

PREDICTION OF FOREX DATA USING NEURAL NETWORK TECHNIQUES WITH FEATURE EXTRACTION

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ABSTRACT

Prediction of Foreign exchange (Forex) rate is a major activity for financial experts. Intelligent techniques are widely used for Forex rate prediction which always performs better than statistical techniques. This paper explores two prediction models namely Recurrent Neural Network (RNN) and Support Vector Regression (SVR). Network accuracy is increasing when increases number of hidden layers in case of RNN while avoid problems arise using linear functions with multiple feature space in case of SVR. We have developed models using 5 years historical data of different exchange rates against US dollar. Feature extraction technique has applied in these data sets to extract new and hidden features to computationally improve the performance of model. To improve the capability of model, 10-fold cross validation technique is employed for dynamic partitioning of data and comparative results have presented based on certain performance measures: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE).

Keywords: Foreign Exchange (Forex) Rate, Recurrent Neural Network (RNN), Support Vector Regression (SVR).

INTRODUCTION

In Forex market, the exchange rates are rates where one currency rate is converted into other currency rate, which is based on selling and buying the currency in exchange rates like Indian Rupee to United State Dollar (INR/USD), European Dollar to United State Dollar (EUR/USD), Hong Kong Dollars to United State Dollar (HKD/USD) etc. Forecasting of Forex data (Majhi et al., 2012) is very complex task due to non-linear behaviour of data. Many traders or economists are interested to forecast Forex data (Sharma et al., 2017). This data is affected by many political or economic factors.

Intelligent techniques are widely used for forecasting the Forex data (Lisi et al., 1999) for N-days-ahead prediction due to uncertain and fluctuating behaviour of Forex data. This paper employs two intelligent techniques namely Recurrent Neural Network (RNN) and Support Vector Regression (SVR) for Forex data prediction. In this paper, three different Forex data; INR/USD, EUR/USD and HKD/USD have used for prediction. Data pre-processing has done using feature extraction technique where new features were extracted (Sharma et al., 2017) from existing one. These extracted data is then partitioned dynamically using k-fold cross validation (Hota et al., 2017), in this paper data is partitioned into 10 folds and each subset has taken part as training as well as testing data. These dynamically partitioned data have applied in RNN (Rehman et al., 2014) and SVM Techniques (Kao et al., 2013) individually in all three Forex data set. We have compared the performance of these two techniques with some error measures like Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

The rest of the study is organized as follows. Section 2 gives a brief overview of the literature. Section 3 describes dataset and process flow of work. Section 4 defines the methodology as have used RNN and SVR. Section 5 explores the experimental results. Finally, Section 6 concludes the findings of the research work.

LITERATURE REVIEW

In the last two decades lots of research work has been done in the field of financial foreign exchange rate prediction (Sharma et al., 2016) and still work is going on continuously to explore novel techniques for more accurate prediction of Forex data. Different machine learning as well as statistical techniques has been applied for FX data prediction but Machine learning techniques provide some evidence that it is performing better than statistical techniques which are depicted in Table 1.

Table 1: Summary of Literature Review		
Year	References	Journal
2017	Sharma et al	Review of Business and Technology Research
2016	Oliveira et al	Neurocomputing
2015	Jena et al	Journal of King Saud University-Computer and Information Science
2015	Handa et al	International Journal for Research in Applied Science and Engineering Technology
2015	Gleshchuk et al	Neurocomputing
2014	Rehman et al	IERI Procedia
2014	Talebi et al	Procedia Computer Science
2013	Kao et al	Neurocomputing
2007	Panda et al	Journal of Policy Modeling

FOREX DATA AND FLOW DIAGRAM OF WORK

In this paper we have used five years weekly Forex data of three different exchange rates: INR/USD, EUR/USD and HKD/USD from January 1, 2012 – September 30, 2017 as described in Table 2.

Table 2: Summary of weekly exchange rates Forex data	
Particular	Detail
Index Data	Three FX Data: INR/USD, EUR/USD and HKD/USD weekly data.
Period	01-January-2012-30-September-2017 (5 years)
Total # of Samples	300
Downloaded From	www.fx.sauder.ubc.ca
Data Partition	10 Fold cross validation
Total Observation	300 (Training-270. Testing-30)

To improve the performance of model, data normalization is done by dividing each sample with the highest value of FX rate to get smooth convergence (Kao et al., 2013) during learning in nonlinear Forex data.

The process of model development of this research work is shown in Figure 1 where feature extraction technique (Handa et al., 2015) is applied to the actual data set to generate new and hidden features from the existing one. There are 5 new features are extracted: Simple Moving Average (SMA), Exponential Moving Average (EMA), Weighted Moving Average (WMA), Variance and Standard Deviation. We have partitioned the dataset into 10-fold cross validation (Hota et al., 2017) to train and test the RNN and SVR model. Finally compared the performance of RNN and SVR in terms of Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE).

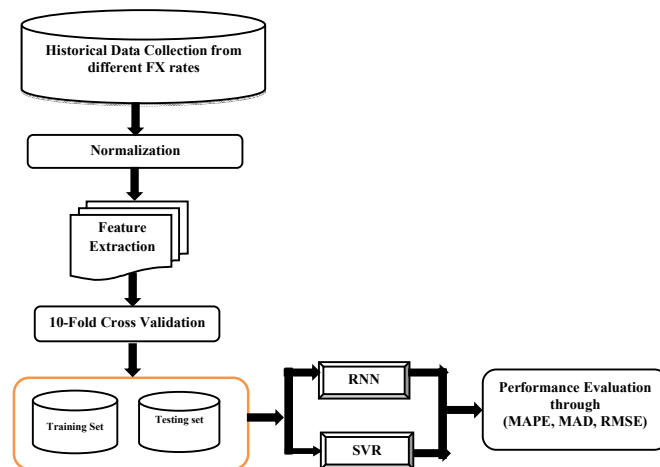


Figure 1: Process flow diagram of proposed work.

METHODOLOGY

In this research work we have used two well known and popular predictive techniques: Recurrent Neural Network (RNN) and Support Vector Regression (SVR).

➤ Recurrent Neural Network (RNN)

RNN (Rehman et al., 2014) is an ANN, where a direct cycle has been formed between different units, which show the dynamic and temporary behaviours of network. In RNN random sequence of inputs are given to network. RNN is a connection of nodes as input, hidden or output node. According to many researchers RNN is performing better than other feed forward networks. RNN has one or more recurrent layers which contains the features of input data as well as previous active input data (RNN-1), so that the proper response of RNN doesn't depends on only current working input but also influenced by previous input as shown in figure 2.

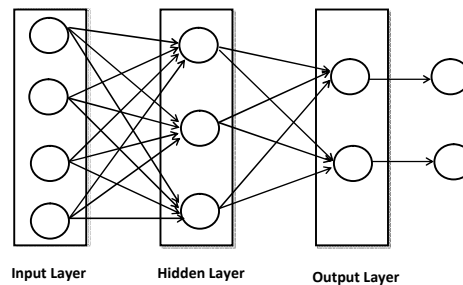


Figure2: Architecture of Recurrent Neural Network (RNN)

We can process the sequence of input vector x by applying a recurrent formula at every time step as shown in equation 1:

$$h_t = f_h(h_{t-1}, x_t) \quad (1)$$

Where f_w recurrent function with parameter is w , h_t is the new hidden state at current time stamp t and $t-1$ where $t-1$ denotes the previous time stamp, x_t is the current input vector for time stamp t as we change the w we get different value of h_t .

In RNN the same function and same set of parameters are used at every time steps through the equation 2 and 3.

$$h_t = f_h(w_{hh}h_{t-1} + w_{xh}x_t) \quad (2)$$

$$y_t = w_{hy}h_t \quad (3)$$

Where h_t is the activation function, w_{hh} is weight of old state, w_{xh} is weight of current state, w_{hy} is weight of new state and y_t is output of new state.

➤ Support Vector Regression (SVR)

SVR method is proposed by (Vapnik and Chervonenkis, 1971) and it is based on the principal of Structure Risk Minimization (SRM), where data generalization has been done (Kao et al., 2013) from large data set to balance the complexity of model. SVR model is represented by equation 4.

$$f(x) = w \cdot \phi(x) + b \quad (4)$$

Where x is input to the model, w is weight vector, b is bias and ϕ is a mapping function. Weight vector is estimated by regularized risk function as shown in equation 5.

$$\frac{1}{2} \|w\|^2 + c \sum_{i=1}^l L(y_i, f(x_i)) \quad (5)$$

SVR uses a loss function called ϵ -insensitive loss function shown in equation 6.

$$L(y, f(x)) = \begin{cases} 0 & |f(x) - y| < \epsilon \\ |f(x) - y| - \epsilon & \text{Otherwise} \end{cases} \quad (6)$$

With ϵ -insensitive function SVR is formulated as equation 7 and 8.

$$\text{Minimize } \frac{1}{2} \|w\|^2 + c \sum_{i=1}^l (\xi_i - \xi_i^*) \tag{7}$$

$$\text{Subject to } \begin{cases} q_i - (v \cdot \phi(x_i)) - b \leq \epsilon - \xi_i \\ (v \cdot \phi(x_i + b - q_i) \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, \text{ for } i = 1 \dots n \end{cases} \tag{8}$$

Where ξ and ξ^* are slack variables that re use for error measurements came from the values outside boundaries.

This problem can be solved by Lagrangian theory, now the SVR function can be expressed as equation 9.

$$f(x, y) = f(x, \alpha, \alpha^*) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) k(x, x_i) + b \tag{9}$$

Where α and α^* are Lagrangian multipliers and $k(x, x_i)$ is a kernel function, where $k(x, x_i) = \exp ((-\|x_i - x_j\|^2)/2\sigma^2)$, where σ is a parameter of Gaussian kernel.

RESULT AND ANALYSIS

Evaluation of model has been done for analysing its performance based on 5 years weekly historical Forex data with 3 different exchange rates INR/USD, EUR/USD and HKD/USD. We have used self-written MATLAB code for building model and measure the performance of models in terms of various error measures. In this paper two models namely RNN and SVR are used for prediction (Huang et al., 2008). In RNN six features are given to model including target values as input, then 10 hidden layers are used for accurate learning of model and sigmoid function is used as an activation function. In SVR six inputs are given to model as five independent variables and one dependent variable which is also called target value, the model is then produces one output and compare with the target value for performance evaluation of model. Feature extraction technique is used to generate new features and form a new data sets , then after these extracted data are partitioned into training and testing data set dynamically by using 10-fold cross validation. These data sets have applied to RNN and SVR for 5-week ahead prediction where window size is 5 as shown in Table3.

Table 3: Comparative MAPE on testing samples for INR/USD, EUR/USD and HKD/USD exchange rates for 5-weeks ahead prediction using RNN and SVR.

Exchange rate	RNN			SVR		
	MAPE	MAD	RMSE	MAPE	MAD	RMSE
INR/USD	0.8066	0.0072	0.0115	0.6358	0.0057	0.0076
EUR/USD	0.0629	6.26E-04	8.45E-04	0.0576	5.73E-04	7.89E-04
HNGKNG/USD	1.7461	0.0152	0.0193	0.8988	0.0079	0.0098

In the above table the performance of model is measured by error measurement MAPE, MAD and RMSE formula as shown in equation 10, 11 and 12.

$$\text{MAPE} = \frac{\sum_{i=0}^n |Y_{a,i} - Y_{p,i}|}{n} \tag{10}$$

$$\text{MAD} = \frac{\sum_{i=0}^n |Y_{a,i} - Y_{p,i}|}{n} \tag{11}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=0}^n (Y_{a,i} - Y_{p,i})^2} \tag{12}$$

Where Y_a =Actual observation, Y_p = Predicted observation and n =Total number of observations.

The simulated result shown in Table 3, While analyzing the table, MAPE is being decreased using SVR technique rather than RNN, at window size 5, say for example MAPE=0.6358 for exchange rate INR/USD, MAPE=0.0576 for exchange rate EUR/USD and MAPE=0.8988 for exchange rate HKD/USD in SVR. The value of MAD and RMSE is also decreased while input is supplied to SVR model.

Comparative graph of RNN and SVR is shown in figure 11 which proves the prediction trends in all three exchange rates. The visualization of comparison between actual and predicted values of INR/USD, EUR/USD and HKD/USD during testing by calculating MAPE using RNN and SVR is depicted in figure 3, 4, 5, 6, 7 and 8 respectively.

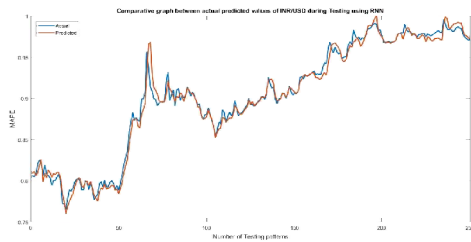


Figure 3: Comparative graph of actual and predicted values of INR/USD during testing using RNN.

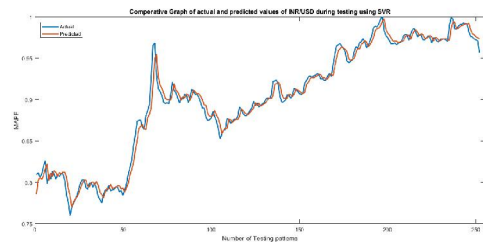


Figure 6: Comparative graph of actual and predicted values of INR/USD during testing using SVR.

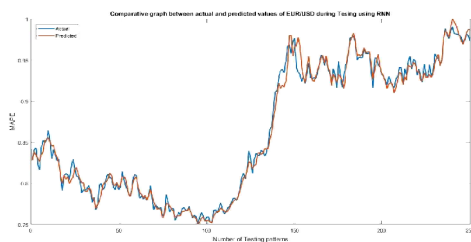


Figure 4: Comparative graph of actual and predicted values of EUR/USD during testing using RNN.

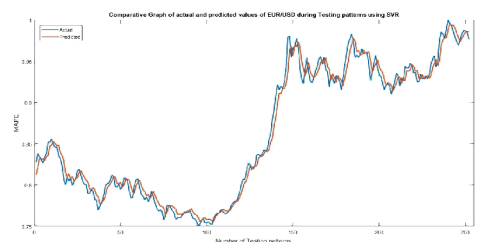


Figure 7: Comparative graph of actual and predicted values of EUR/USD during testing using SVR.

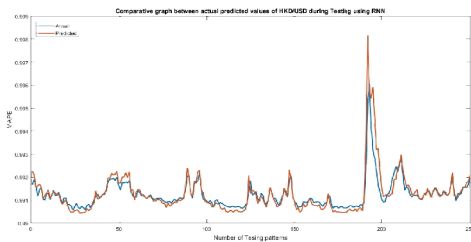


Figure 5: Comparative graph of actual and predicted values of HKD/USD during testing using RNN.

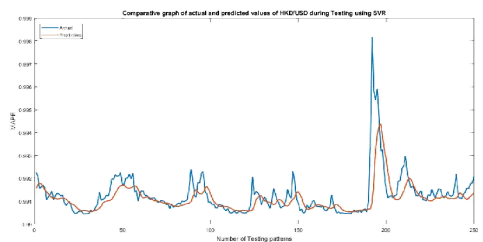


Figure 8: Comparative graph of actual and predicted values of HKD/USD during testing using SVR.

CONCLUSION

Forex prediction is very tedious and challenging task for non linear data set. Two ANN techniques RNN and SVR are considered in this research work for development of efficient predictive model, with respect to three Forex data INR/USD, EUR/USD and HKD/USD. The model is performing better while extracting five new features from original data set suggested by many researchers and accuracy of model is increased while using dynamic partitioning of data using K-fold cross validation. Empirical research shows that SVR is performing better than RNN model for N-days ahead prediction using different error measurement techniques like MAPE, MAD and RMSE.

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