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# Ensemble Method for Forex Rate Prediction using OHLC Data

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***Abstract: Forex rate is a crucial indicator of the economic health of the country. Accurate prediction of forex rates thus becomes essential to take necessary steps to ensure the sound economic health of its citizens. Due to the chaotic and nonsta-tionary nature of the data, its prediction becomes a complicated task. Through the results obtained from various researches, it becomes evident that hybrid models have outperformed individual base learners in resembling the actual data generation process and forecasting future data. In this paper,an ensemble-based approach is adopted to enhance forecasting accuracy. The model is trained on the OHLC data (high, low, open, and close) of the previous day for enhanced exchange rate prediction of USD compared to different currencies. This paper applies a hybrid model of Convolution Neural Network ,Long Short Term Network and Support Vector Regression trained on the previous peak data. Results obtained after experiments indicate that a hybrid model improved the prediction accuracy when compared to individual models.***
***Keywords: Long Short Term Memory, Support Vector Regression, Convolution Neural Network, Ensemble model, OHLC***

## I. INTRODUCTION

Exchange rates determine how much one currency is paid in terms of another. They are the crucial indicators of a country's economic health, which in turn affect the well being of its citizens. Forex rates are affected by several macroeconomic factors and, based on their value, can affect a specific section of people. High exchange rates are beneficial for exporters; on the other hand, it hurts the interests of the importers. Hence accurately predicting forex rates is of utmost importance. Based on the outcomes, economic policies can be altered suitably by the government to benefit its citizens economically.

Time series analysis is generally employed for the task of forex rate prediction. A time series, by definition, is a collection of sequentially observed data over a period of time. Financial time series data is chaotic and non-stationary in nature [1]. The non-stationarity of data conveys that its properties are varying with respect to time, which is the main reason why the AR model does not fare well in the task of prediction as the preliminary assumption of the AR model is stationarity. Chaotic time series implies the data is nonlinear, deterministic, and sensitive to the initial condition [2]. It is the chaotic nature of the data, which makes the task of prediction reasonably complicated. It requires an accurate analysis of both the current and past data trends to make a future prediction.

The use of CNN for sequential data is relatively new with Abdel et al [3] employed limited weight sharing for the task of speech recognition in which speech signals are used as input data. In 2016 Cui et al [4] employed a multi-scale convolution neural network for the task of enhanced time series prediction. In the same year, Wang et al [5] proposed Earliness-Aware Deep Convolutional Networks (EA-ConvNets), an end-to-end deep learning framework to improve the quality of time series classification.

Ding-Zhou Cao et al. used support vector regression to forecast USD/GBP exchange rates. The model mentioned in the paper is trained on daily exchange rates. The result obtained, established the fact that support vector regression can be used for forecasting financial time series [6]. Another work by Kaijian He et al. proposed a novel wavelet denoising support vector regression (SVR) ensemble forecasting model for the task of forex rate prediction [7]. Recent work by Georgios sempinis introduces a hybrid Rolling Genetic Algorithm-Support Vector Regression (RG-SVR) model for optimal parameter selection and feature subset combination. The algorithm proposed is used for the prediction of EUR/USD, EUR/JPY, and EUR/GBP exchange rates [8].

The hybrid model combines multiple models to accomplish the task of future time-series predictions. It is trained on the past and current data to simulate the data generation process. With each component method of the model capturing different aspects of the data generation process, combining these models give outputs which are more close to actual values [9]. Thus, hybrid models most closely resemble the actual data generation process. The various advantages that hybrid models offer are they overcome deficiencies of the individual models, reduction of uncertainty of predictions, and thus improve the forecasting performance [10].

The hybrid models have been depicted in several earlier pieces of research. The first of the models being depicted in the 1970s by Reid [11] and also by Bates and Granger [12]. The results shown in the latter model showed that the hybrid model outperforms the individual models. Later works followed also support the outcomes of the previous ones. With the use of neural networks for the prediction tasks, it becomes one ofthe essential components of hybrid models. In 1992 Pelikan and De Groot [13] and in 1993 Ginzburg and Horn [14] combined different neural networks to improve the accuracy of the predictions.
In this paper we have employed ensemble model for forex rate predictions. Recent work in this domain is by D Pradeepkumar et al [15]. The paper discusses a combination of prediction models such as chaos, Neural Network (NN), and PSO for predicting future forex rates. Another work by Mehta et al [16] also discusses the hybrid model but is employed for the task of stock price prediction.

## II. ENSEMBLE MODEL FOR FOREX RATE PREDICTION

Machine learning algorithms use statistics to find out patterns in a vast amount of data. They are classified as supervised and unsupervised learning algorithms. In the unsupervised model, the unlabelled dataset is used, and the model finds the pattern in a given class. In the supervised model, the labeled dataset is used, and the trained model is used to predict a new instance. According to Vijay Kotu [17], Ensemble modeling is a process where multiple diverse models are created to predict an outcome, either by using many different modeling algorithms or using different training data sets. The main objective of combining independent and diverse models to create a single model is to reduce the generalization error and to improve the quality of predictions. The various ways of combining the models for continuous predictions are average, weighted average, and maximum, minimum or median rule. In the average method, the outputs of different models are given equal weight. However, in the weighted average model, the outputs are assigned weights, depending upon the importance of respective models in making the final predictions. The final output of such a model is the weighted sum of outputs from different models. Similar work for stock market prediction is depicted by S Mehta et al [16]. An Ensemble is a supervised learning algorithm. It combines multiple models called base learners. Each of these base learners captures a different perspective of the data. Thus, the resulting model combining these models performs better than the component models. With the combination of diverse and accurate base learners, a robust ensemble model can be created, which has more accuracy and each of its components. Bias variance dilemma provides mathematical support to the property mentioned above [18].
There are several ways to generate diverse predictors, some of them are: Learning from different subsets of data, changing the internal structure of the algorithm and combining them together or using different algorithms to model the data.
In this paper, we have utilized the third way of ensembling for the task of foreign exchange rate prediction.
Forex rate prediction is a supervised learning problem where future forex rates are predicted. In this paper ensemble learning model combines the decision of three base learners Convolution Neural network(CNN), Long Short Term Memory(LSTM) and Support Vector Regression(SVR) for future forex rate prediction through the weighted averaging method. The next subsection discusses the algorithms of the base learners and method for constructing ensemble learning.

## III.PROPOSED MODEL

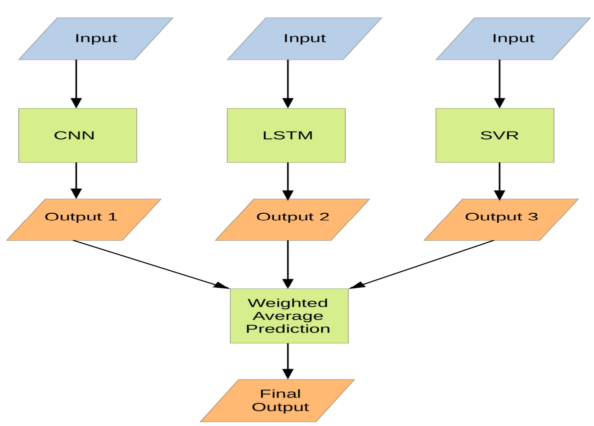


Fig 1. Proposed Model Architecture

Figure 1 shows the architecture of the proposed ensemble model. Input is the OHLC data provided to each model. Output 1 depicts the output predicted by the CNN Model, Output 2 depicts the output predicted by the LSTM Model and Output 3 depicts the output predicted by the SVR model. Final Output is the prediction made by the proposed model.

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Three different models SVR, LSTM, and CNN, are the base learners for the proposed ensemble model. Each of the models is trained on the EUR/USD forex dataset. The trained models are then combined using a weighted average model to make final predictions. The weights are necessarily coefficients of the linear model, which are assigned based on the accuracy of the individual models. The various components of the model used are explained below.

*A. Convolution Neural Network*

Since the financial time series data is highly nonlinear, a large number of nonlinear structures can be used to approximate the data generation process and forecast future values. CNN can be used for processing the data that has grid like topology. Time series data can be assumed as one dimensional data and CNN can be employed for processing it.

The architecture of a convolution neural network has been shown in Figure 2:

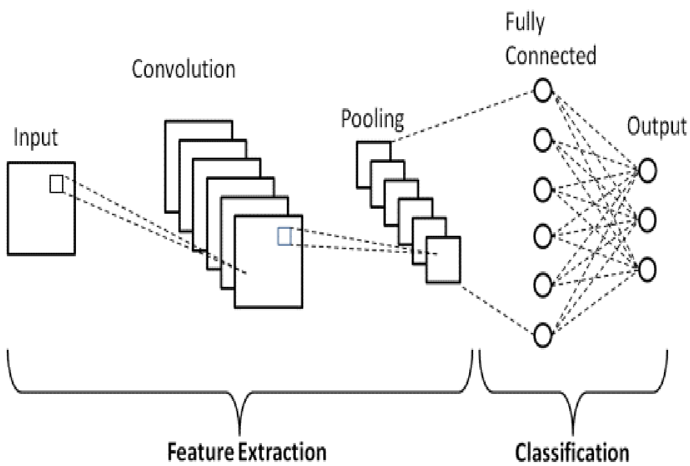


Fig. 2 Convolution Neural Network Architecture.

CNN is composed of alternating pooling and convoluting layers. These layers are used to create features out of the dimensional data. The obtained features then pass through the dense layer to produce the final output [19].

1) *Convolution:* In this process, two functions are combined mathematically to produce a third function. In the case of CNN's, this process is undertaken using filters. These filters are slid over the input data. At each location, an addition is followed by matrix multiplication, the sum values thus obtained are stored in the feature map. Generally, an activation function is also used to make the output nonlinear.
2) *Pooling:* This layer functions to reduce the dimensionality of the data. Common examples of pooling are max pooling, which takes the maximum value of a window, min pooling, which extracts the minimum and average pooling.

In this prediction problem, the input vector comprises the previous value vector with its elements as open, close, high, and low values of the previous day, and output is thefuture close value of the exchange rate. A CNN performs the following mapping from the inputs to the output:

$$y_t = f(\text{close}(y_t - 1), \text{open}(y_t - 1), \text{high}(y_t - 1), \text{low}(y_t - 1))$$

where close($y_t$-1), open($y_t$-1), high($y_t$-1) and low($y_t$-1)is close, open, high and low price of the previous day.

*B. Long Short Term Memory*

It is a select type of Recurrent Neural Network(RNN) that are used for predicting sequential data given by Hochreiter and Schmidhuber [20]. One significant limitation of RNN is to capture long term dependencies of data caused due to vanishing gradients. LSTMs with the use of a memory line can solve the problem mentioned above [21].

LSTM structure: The core structure of LSTM is composed of cells that function to capture the past data and gather them for the present one. Each cell consists of gates that perform the function of producing the output for the next cell, disposing of the data, or filtering the new data. The gates involve pointwise multiplication with a sigmoidal neural network with the output of the network ranging from 0 to 1. Zero means information is not allowed to pass, whereas one implies all the information is allowed.

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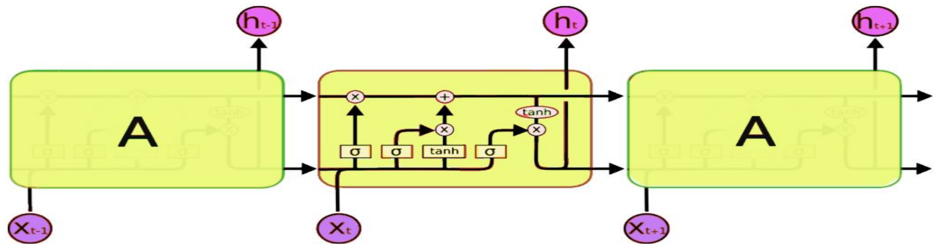


Fig. 3 LSTM Architecture

Figure 3 shows the architecture of Long Short Term Memory

*C. Support Vector Regression*

Support vector regression is an extension of the support vector machine, a classification algorithm. It is developed to model the nonlinear regression problem. To solve a nonlinear regression problem in SVR the inputs are first nonlinearly mapped into a high dimensional feature space(F) wherein they are correlated linearly with the outputs. In SVR, the problem of nonlinear regression in the lower dimension input space(x) is transformed into a linear regression problem in high di- mensional feature space(F). That is, the original optimization problem involving a nonlinear regression is recast as searching the flattest function in the feature space, and not in the input space [22].

## IV. EXPERIMENTAL RESULTS AND ANALYSIS

*A. $R^2$ as a Measure of Fit*

It explains the proportion of variation in the output variable, which can be explained by dependent variables. The closer the predicted values are to the actual values, the more is the $R^2$ value. $R^2$ score of 1 suggests that the predicted and actual data are the same. The $R^2$ values are multiplied by 100 to express them in terms of percentage.

Bloomberg Data on EUR/USD, exchange rates (1999-2019) has been used for training base learners, and the hybrid model. The model results are tested on EUR/USD, GBP/USD, and USD/CHF exchange rates of 1 year. Dataset comprises of a total of 5215 values and five features. The list of the features is mentioned below:

*1)* Date
*2)* Open Price
*3)* Close Price
*4)* High Price
*5)* Low Price

Table I enlists the different parameters and their corresponding values for each base learner in the proposed model.:

Table I. Parameter of Models

| Algorithm | Parameters | Values |
|---|---|---|
| Long Short Term Memory | Activation Loss Optimizer<br>Epochs<br>Batch Size<br>Verbose | Linear MSE<br>adagrad<br>20<br>1<br>2 |
| Support Vector Regression | C<br>Intercept Scaling<br>max iter<br>tolerance | 0.1<br>1<br>1500<br>0.1 |
| Convolution Neural Network | Filters kernel size<br>Activation (Layer 1)<br>pool size<br>epochs | 1<br>1<br>RelU<br>1<br>20 |

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## V. PLOTS AND RESULTS

Figure 4, Figure 5, and Figure 6 graphs the output of different base learners, namely convolution neural network, long-short memory networks, and support vector regression respectively. The graph of the combined model is represented in Figure 7.For these plots the Y-axis represents EUR/USD rate in rupees and the X-axis denotes the number of days.For the figures Figure 8, Figure 9,Figure 10 and Figure 11,the Y-axis represents GBP/USD rate in rupees and the X-axis denotes the number of days.For the figures, Figure 12, Figure 13,Figure 14 and Figure 15,the Y-axis represents USD/CHF rate in rupees and the X-axis denotes the number of days. These are the top three traded currencies traded by volume. In each graph, the blue line represents actual output, whereas the red line represents predicted output.

The linear regression model assigns weights to the outputs of different base earners depending upon their accuracy score, which here is the 100×$R^2$ score.

TABLE II

$R^2$ Value of the Base and Ensemble Learner

| Currency | Algorithm | Values |
|---|---|---|
| EUR/USD | Support Vector Regression<br>Long Short Term Memory<br>Convolution Neural Network<br>Ensemble Model | 95.297756837118158<br>94.188565359479085<br>93.354222036809404<br>95.722829319770597 |
| GBP/USD | Support Vector Regression<br>Long Short Term Memory<br>Convolution Neural Network<br>Ensemble Model | 94.224829319084790<br>93.913209081445913<br>91.282816045727472<br>94.986163019367424 |
| USD/CHF | Support Vector Regression<br>Long Short Term Memory<br>Convolution Neural Network<br>Ensemble Model | 88.504067806128518<br>84.871356055559176<br>88.884415610058966<br>90.561422570409249 |

Table II conveys the performance of different models measured in terms of the metric 100×$R^2$

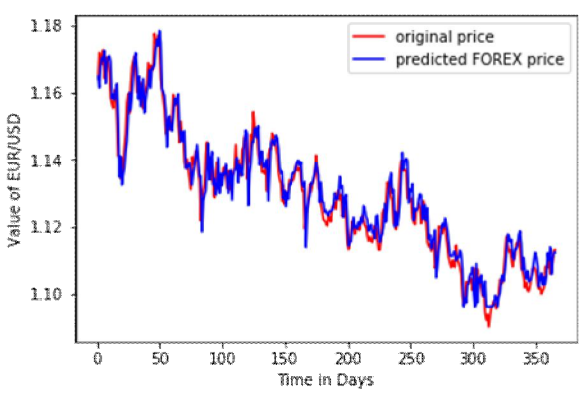


Fig. 4. EUR/USD price prediction by CNN.

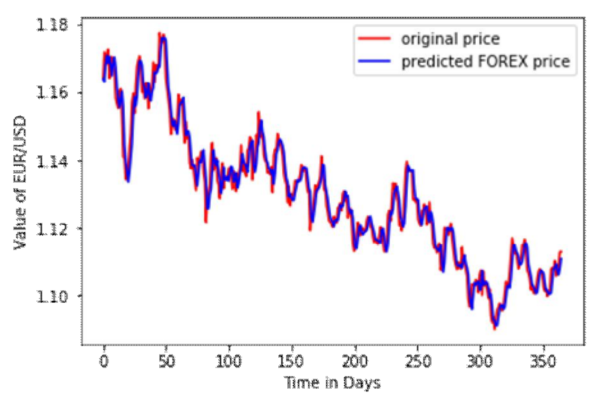


Fig. 5. EUR/USD price prediction by LSTM.

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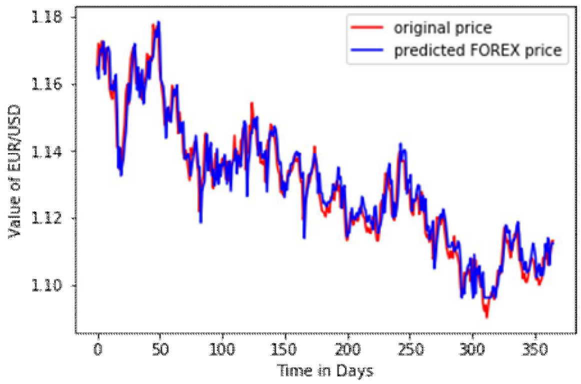


Fig. 6. EUR/USD price prediction by SVR.

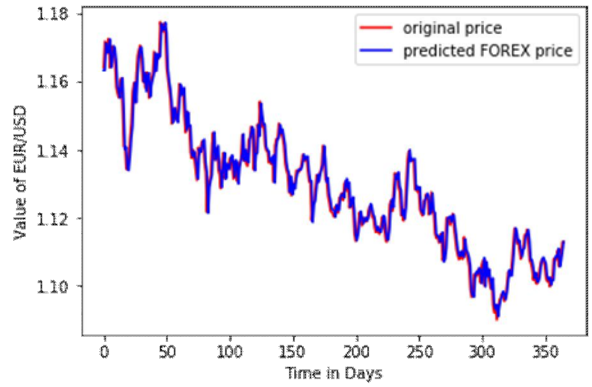


Fig. 7. EUR/USD price prediction by ENSEMBLE METHOD.

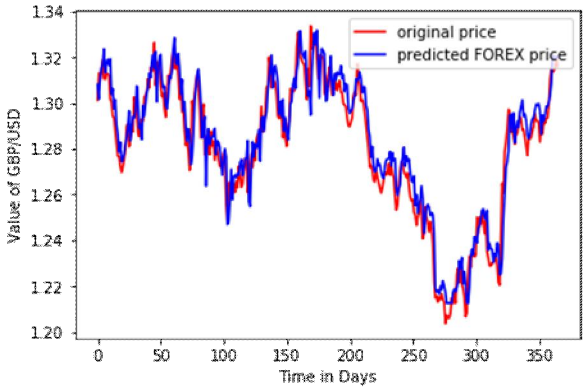


Fig. 8. GBP/USD price prediction by CNN.

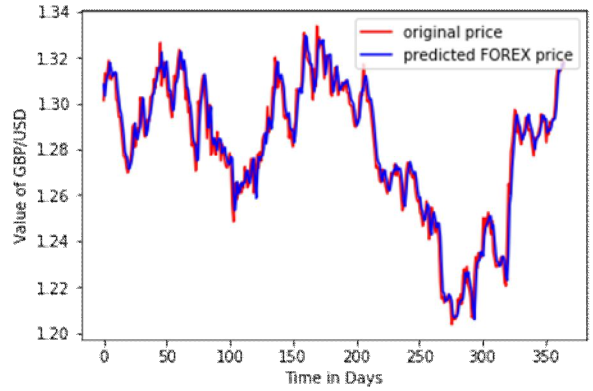


Fig. 9. GBP/USD price prediction by LSTM.

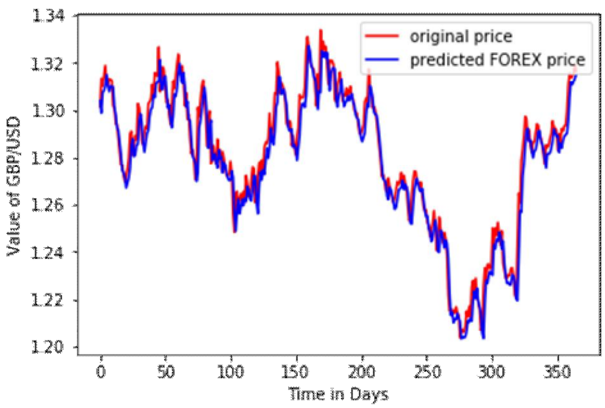


Fig. 10. GBP/USD price prediction by SVR.

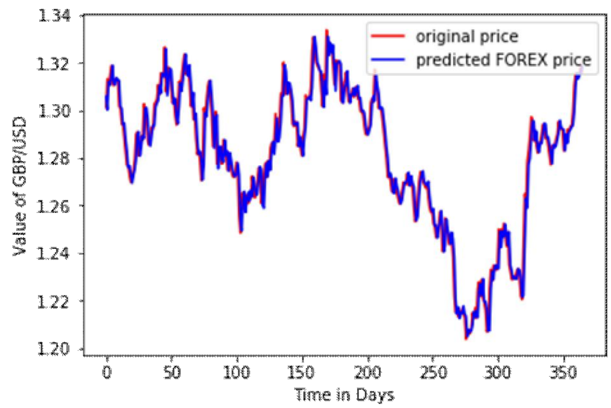


Fig. 11. GBP/USD price prediction by ENSEMBLE METHOD.

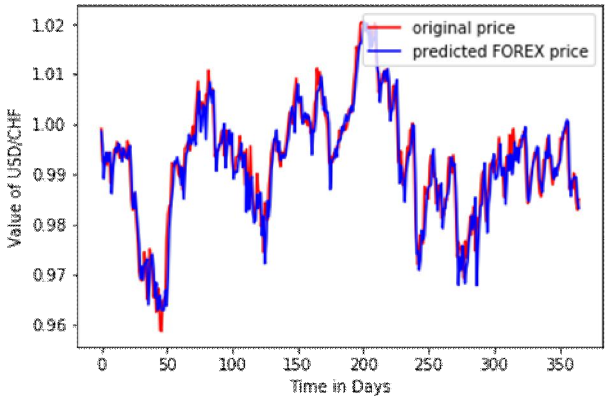


Fig. 12. USD/CHF price prediction by CNN.

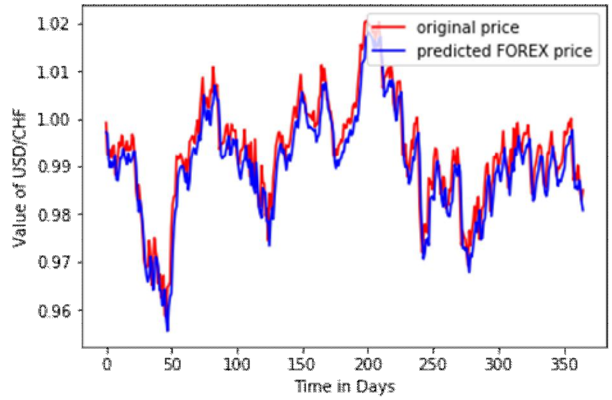


Fig. 13. USD/CHF price prediction by LSTM.

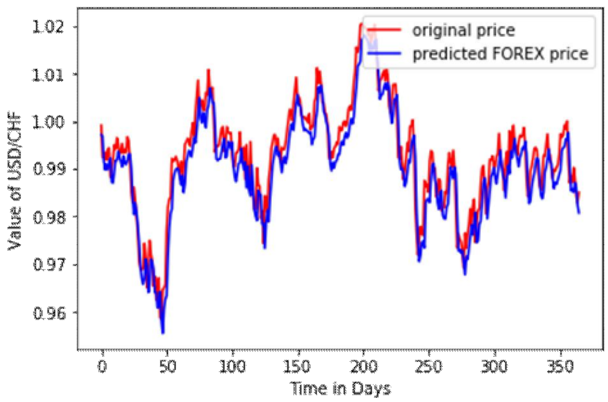


Fig. 14. USD/CHF price prediction by SVR.

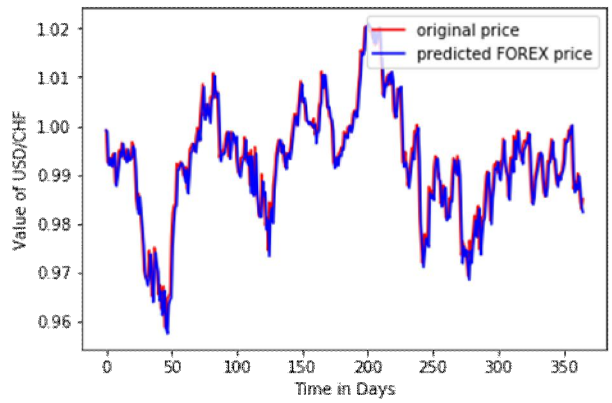


Fig. 15. USD/CHF price prediction by ENSEMBLE METHOD.

## VI. CONCLUSIONS

As observed from the graphs, further strengthened by the $R^2$ scores obtained for different exchange rate of different currency pairs, the ensemble model outputs most closely resembles the actual output results.The proposed model out- performs the individual models as it extracts the best of the individual learners and makes the more accurate predictions.

## REFERENCES

[1] J. Yao and C. L. Tan, “A case study on using neural networks to perform technical forecasting of forex,” Neurocomputing, vol. 34, no. 1-4, pp. 79–98, 2000.
[2] C. Dhanya and D. N. Kumar, “Nonlinear ensemble prediction of chaotic daily rainfall,” Advances in Water resources, vol. 33, no. 3, pp. 327–347, 2010.
[3] O. Abdel-Hamid, A.-r. Mohamed, H. Jiang, and G. Penn, “Applying convolutional neural networks concepts to hybrid nn-hmm model for speech recognition,” in 2012 IEEE international conference on Acoustics, speech and signal processing (ICASSP). IEEE, 2012, pp. 4277–4280.
[4] Z. Cui, W. Chen, and Y. Chen, “Multi-scale convolutional neural net- works for time series classification,” arXiv preprint arXiv:1603.06995, 2016.
[5] W. Wang, C. Chen, W. Wang, P. Rai, and L. Carin, “Earliness-aware deep convolutional networks for early time series classification,” arXiv preprint arXiv:1611.04578, 2016.
[6] D.-Z. Cao, S.-L. Pang, and Y.-H. Bai, “Forecasting exchange rate using support vector machines,” in 2005 International Conference on Machine Learning and Cybernetics, vol. 6. IEEE, 2005, pp. 3448–3452.
[7] K. He, C. Xie, and K. K. Lai, “A wavelet denoising support vector regression ensemble model for exchange rate prediction,” in 2008 4th International Conference on Wireless Communications, Networking and Mobile Computing. IEEE, 2008, pp. 1–4.
[8] G. Sermpinis, C. Stasinakis, K. Theofilatos, and A. Karathanasopoulos, “Modeling, forecasting and trading the eur exchange rates with hybrid rolling genetic algorithms—support vector regression forecast combinations,” European Journal of Operational Research, vol. 247, no. 3, pp. 831–846, 2015.
[9] N. Terui and H. K. Van Dijk, “Combined forecasts from linear and nonlinear time series models,” International Journal of Forecasting, vol. 18, no. 3, pp. 421–438, 2002.

[10] D. Pradeepkumar and V. Ravi, "Soft computing hybrids for forex rate prediction: A comprehensive review," Computers & Operations Research, vol. 99, pp. 262–284, 2018.

[11] D. J. Reid, "Combining three estimates of gross domestic product," Economica, vol. 35, no. 140, pp. 431–444, 1968.

[12] J. M. Bates and C. W. Granger, "The combination of forecasts," Journal of the Operational Research Society, vol. 20, no. 4, pp. 451–468, 1969.

[13] E. Pelikan, C. De Groot, and D. Wurtz, "Power consumption in west-bohemia: improved forecasts with decorrelating connectionist networks," Neural Network World, vol. 2, no. 6, pp. 701–712, 1992.

[14] I. Ginzburg and D. Horn, "Combined neural networks for time series analysis," in Advances in Neural Information Processing Systems, 1994, pp. 224–231.

[15] D. Pradeepkumar and V. Ravi, "Forex rate prediction using chaos, neural network and particle swarm optimization," in International Conference in Swarm Intelligence. Springer, 2014, pp. 363–375.

[16] S. Mehta, P. Rana, S. Singh, A. Sharma, and P. Agarwal, "Ensemble learning approach for enhanced stock prediction," in 2019 Twelfth International Conference on Contemporary Computing (IC3). IEEE, 2019, pp. 1–5.

[17] V. Kotu and B. Deshpande, Predictive analytics and data mining: concepts and practice with rapidminer. Morgan Kaufmann, 2014.

[18] T. Rashid, "A heterogeneous ensemble network using machine learning techniques," International Journal of Computer Science an Network Security, vol. 9, no. 8, pp. 335–339, 2009.

[19] B. Zhao, H. Lu, S. Chen, J. Liu, and D. Wu, "Convolutional neural networks for time series classification," Journal of Systems Engineering and Electronics, vol. 28, no. 1, pp. 162–169, 2017.

[20] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[21] S. Siami-Namini and A. S. Namin, "Forecasting economics and financial time series: Arima vs. lstm," arXiv preprint arXiv:1803.06386, 2018.

[22] C.-J. Lu, T.-S. Lee, and C.-C. Chiu, "Financial time series forecasting using independent component analysis and support vector regression," Decision support systems, vol. 47, no. 2, pp. 115–125, 2009.