SVM Based Analysis of Indian Rupee Strength

Prof. (Mrs) Chetashri Bhadane, Neel Shah, Pinank Shah, Rushabh Vakharia

***Abstract* - Financial forecasting in general, and exchange rate prediction in particular, is an issue of much interest to both academic and economic communities. The basic aim of this project is to provide a machine-learning model to explain the strength of the Indian Rupee. Support vector machine (SVM) is a promising method for the analysis of financial time series that we employ. Macroeconomic factors such as BSE index, oil prices, gold prices and commodities are selected as features of the model. These factors are gathered from databases available from the Reserve Bank of India (RBI) website. This research will examine the features of both fundamental analysis and technical analysis. The performance of Indian Rupee will also be studied against a basket of other currencies like USD, GBP, JPY and EUR [1].**

***Index Terms* - Financial Forecasting, SVM, Macroeconomic factors**

I. INTRODUCTION

Foreign exchange markets are highly fluctuating and generally tough to predict. History has shown that the market does not follow a certain pattern based on a particular function , hence future values cannot be predicted just on the basis of looking at the past values of the exchange rate. But the exchange rate of Indian rupee is based on a lot of macroeconomic factors that determine its movement like the BSE index, oil prices, gold prices and commodities. So to sufficiently analyze the foreign exchange rate we have to consider all these factors. One of the major obstacles to the prediction is the number of factors that actually affect the exchange rate. Of the many factors that affect we have selected the four most important factors namely BSE index, oil prices, gold prices and commodities. We have used the Support Vector Machine (SVM) algorithm to achieve our goal and compared different kernels like Polynomial, RBF and Linear. We have also used the Holt-Winters algorithm to predict the volatility of the foreign exchange market and compared it to other methods like Moving Average (EM) and Exponential Moving Average (EMA).

Most of the available models are used to predict the stock market, very few models are available to help predict the exchange rate of INR with respect to other currencies. In out model, the currencies we are using include the USD, GBP, YEN and EURO[1]. The models used for stock market prediction cannot be extrapolated for foreign exchange because the factors that affect stocks and currencies are very different. Many attempts have been made to predict using historical data of exchange rate. This approach is flawed. Historical data can only be used to predict the future when the trend follows a particular function and does not depend on any other external factor. Hence, we have considered 4 different factors that in our opinion affect the FOREX market namely Gold, BSE, Oil and Commodities. In our approach, we first predict the currency that is expected to undergo maximum volatility in the coming week. More volatility means more chance of profit. After this in the second part we predict whether that currency will move upwards or downwards i.e. whether its price with respect to INR will rise or fall.

Prof. Chetashri Bhadane, Computer Science, D.J.Sanghvi College of Engineering, Mumbai, India, +918097767776.

Rushabh Vakharia, Computer Science, D.J.Sanghvi College of Engineering, Mumbai, India, +918097902650.

Pinank Shah, Computer Science, D.J.Sanghvi College of Engineering, Mumbai, India,+19293738675.

Neel Shah, Computer Science, D.J.Sanghvi College of Engineering, Mumbai, India, +12138222383.

SVM

A support vector machine (SVM), a novel neural network algorithm, was developed by Vapnik and his colleagues. SVM uses linear model to implement nonlinear class boundaries through some non-linear mapping the input vectors into high-dimensional feature space. Therefore, SVM is known as the algorithm that finds a special kind of linear model, the maximum margin hyper plane, which gives the maximum separation between the decision classes.

For a linearly separable set of 2D-points which belong to one of two classes, find a separating line.

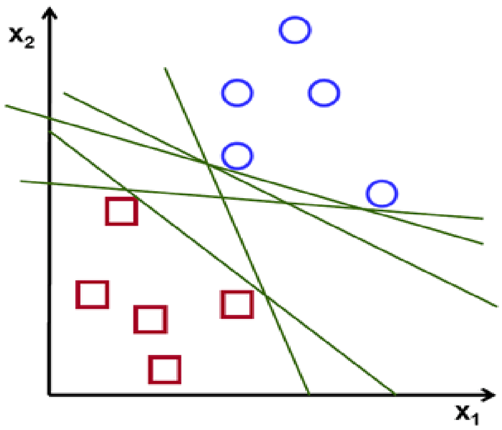

Fig 1. Linearly separable dataset

In the above picture there exist multiple lines that offer a solution to the problem. A line is bad if it passes too close to the points because it will be noise sensitive and it will not generalize correctly. Therefore, our goal should be to find the line passing as far as possible from all points. Then, the operation of the SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples. Twice this distance receives the name of margin within SVM's theory. Therefore, the optimal separating hyper plane maximizes the margin of the training data.

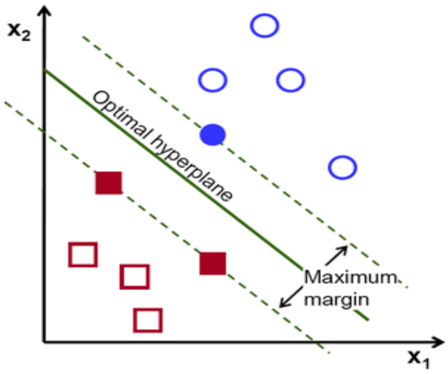

Fig 2. SVM Classification (Margin)

If the transformation is nonlinear and the dimensionality of the feature space is high enough, then input space may be transformed into a new feature space where the patterns are linearly separable with high probability. This nonlinear transformation is performed in implicit way through so-called kernel functions.

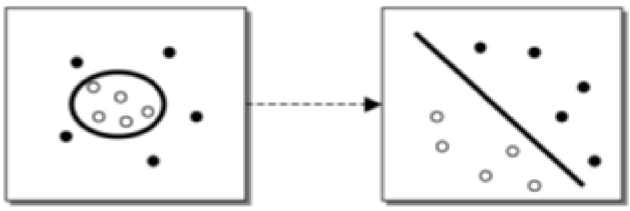

Fig 3.Kernel Function

II. PROPOSED SOLUTION

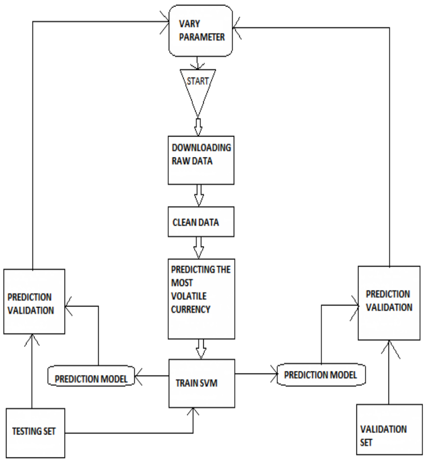

Fig 4.

PART I :

- Download exchange rate data from RBI website
- Normalize the data
- Apply Holt Winter's Algorithm and predict next week's volatility.
- Repeat steps 1-4 for the four types of currencies viz, USD, JPY, EUR and GBP.
- The currency with highest volatility is displayed.

PART II :

- Select currency and window
- Download the macro-economic features for training SVM
- Normalize features
- Compare the past exchange rates with the previous day and assign binary 0 or 1 accordingly.
- Train different SVM kernels and predict whether the currency will strengthen or weaken in the coming week.
- Plot different SVM kernels.

III. LITERATURE REVIEW

Exchange rate predictions is one of the challenging applications of modern time series forecasting and very important for the success of many businesses and financial institutions. The rates are inherently noisy, non-stationary and deterministically chaotic. There are several forecasting techniques available; those are developed mainly based on different assumptions, mathematical foundations and specific model parameters. However, for better result, it is important to find the appropriate technique for a given forecasting task. Recent research has been directed to Support Vector Machine (SVM) which has emerged as a new and powerful technique for learning from data and in particular for solving classification and regression problems with better performance. SVM uses linear model to implement nonlinear class boundaries through some non- linear mapping the input vectors into the high-dimensional feature space. Technical and fundamental analyses are the two major financial forecasting methodologies. In recent times, technical analysis has drawn particular academic interest due to the increasing evidence that markets are less efficient than was originally thought[3].

IV. EXPERIMENT

A. Selection of Data

We have considered daily data from 1st January 2000 to 11th March 2015. In all there are around 29000 values we are working with. The exchange rate data was obtained from the Reserve bank of India (RBI) website archives and the database of the features was obtained from the Bombay Stock Exchange (BSE) website archives. This data was saved in Excel files.

B. Cleaning of Data

The database we received was in a raw form. We had to write cleaning programs for all the databases, wherein first we changed the data type of the values to "number" from "string" which makes it easier to work with. Further there were a lot of discrepancies in different database and for the project to work we had to have all databases in the same format and also the number and sequence of values must match. To achieve this we wrote a python program and got rid of all the redundancies.

The amount of profit is directly proportional to the volatility of a particular currency. If the volatility is high, the amount of profit that can be made is also high. That is why there are two parts of our project.

C. Volatility Prediction

In the first part, on entering the date for which the prediction is to be made, firstly the currency that is expected to have maximum volatility is calculated. This is achieved by using three methods namely- Moving average (MA), Exponential Moving Average (EMA) and Holt-Winters algorithm and we have compared the efficiency of the three.

a) Moving Average

In financial applications, simple moving average is the unweighted average of the past n data. This ensures that the variation in mean are aligned with the variation in data rather than being shifted with time. An example for a simple equally weighted running mean for a 'n' day sample of closing price is the mean of the previous 'n' day closing price if those prices are Pm, Pm-1 ……..Pm-(n-1) then formula is :

SMA= $p_m + p_{m-1} + \ldots + p_{m-(n-1)} /n$

b) EXPONENTIAL MOVING AVERAGE

The "Exponential Moving Average", or "EMA", indicator was developed to counter the lagging weakness of the SMA indicator by weighting more recent prices more heavily. Its origins are unknown, but its use was designed to smooth out the effects of price volatility and create a clearer picture of changing price trends. Traders use an EMA, sometimes in concert with another EMA for a different period, to signal confirmation of a change in price behavior.

The EMA indicator uses "period" and "price", as does the SMA, but fresher prices are given more weight to make the indicator respond more quickly to market changes. Since it reacts more quickly, it is prone to generate more false signals. The EMA works well in tandem with another EMA in strong trending markets, but the use of an EMA in a sideways market is not recommended. Since the EMA is so popular, it can often form a support or resistance line, depending on the type of trend that traders respect in their decision-making process.

EMA Formula:

The calculation formula is more complex then that for an SMA:

1. Choose a "price" setting – assume "closing price";
2. Choose a "period" setting – assume "10" for example;
3. Calculate the "Smoothing Factor" = "SF" = 2/(1 + "10");
4. New EMA value = SF X New Price + (1- SF) X Previous EMA value.

c) HOLT WINTER'S ALGORITHM

Often, time series data display behavior that is seasonal. Seasonality is defined to be the tendency of time-series data to exhibit behavior that repeats itself every L periods. The term season is used to represent the period of time before behavior begins to repeat itself. L is therefore the season length in periods. For example, annual sales of toys will probably peak in the months of November and December, and perhaps during the summer (with a much smaller peak). This pattern is likely to repeat every year, however, the relative amount of increase in sales during December may slowly change from year to year.

For example, during the month of December the sales for a particular toy may increase by 1 million dollars every year. Thus, we could add to our forecasts for every December the amount of 1 million dollars (over the respective annual average) to account for this seasonal fluctuation. In this case, the seasonality is additive. Alternatively, during the month of December the sales for a particular toy may increase by 40%, that is, increase by a factor of 1.4. Thus, when the sales for the toy are generally weak, then the absolute (dollar) increase in sales during December will be relatively weak (but the percentage will be constant); if the sales of the toy are strong, then the absolute (dollar) increase in sales will be proportionately greater. Again, in this case the sales increase by a certain factor, and the seasonal component is thus multiplicative in nature (i.e., the multiplicative seasonal component in this case would be 1.4).

In plots of the series, the distinguishing characteristic between these two types of seasonal components is that in the additive case, the series shows steady seasonal fluctuations, regardless of the overall level of the series; in the multiplicative case, the size of the seasonal fluctuations vary, depending on the overall level of the series.

This Holt-Winters method is used when the data shows trend and seasonality. The exponential smoothing formulae applied to a series with a trend and constant seasonal component using the Holt-Winters additive technique are:

$$a_t = \alpha(Y_t - s_{t-p}) + (1-\alpha)(a_{t-1} + b_{t-1})$$
$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1}$$
$$s_t = \gamma(Y_t - a_t) + (1-\gamma)s_{t-p}$$

Where :

α, β and γ are the smoothing parameters

a_t is the smoothed level at time *t*

b_t is the change in the trend at time *t*

s_t is the seasonal smooth at time *t*

p is the number of seasons per year

The Holt-Winters algorithm requires starting (or initializing) values. Most commonly:

$$a_p = \frac{1}{p}(Y_1 + Y_2 + \ldots + Y_p)$$

$$b_p = \frac{1}{p}\left[\frac{Y_{p+1} - Y_1}{p} + \frac{Y_{p+2} - Y_2}{p} + \ldots + \frac{Y_{p+p} - Y_p}{p}\right]$$

$$s_1 = Y_1 - a_p, \quad s_2 = Y_2 - a_p, \quad \ldots, \quad s_p = Y_p - a_p$$

The Holt-Winters forecasts are then calculated using the latest estimates from the appropriate exponential smooth that have been applied to the series [2]

D. Currency Value Fluctuation Evaluation

In the second part of our project, once we have predicted which currency is going to have maximum volatility, it is important to know what direction the price is going to move in. it means that the user needs to know whether the value of the currency compared to INR is going to go up or down. This is done using Support Vector Machine Algorithm (SVM). Here we consider different macroeconomic factors like- BSE Index, Oil Prices, Gold, and Commodities. We believe that these factors affect the exchange rate of INR the most. In typical setting of Classification problem, we'd be given some red dots and some blue dots in some space and we'd be required to find out a curve (called separating boundary) that can separate all blue dots from all red dots.

As it turns out, it is much easier and efficient to find out boundaries which are in the form of a straight line (or an analogous construct in higher dimensions called hyper plane) compared to curvy boundaries. Hyper-plane is just a generalization of a line in 2D and plane in 3D. SVMs help us to find a hyper plane that can separate red and blue dots.

The SVM kernels can roughly be divided into linear kernels and non linear kernels.

The most commonly used kernels for the SVM are the d-degree polynomial kernel with the linear kernel for d=1, the radial basis function (RBF) kernel, also known as the Gaussian kernel, and the sigmoid kernel. These kernels have been shown before, and are again listed below. The first kernel is a linear kernel, while the other three kernels are nonlinear.

V. RESULTS

As we have seen, SVM is a classification algorithm that can be applied to the problem at hand as it can classify non-linearly also. The negative aspect is the time complexity specially when we consider the last 100 days. The RBF kernel is observed to have the maximum accuracy compared to Linear and Polynomial. As far as prediction for volatility is concerned. Holt Winter's is the most accurate method. Though a lot remains to be done in terms of selection of parameters.

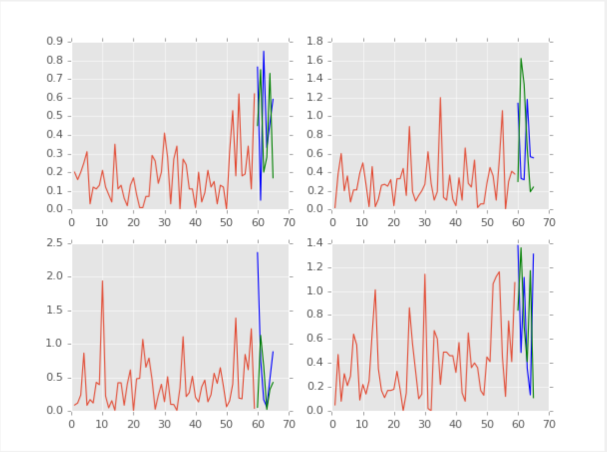

Fig 5 : Volatility of the 4 currencies (In clockwise direction from top left : USD, EURO,YEN and GBP with YEN showing the maximum volatility)

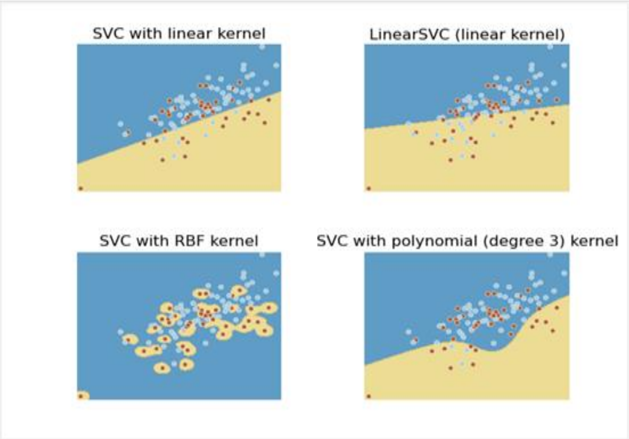

Fig 6 : Accuracy of the 4 kernels in prediction

VI. CONCLUSION

This research has shown that SVMs offer some advantages in comparison to predicting it just by pattern finding from historical data in financial forecasting. Future research may explore the possibility of refining the SVM in order to achieve a higher generalization performance. Refining the SVM may lie in finding a better structure in terms of the kernel function, which might be a combination of various kernels. It might also lie in how the free parameters for the SVM are selected, perhaps by an alternative computational intelligence method. This would require further research on the topic that points to the direction of genetic algorithms in combination with SVMs.

ACKNOWLEDGMENT

We, hereby take this opportunity to thank all those who have helped us in making this paper a success. We would also like to thank Dr. Narendra Shekokar, HOD, Computer Science Department, D.J.Sanghvi College of Engineering and Dr. Hari Vasudevan, Principal, D.J.Sanghvi College of Engineering for giving us the necessary facilities in the college without which this would not have been possible.

REFERENCES

[1] Kamruzzaman, J, Sarker R.A, Ahmad I. "SVM based models for predicting foreign currency exchange rates", Data Mining, 2003. ICDM 2003. Third IEEE International Conference, Nov 2003.

[2] Prajakta S. Kalekar, "Time series forecasting using Holt-Winters Exponential Smoothing", Dec 2004,

[3] Piyush Dharnidharka. "Forecasting Foreign Currency Exchange Data using SVM Based Models", Academia.edu, 2012.

Prof Chetashri Bhadane – Assistant Professor at D.J.Sanghvi College of Engineering. Prof Bhadane has pursued her BE from North Maharashtra University, Jalgaon and M.Tech from NMIMS, Mumbai. She has a teaching experience of 9 years. Prof Bhadane has authored 3 international papers.

Rushabh Vakharia pursued BE in Computer Engineering from DJ Sanghvi College of Engineering. He is currently working as a Junior Software Developer in BNP Paribas India Solutions Pvt. Ltd.

Pinank Shah pursued BE in Computer Engineering from DJ Sanghvi College of Engineering. He is currently pursuing MS in Operations Research from the Columbia University in the City of New York.

Neel Shah pursued BE in Computer Engineering from DJ Sanghvi College of Engineering. He is currently pursuing MS in Data Analytics from the University of Southern California, Los Angeles.