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Financial Time Series Forecasting using Back Propagation Neural Network and Deep Learning Architecture

Richa Handa, A.K. Shrivas, H.S. Hota

Abstract: ***Artificial neural network is widely used for time series data which have got impact in today's economy with advancement of new artificial techniques. In this study we have used three time series data i.e.BSE30 stock data, INR/USD Foreign Exchange (FX) data and Crude Oil Data for prediction. Many linear and non linear models have been developed for these time series prediction. Our approach in this work is to comprise a robust predictive model for next day ahead prediction. In this paper we have done comparative study of traditional artificial neural network: Error Back Propagation Network (EBPN) and Deep Neural Network: Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) for financial time series prediction. It has been observed that Deep Neural Network is outperforming the traditional Neural Network EBPN. The performances of models are measured by error measures: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).***

Index Terms: ***Deep Neural Network, Error Back Propagation Network (EBPN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN).***

I. INTRODUCTION

Forecasting of time series data is a prediction of any event by analysing the historical data collected from various sources. Time series data are affected by many factors and events some of them effect it directly and some do it indirectly[1], [2], [3] which influence the economy of any country. Financial time series data are affected by various events such as demonetization [4], war, terrorism, natural disasters, political events etc [5]. In our case we have use three different types of financial time series data: BSE30 Stock Data, INR/USD Foreign Exchange Data and Crude Oil Data. Analysis of financial time series data is used to identify the trends and patterns in data and can involve two classes of algorithms for analysis i.e. Linear Model and Non-Linear Model; various linear models that are used for prediction are: Autoregressive (AR)[6], Autoregressive Moving Average (ARMA)[7] and Autoregressive Integrated Moving Average (ARIMA)[8] in which some predefined functions are used to invariant time series data[9]. The drawback of this model is that they are not able to understand the latent dynamics that exist in time series data due to equivocal and chaotic nature of data. This is the reason that these models are not frequently used now days to identify the trends and patterns of historical time series data and also not suitable for accurate prediction of time series data due to its unforeseeable nature. To overcome the difficulty occurs while analysis and prediction of time series data Non-Linear models are used, they includes methods like Autoregressive Conditional Heteroskedasticity (ARCH), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Machine Learning, Deep Learning etc. Our proposed work focus on the two architecture of Deep Learning: Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) and has done comparative study between machine learning technique EBPN [10] and Deep Learning techniques: RNN and LSTM for prediction of financial time series data[[11]. Deep learning is a type of neural network with plenty of layers where deep represents the depth of network. This Neural Network is successful in the field of Image Processing, Speech Recognition and Video Processing and now it is also gain great achievement in field of Time Series Forecasting[12], [13],[14]. Deep learning algorithms are capable to identify the hidden trends and patterns of data due to its fluctuating behaviour. From last few decades intelligent techniques are gaining importance in time series prediction because of its accuracy. Many research articles are found useful for prediction of financial time series data, some articles are based on linear model and some are based on non-linear models. We found plenty of literatures on traditional neural network techniques; however very few literatures are available for implementing Deep Neural Network for financial time series forecasting. Hota, H. S. et al. [10]analyses BSE 30 and INR/USD foreign Exchange (FX) data using two neural network techniques: Radial Basis Function Network (RBFN) and Error Back Propagation Network (EBPN) and author suggested RBFN is outperforming EBPN in validation dataset. Handa, R. et al. [15] explores an Artificial Neural Network (ANN) technique:

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***** Correspondence Author
Richa Handa*, Department of Computer Science, Dr. C.V. Raman University, Bilaspur(C.G.), India.
A.K. Shrivas, Department of Computer Science, Dr. C.V. Raman University, Bilaspur(C.G.), India.
H. S. Hota, Department of Computer Science and Application, Atal Bihari Vajpayee University, Bilaspur (C.G.), India

Radial Basis Function Network (RBFN) for data prediction using the concept of sliding window, which produces data for next day prediction using historical data of earlier days calculated by Weighted Moving Average (WMA). Sharma, D.K. et al, [16] has examines the prediction of foreign exchange rate using regression techniques i.e. Regression and ensemble regression techniques: Bagging and Boosting and author also observed that MAPE value increases with increasing value of N in case of N-Days ahead prediction of FX rate. Hiransha, M. et al. [12] use deep learning models RNN, LSTM and CNN for NSE and NYSE stock market prediction and compared it with ARIMA model and it has been observed that CNN is outperforming other models . Fischer, C. et al. [17] analyse Deep learning with long short-term memory(LSTM) networks for financial market Predictions for predicting out-of-sample directional movements for the constituent stocks of the S&P 500 and find LSTM networks to outperform memory- free classification methods, i.e., a random forest (RAF), a deep neural net (DNN), and a logistic regression classifier (LOG). Zhao, Y. et al. [18] uses a deep learning ensemble approach and bootstrap aggregation (bagging) , author combines the merits of these two techniques especially suitable for oil price forecasting. Selvin, S. [19] study Short Term Stock Price Prediction Using Deep Learning and discusses about two distinct sorts of Artificial Neural Networks, Feed Forward Neural Networks and Recurrent Neural Networks. Khare, K. [9] focuses on deep learning architecture i.e. LSTM, RNN and CNN-Sliding for stock price prediction As seen from the results, MLP has outperformed LSTM model, in predicting short term stock prices. Event handling is also performed by Chatzis, S.P. et al. [13] for stock market crisis events using deep as well as statistical machine learning techniques. The rest of the part of this paper is organized as follows : Section 2 gives a brief over-view of the dataset and process flow diagram of proposed work, section 3 describes methodology used that is EBPN, RNN and LSTM, section 4 analyse experimental result, finally section 5 concludes the findings of the research work.

II. DATASET AND PROCESS FLOW DIAGRAM

In order to perform prediction on financial time series data, we have collected information's from various sources and databases. We have collected three different historical financial time series data of five years from various sources i.e. BSE 30 Stock data from http://www.yahoofinance.com, INR/USD FX data from http://www.fx.sauder.ubc.ca and crude oil WTI (West Texas Intermediate) historical data from https://in.investing.com. The collected dataset is partitioned into training (80%) and testing (20%) dataset. The raw data is normalized using normalization equation in which each sample value of data is divided by max value among all data samples. Normalization is a technique which is applied as part of data preparation for machine learning techniques.

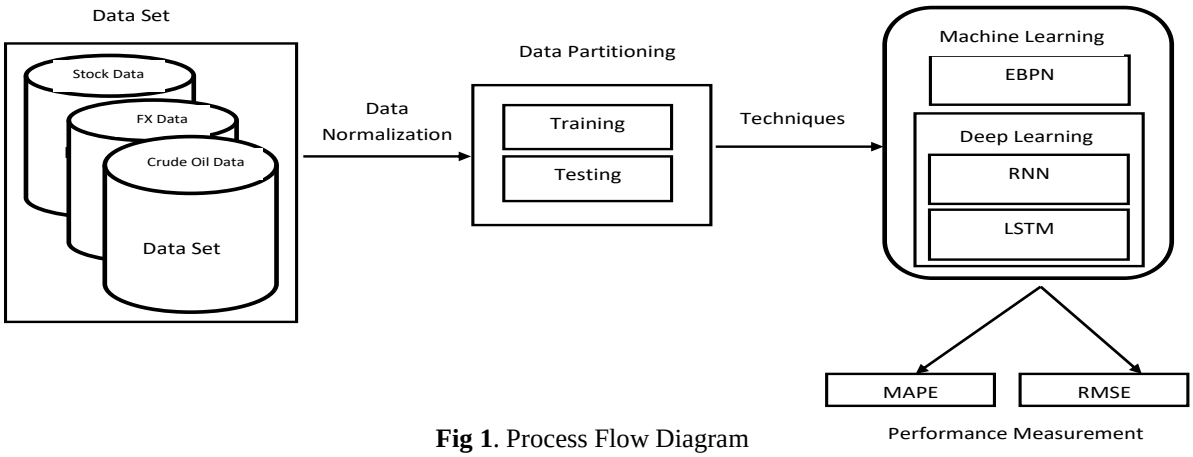

Fig 1. Process Flow Diagram

Fig. 1 depicts the process flow of proposed work in the form of a diagram where three datasets (Stock Data, FX Data and Crude Oil Data) are used in the form of raw data. In BSE30 stock data five features Open, high, low, close and volume are included and in INR/USD and crude oil data only one feature close is used, for all dataset we have used 1200 data samples for observation, then after data normalization has been done. The objective of normalization is to change the values of the dataset to a common scale between 0-1, without affecting its originality. Normalized data will show its effect on model accuracy. The data is then partitioned into training and testing data, where 80% of data is used for training and 10% data is used for testing the model, then prepared dataset is given to EBPN and two deep learning architectures i.e. RNN and LSTM to generate predictive model. The performance of model is measured by two error measurements called MAPE and RMSE to make robust model.

III. METHODOLOGY

A. Error Back Propagation Network (EBPN)

EBPN is one of the popular method of ANN[20], which is three layers neural network where input is given to the input layer which is taken from previous layer, and is propagated forward to the network to reach the output layer and output is send to next layer that is compared with actual output and produce the comparative difference between them called error value, which is propagated back to the network to update the weight between connection layers to train network[10]. This process is repeated until it approaches the desired output.

B. Recurrent Neural Network (RNN)

RNN is ANN [21] which is also connection of three nodes Input, hidden and output nodes. Author [15] RNN takes input from two sources one is from current input node and other is from the output of previous session[14], where output of each instance is treated as input to the next movement of network, the proper response and behaviour of RNN is not only based the current working layer but also based on the previo working layer[12]. Each input sequence of RNN has number information which is recursively used in the network is stor in the hidden form in RNN, so we can say that RNN also h memory to store the information from all input sequenc which go forward to deal with new sample of dataset a decide how to react with it. Fig. 2 depicts the architecture Recurrent Neural Network (RNN).

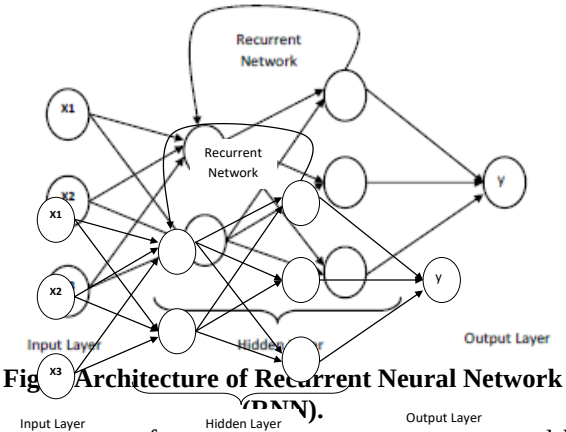

Fig 2. Architecture of Recurrent Neural Network (RNN).

The sequence of current input vector x is processed by applying recurrent equation at every time steps as shown in Eq. 1.

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

Here h_t is the new state and h_{t-1} is previous state, x_t is the input at time t and f() is the recurrent function. To define function f() we take tanh as activation function shown in Eq. 2.

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

Where weights are defined by the matrix w_{hh} and the input is defined by the matrix w_{xh}. Finally the output of the network is calculated using Eq. 3.

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

Where y_t is the output, which is compared to the actual output with desired output and then an error value is computed. The network learning has been done by back propagating the error via the network to update its weights.

C. Long Short-Term Memory (LSTM)

LSTM is a kind of RNN which is a powerful time series model which predict random number of steps in future. LSTM is a combination of five special components [22], [14] called gates which can model both long term as well as short term data they are: Cell State, Hidden State. Input Gate, Forget Gate and Output Gate.

Cell State(C_t): It represents the internal memory of cell in which LSTM have the ability to remove or add information.

Hidden State (h_t): This is output state information calculate with respect to current input, previous hidden state and current cell state to predict the future data.

Input Gate (i_t): Input Gate consists of input and decides the information flows from current input to cell state.

Forget Gate (f_t): Decides the flow of fraction of information current input and previous cell state to current cell state.

Output Gate (o_t): It describes the output generated by LSTM

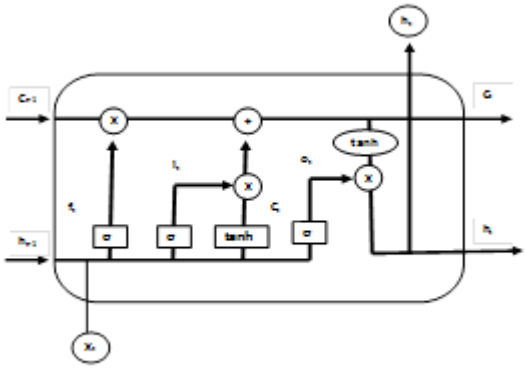

Fig 3. LSTM architecture.

Fig. 3 shows the architecture of LSTM where horizontal line at the top of diagram known as cell state C_{t-1}, C_t, it passes the information flow from previous cell to current cell. The decision what information we're going to throw away from the cell state is taken by forget layer f_t. In the next step the network decides what new information we're going to store in the cell state which is done in two parts. First, a sigmoid layer called the "input gate layer" decides which values we'll update. Second, a tanh layer creates a vector of new candidate values, C_t, which could be added to the state. After that network update the old cell state C_{t-1}, into the new cell state C_t, then we add $i_t * C_t$, this is the new candidate values, scaled by how much we decided to update each state value. Finally, we need to decide what we're going to output; this output will be based on our cell state,

IV. RESULT ANALYSIS

In this paper the model evaluation is based on three different five years historical financial time series data i.e. BSE 30 Stock data, INR/USD FX data and Crude Oil data using EBPN and two deep learning architectures namely RNN and LSTM for next day ahead prediction. The models were simulated using MATLAB code. The performances of models were evaluated by two error measures: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The outputs produced by various developed models were compared with target output of corresponding data and result of deep learning based models were compared with traditional EBPN model. The comparative result in terms of MAPE and RMSE of EBPN and both Deep Learning architecture: RNN and LSTM are shown in Table1. These results shows that Deep Learning based techniques is outperforming EBPN and out of two deep learning techniques LSTM is performing better.

Table 1. Comparative result in terms of MAPE and RMSE in three financial time series data using EBPN, RNN and LSTM.

Financial Time series data	Technique used					
	EBPN		RNN		LSTM	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
BSE30	2.01	1.14	1.94	0.03	1.35	0.02
INR/USD	1.45	0.12	1.38	0.02	0.87	0.01
Crude Oil	1.72	0.09	1.24	0.01	1.09	0.01

The performance graph of all three financial time series data in terms of MAPE using EBPN and both deep learning models RNN and LSTM are depicted below from Fig. 4 to 12. These figures clearly reflect the performance of developed models as predicted output and actual output are almost closure to each other. Especially in case of deep leaning bases models for all three financial time series data set considered for checking the performance of the model which produces acceptable range of error measured in term of MAPE and RMSE for prediction.

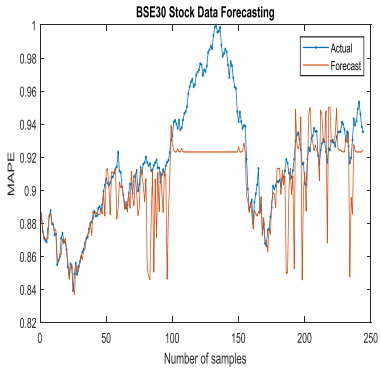

Fig 4. Comparative graph of predictive value and actual value of BSE30 Stock data forecasting using EBPN.

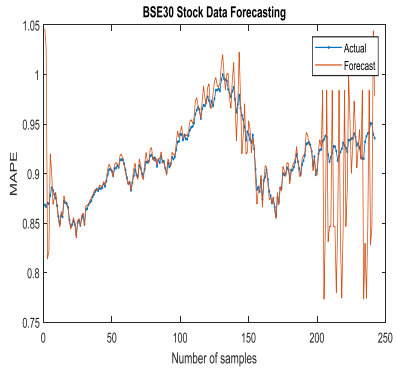

Fig 5. Comparative graph of predictive value and actual value of BSE30 Stock data forecasting using RNN.

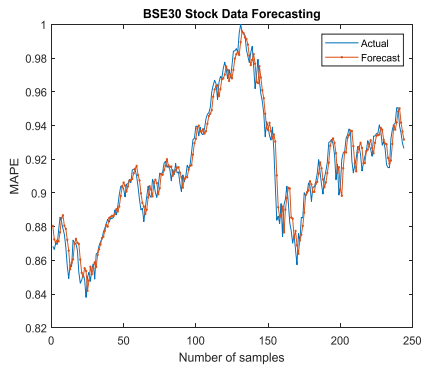

Fig 6. Comparative graph of predictive value and actual value of BSE30 Stock data forecasting using LSTM.

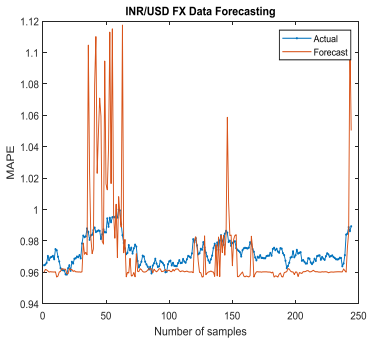

Fig 7. Comparative graph of predictive value and actual value of INR/USD FX data forecasting using EBPN.

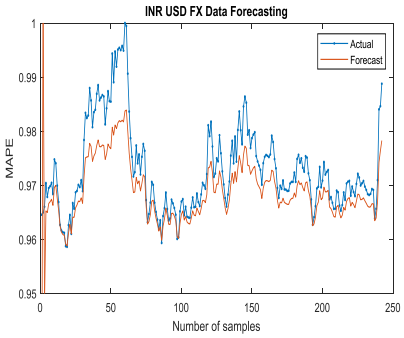

Fig 8. Comparative graph of predictive value and actual value of INR/USD FX data forecasting using RNN.

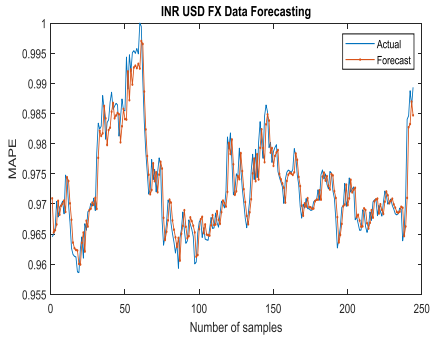

Fig 9. Comparative graph of predictive value and actual value of INR/USD FX data forecasting using LSTM.

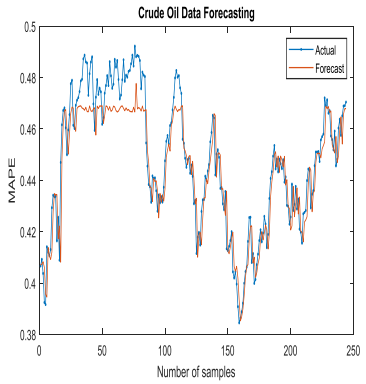

Fig 10. Comparative graph of predictive value and actual value of Crude Oil data forecasting using EBPN.

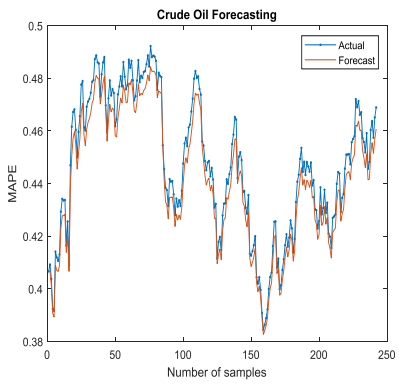

Fig 11. Comparative graph of predictive value and actual value of Crude Oil data forecasting using RNN.

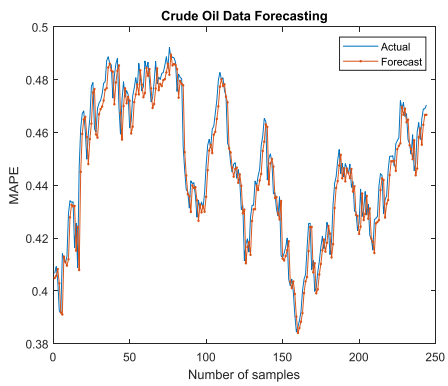

Fig 12. Comparative graph of predictive value and actual value of Crude Oil data forecasting using LSTM.

Fig. 13 shows the comparative MAPE for all three financial time series data using three different techniques which also reflects performance of deep learning model as MAPE=2.01, MAPE= 1.94 and MAPE=1.36 for BSE30 Stock Data and MAPE=1.45, MAPE= 1.38 and MAPE=0.87 for INR/USD FX data and MAPE=1.72, MAPE= 1.24 and MAPE=1.09 for Crude Oil Data respectively.

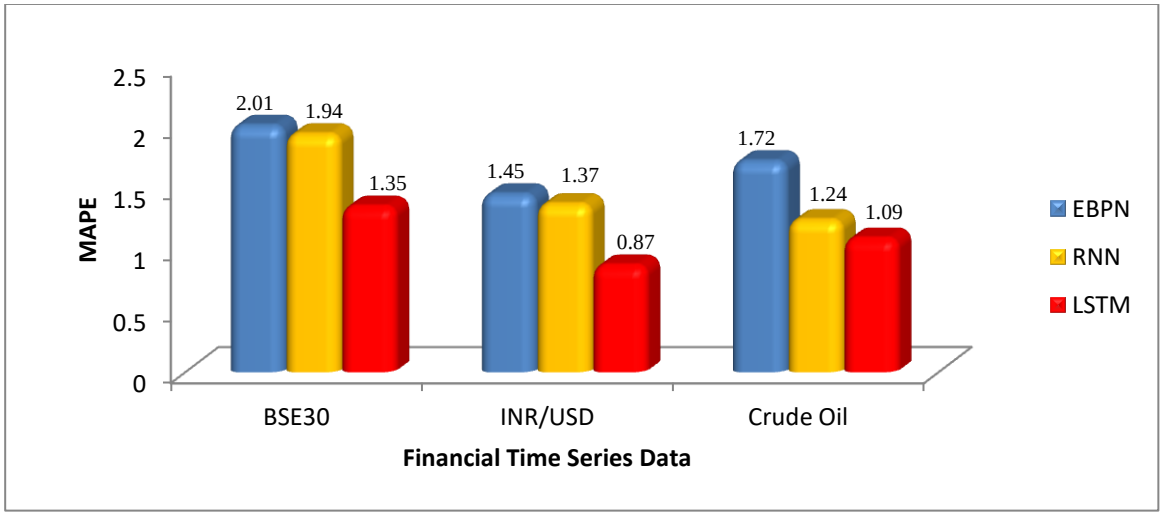

Fig 13. Comparison of MAPE of Three financial time series data using EBPN, RNN and LSTM.

V. CONCLUSION

Revolution of Artificial Neural Network is continuously going on with advancement of new artificial techniques. In continuation to this; Deep Learning is now days widely used for financial time series data forecasting due to this ability to learn non-linear and high dimensionality data in better way. Available literature of Deep Learning proven that it is widely used for various applications like Image Processing, Speech Recognition and Video Processing and now it is widely used in the field of Time Series Forecasting. It is seen that the deep learning architectures are able to capture the hidden dynamics of network and generate a robust forecasting model. In this paper deep learning model is compared with traditional neural network like EBPN and explores the effectiveness of Deep Neural Network for forecasting financial time series data. For checking the performance three different financial time series data: BSE30 Stock data, INR/USD FX data and Crude Oil data were used and models were developed. The comparative analysis of forecasting result shows that Deep Neural Network is performing better than EBPN and LSTM is outperform RNN with MAPE =1.35 for BSE30 Stock Data, MAPE =0.87 for INR/USD FX data and MAPE =1.09 for Crude Oil Data.

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