E}$)are penalized respectively, to control the over-fitting and under-fitting problems. The max upper distance of the misclassification value is (ξ_i^+)and the max lower distance of the mis-classification value is ξ_i^-. To solve the quadratic of equation 7 and to adopt this model for nonlinear functions, the Lagrangian [26] nonnegative multipliers (α_i and α_i^*) and the dual formulation of nonlinear SVR are substituted in equation 7. At Final the standard equation (5) related decision function $f(x)$ is defined as shown in equation 8:

$$f(x) =\ \sum_{i=1}^{m} (\,\alpha_i -\ \alpha_i^*)\ K(\varkappa_i, \varkappa_j) + b \qquad (8)$$

Where the training data weight vector W is represented with the Lagrangian multipliers as shown in equation 9:

$$W\ =\ \sum_{i=1}^{m} (\,\alpha_i -\ \alpha_i^*) \qquad (9)$$

Here the inner products of the predictor variables $\langle \varkappa_i\ .\varkappa_i \rangle$ are substituted with kernel functions $K(\varkappa_i, \varkappa_j)$ to map the predictor vectors $\varkappa_i$ and $\varkappa_j$ to the high dimensional feature space models like $\Phi\ (\varkappa_i)$ and $\Phi\ (\varkappa_j)$. Most frequently using semi-definite nonlinear kernel functions are shown in equation 10 and equation 11:

$$K(\varkappa_i, \varkappa_j) =\ \ (\varkappa_i, \varkappa_j)^d$$

Polynomial Kernel Function (10)

$$K(\varkappa_i, \varkappa_j) =\ exp\left[-\frac{\|\varkappa_i - \varkappa_j\|^2}{2\sigma^2}\right]$$

Gaussian Radial Basis Function (11)

3.3. Fuzzy reliance Support Vector Regression (F-SVR)

Fuzzy logic mimics the human behavior, while making the decisions on uncertain data. Unlike the Boolean logic (0 or 1), fuzzy expands the decision criteria by increasing the possible decision targets (0, 0.1, 0.2 …, 1). This is a reliable methodology to solve the fuzziness of any real world problems with feasible solutions. In forecasting the time series data, SVR became a reliable model with assured max$\mathcal{E}$ deviation, but it is slightly suffering in maintaining the consistency in accuracy and prediction error rate values. Some former research [16] and [27] also discussed the sensitiveness of SVM with noisy data and outliners. To suffer from these limitations the main issues associated with support vector regression are: SVR is unable to calculate the priority of dataset variables in predictions and SVR cannot assign the time coefficients with data points. From the dataset analysis, we noticed that the foreign exchange value prediction process mostly relies on recent past history points than its earlier ones. Providing the uniform weights to all data points of a time series training set, leads to increase the error rate in future predictions. In order to address these limitations, we proposed the use of fuzzy membership functions with SVR is termed as Fuzzy SVR (F-SVR) in this paper. In F-SVR method, the fuzzy membership function [28] and [29] assigns the time coefficient value (t_i) using the fuzzy membership (q_i) functions.

The fuzzy membership value (q_i) (denotes the attitude) of a predictor variable ($\varkappa_i$), which is a non-negative value ($0 < q_i \leq 1$) and is labeled with the points of training dataset Ḏ as $\{(\varkappa_1, \gamma_1, q_1), (\varkappa_2, \gamma_2, q_2) \ldots (\varkappa_m, \gamma_m, q_m)\}$.

In this F-SVR model, the dataset main variable ($\varkappa_k$) vector size is calculated and the fuzzy memberships are assigned by starting from the lower bound ($\sigma > 0$) points in a sequential manner. In this case the linear membership function of time t_i from q_i is defined as shown in equation 12:

$$q_i = f(t_i) = w.t_i + b \qquad (12)$$

Subject to $\begin{Bmatrix} t_1 > 0 \\ t_m = 1 \\ f(t_1) = \sigma \end{Bmatrix}$

By applying the boundary constraints, we defined the fuzzy membership function of time (t_i) as in equation 13:

$$q_i = f(t_i) = (1-\sigma)\left(\frac{t_i - t_1}{t_m - t_1}\right)^2 + \sigma \qquad (13)$$

Now the fuzzy membership formula (q_i) defined with equation 13 is substituted in equation 7 to represent the redesigned soft margin with slack variables. In F-SVR model the fuzzy membership of time(q_i) is multiplied with slack variables to obtain a different weight, which impacts on the regression error values of various data points directly.

$$(min)\frac{1}{2}W^TW + \mathrm{C}\sum_{i=1}^{m}(q_i)(\xi_i^+ + \xi_i^-) \qquad (14)$$

Subject to:

$(y_i - W^T.\Phi(\varkappa_i) - b) \leq \mathcal{E} + \xi_i^+$

$\mathcal{E} + \xi_i^- \geq (b + W^T.\Phi(\varkappa_i) - y_i) \quad where\ q_i > 0\ and\ \xi_i^-, \xi_i^+, \mathrm{C} \geq 0$

From the equation 14, we observed the low (q_i) valuereduces the impact of the slack variableξ in SVR, which leads to reduce the impact of the respective data point ($\varkappa_i$) in predictions. To address these optimization issues, the Lagrangian dual formulation is defined as equation 15:

$$L(\alpha) = \frac{1}{2}W^TW + \mathrm{C}\sum_{i=1}^{m}(q_i)(\xi_i^+ + \xi_i^-) - \sum_{i=1}^{m}(\eta_i^+\xi_i^+ + \eta_i^-\xi_i^-)$$
$$-\sum_{i=1}^{m}\alpha_i^+(\mathcal{E} + \xi_i^+ - y_i + W^T.\Phi(\varkappa_i) + b)$$
$$-\sum_{i=1}^{m}\alpha_i^-(\mathcal{E} + \xi_i^- + y_i - W^T.\Phi(\varkappa_i) - b) \qquad (15)$$

Subject to $\eta_i^+, \eta_i^-, \alpha_i^+, \alpha_i^- \geq 0\ and\ q_i > 0$

Now the dual formulation for the non-linear F-SVR is designed as presented in equation 16

$$(\mathrm{Max}) \quad \frac{1}{2}\sum_{i,j=1}^{m} K(\varkappa_i, \varkappa_j)(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) + \mathcal{E}\sum_{i=1}^{m}(\alpha_i + \alpha_i^*) - \sum_{i=1}^{m} y_i(\alpha_i - \alpha_i^*) \ (16)$$

Subject to

$$\sum_{i=1}^{m}(\alpha_i - \alpha_i^*) = 0, \qquad 0 \leq \alpha_i \leq q_i\mathrm{C}\ and\ \alpha_i, \alpha_i^* \ \dot{\in}\ (0, \mathrm{C})$$

In traditional SVR, only one regularization parameter C is defined, where as in proposed F-SVR the data point $\varkappa_i$contains regularization constant C along with multiple $q_i$values to get the better control over training and predictions.

Algorithm 1 Fuzzy SVR Algorithm

Procedure FSVR(training_data, test_ data, kernel_name, constent)

set δ = 0

data_sample (x_k, y_k) = training_data.extractSample()

Evaluate $f(x_k)\ and\ h(x_k)$

if $|h(x_k)| < E$:

add dataSample to R then quit

for i=0 to n evaluate $h(x_w)$ in range from $w = 1 \ldots n$

if ($h(x_w) \notin \{R, S, E\}$) then

update the vectors $\gamma\ and\ \beta$

find least and min variations

update the weight values for $\theta_k\ and\ \theta_w$

update $h(x_k)$ with k from E and R

continue the eval of fuzzy_rbf_kernel($h(x_k), x, y$) and result flag σ with updated values based on flag σ value

add sample to S, R and E

move samples as S → R, S→ E, E→S and R→S

end

procedure

fuzzy_rbf_kernel($h(x_k), x, y$)

x, y =chk_pair_wise_samples(x, y)

K =euclidean_distances($h(x_k), x, y$, squared=True)

K *= -(1.0 /dimension(x))

σ = exponent(K)

return σ

end

Algorithm 1 describes the process adopted to incorporate the fuzzy SVR algorithm with RBF Kernel applied.

4. Experimental Analysis

This section describes the selected USD-INR dataset for experiments and the results obtained with F-SVR algorithm. In order to conduct the experiments on foreign exchange value predictions using F-SVR model, USD-INR dataset with 3 years data (i.e. since May-2017 to May-2020) is selected. This data set contains total 6 columns (price, open, high, low, volume and change) and hundreds of rows. We designed the prototype of F-SVR using python programming language and executed the experiments on a PC with Intel core - i3-4030 @ 1.9GHz processor, 4 GB RAM, 500 GB hard disk and windows 7 OS.

In order to conduct the F_SVR experiments, the total dataset with (800+) records are trained and this knowledge is used to forecast the final year data using various kernel models. Mean Squared Error (MSE), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Max Positive Prediction Error (MPPE) and Max Negative Prediction Error (MNPE) are the selected metrics [30] to measure the performance of F-SVR model.

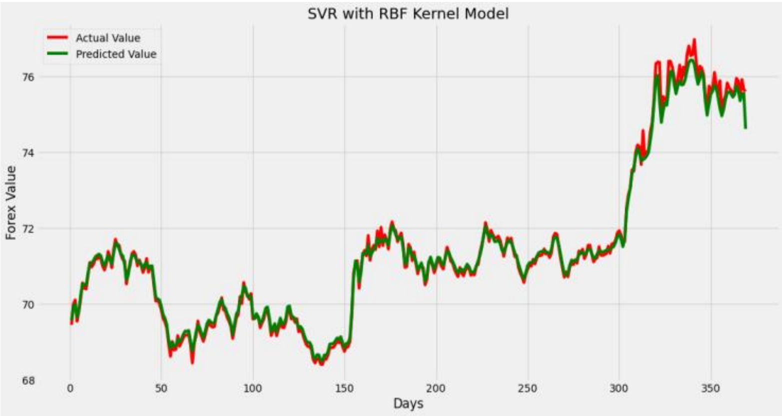

Fig 2. SVR predictions with Radial Basis Function kernel model

Proposed F-SVR prototype is executed on same USD-INR dataset using various kernels functions (Linear, Polynomial and Radial Basis) [31]. The results obtained from the traditional SVR kernels are shown in Figure 2.

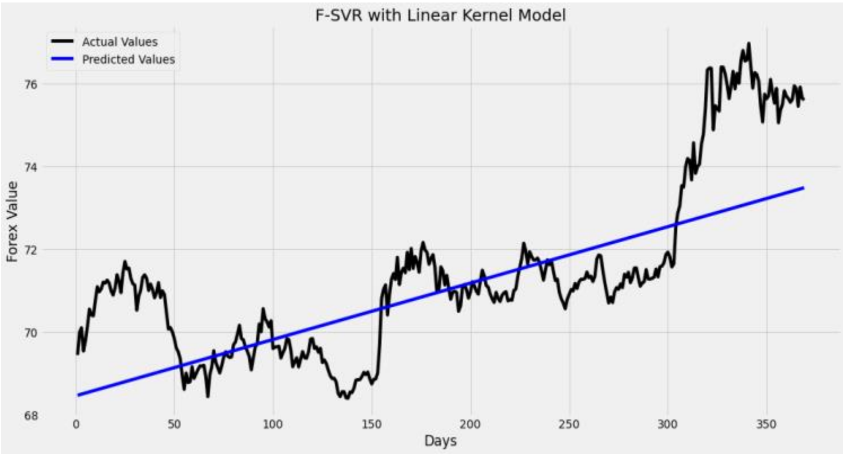

Fig 3. F-SVR predictions with linear kernel model

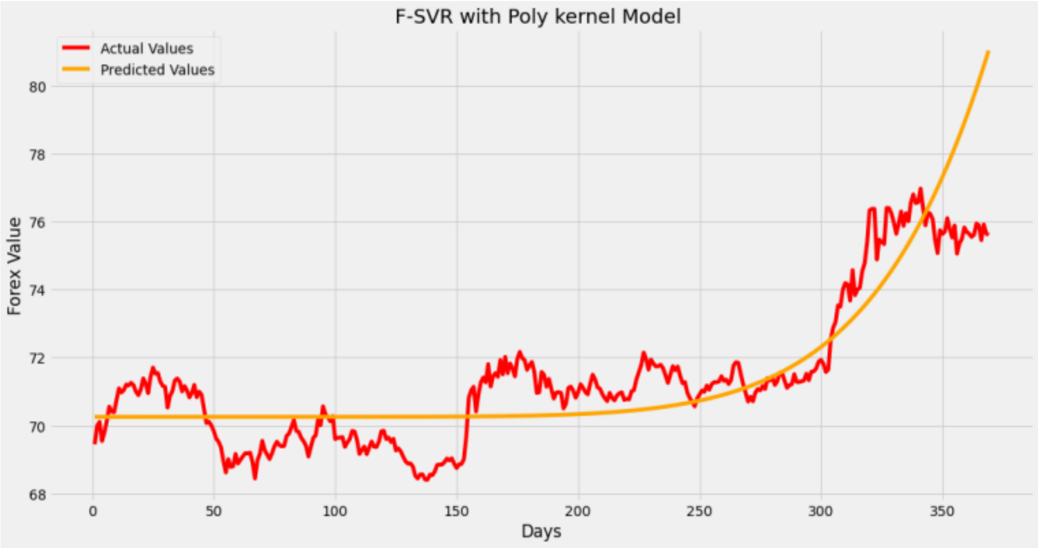

Fig 4. F-SVR predictions with polynomial kernel model

From Figure [3 to 5], the three graphs are representing the results of experimental activities conducted on USD_INR dataset using the proposed F-SVR method with various kernel functions. Figure 3 shows the performance of predictions with F-SVR method using linear kernel, Figure 4 shows the F-SVR predictions with polynomial kernel, Figure 5 shows the F-SVR with RBF kernel.

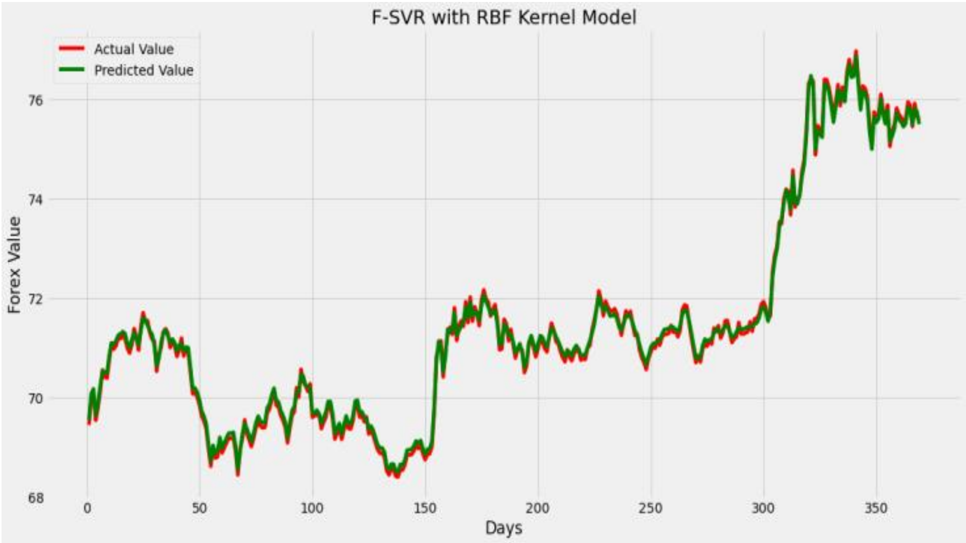

Fig 5. F-SVR predictions with Radial Basis Function kernel model

The above graph representations (Figure 3 and 4) are clearly exposing that, the F-SVR linear and polynomial kernels are recorded less accuracy and high error rate, in finding the best fit hyper planes and forecasting the future values.

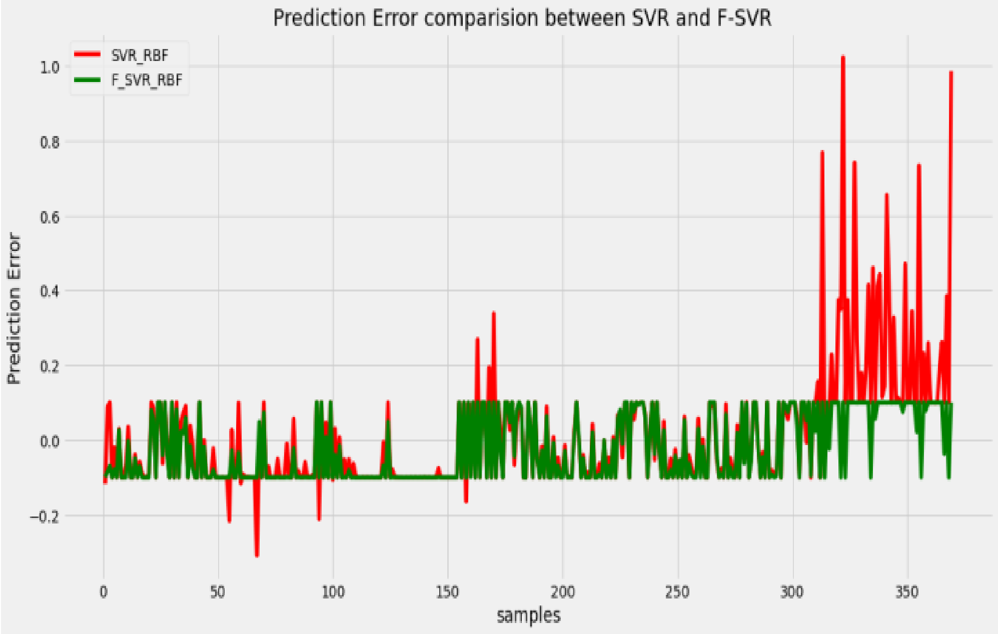

Fig 6. SVR vs. F-SVR prediction error comparison with RBF kernel model

At the same time the Radial Basis Function (RBF) kernel with SVR (Figure 2) shown the better results than F-SVR linear and polynomial kernels (Figure 3 and 4). Finally, our proposed approach F-SVR with RBF kernel is proven as more accurate prediction model than the other three kernel models.

Table 1.Experimental Results comparison on USD-INR dataset

	MSE	*RMSE*	*NRMSE*	*MPPE*	*MNPE*
F-SVR(Linear)	2.18	1.47	0.17	3.86	-1.93
F-SVR(Poly)	1.58	1.25	0.14	2.62	-5.43
SVR (RBF)	0.02	0.16	0.02	1.02	-0.3
F-SVR(RBF)	0.008	0.09	0.01	0.1	-0.1

To prove the efficiency of F_SVR in controlling the prediction error range, the prediction error values of the traditional SVR with RBF kernel and the F-SVR with RBF kernel are compared (as shown in Figure 6). From this comparison, we noticed that the F_SVR with RBF kernel perfectly limited the error ranges to a least possible value with small deviations. In other hand the traditional SVR with RBF kernel lost the grip on controlling the error range to a specific least possible value. This is another prominent dimension we have chosen to prove the efficiency of our proposed F_SVR model. Finally, the experimental statistics were presented in Table 1, to represent the accuracy of proposed F-SVR model with various kernel functions.

5.Conclusion

Support vector regression is a prominent supervised prediction model, which is used for test set values prediction based on training knowledge. While predicting the foreign exchange information, recent data values have the higher impact on predictions than its earlier data values. Traditional SVR cannot consider the time coefficient values impact on time series value predictions. In this paper, fuzzy based support vector regression model F-SVR is proposed to forecast data values from the linearly inseparable foreign exchange datasets. Experiments are conducted on USD-INR dataset with 3 years data (May-2017 to May-2020) which contains total 6 columns (price, open, high, low, volume and change) and hundreds of rows. In F-SVR, the fuzzy membership function assigns the time coefficient values with respective predictor variables using the fuzzy membership function to minimize the prediction errors. Experiments on USD-INR dataset using the F-SVR prototype proven that, the F-SVR with RBF kernel function recorded low predictions errors and high prediction accuracy. Prominent metrics of machine learning like MSE, RMSE, NRMSE and prediction errors are used to measure the performance of the proposed F-SVR model with various kernel functions. The experimental results shows that F-SVR with Radial Basis Function outperforms when compared to the other kernel functions with less error values on the USD-INR dataset. The F-SVR with radial basis function also outperforms the basic machine learning models such as ARIMA, Artificial Neural Networks and Support Vector Machine developed by former researchers in terms of prediction accuracy.

Conflict of Interest

Authors declared that there is no conflict of interest in publication.

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