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Empirical analysis of machine learning techniques for prediction of indian exchange rate

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Abstract

Throughout the past few decades, there has been a dramatic surge in the currency market. The changes play an important role in balancing the market's characteristics. As a result, accurate change price forecasting is essential to improve the success rate of many businesses and fund managers. Despite the fact that the market is renowned for its erratic behavior and volatility, there are organizations like agencies, banks, and others. In order to estimate the extraneous interchange rate of the dollar against the rupee with a high degree of accuracy, we used three distinct types of methodologies in this article. This research uses three different types of neural network models: ANNs (Artificial Neural Networks), LSTMs

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(Long Short-Term Memory Networks), and GRUs (Gated Recurring Units). The results depict that GRU's model is outperforming the other two models.

Subject Classification: *68T07*

Keywords: *Exchange currency rates, Economic forecasting model, ANN, LSTM, GRU.*

1. Introduction

Throughout the last few years, the market has grown incredibly. The volatile nature of the exchange market is significantly influenced by exchange rates. So, precise exchange rate forecasting is necessary for corporate investments to succeed. Historical data is a key component in the forecasting process [4], [5]. "Time series modelling" is the traditional method or model used to predict exchange rates. The issue with this method is that the interchange rate series is chaotic and non stationary. One of the most difficult uses of the modern era is exchange rate forecasting. Interchange proportions are deafening, volatile, messy, and non-stationary in an unpredictable way. These characteristics suggest that the information is incomplete. The purpose is to examine and compare the forecast of the exchange rate compared to the USD and the Rupee.

2. Methods / Techniques

Several unique neural network algorithms are based on investigations. Yet, too far, no study has been discovered to rigorously control the efficiency of each algorithm. In this article three alternative neural network models—ANN, LSTM, and GRU—have been implemented [1], [6], [10] and [16], to determine which model is more accurate in predicting the pace of change for the Indian Rupee.

2.1 *ANN-Artificial Neural Network*

In artificial neural networks, the human brain is simulated. Each sensory organ transmits information to the brain. The neuron takes, progression, and produces the necessary output to cause a response [14] [18]. ANN is trained by data and then used to provide results based on testing data [3]. According to Figure 1, it has three layers: Input-layer, Hidden-layer, and Output-layer [7][8][9].

$$n_j^{et} = \sum_i w_{ij^*} x_i \tag{1}$$

$$\varphi = \frac{1}{1+e^{-net}} \tag{2}$$

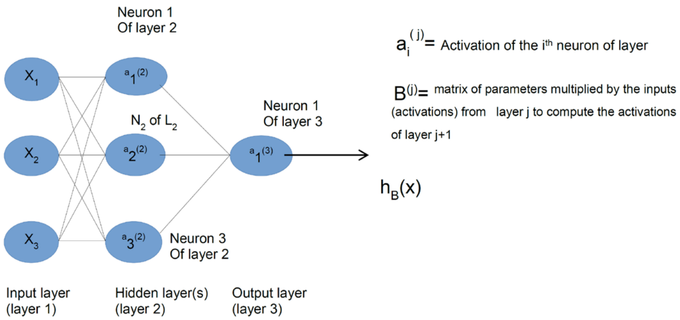

Figure 1

Artificial Neural Network

2.2 *RNN-Recurrent Neural Network*

The improved description of ANN is RNN. This word "Recurrent" denotes repetition by that one. As demonstrated in Figure 2, what happens in RNN is that the previous output is continually taken into consideration as input in addition to the current input. This enables the network to produce results that are superior to ANN's. The primary distinction is that while neurons are present in ANNs, they are replaced in RNNs by memory blocks that store prior output [8]. The ability of machines to understand and listen has improved since the discovery of RNN [7] [11].

- Method for manipulative existing state:

$$s_t = f(s_{t-1}, a_t) \tag{3}$$

Where: s_t = current state

s_{t-1} = previous state

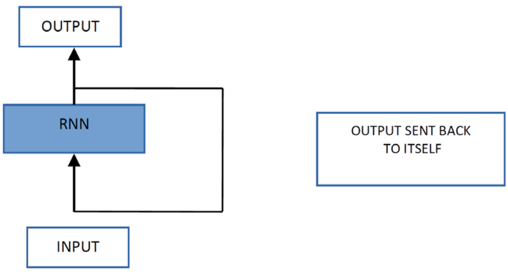

Figure 2

Recurrent Neural Network

a_t = input state

$$s_t = \tanh(W_{hh}s_{t-1} + W_{xh}x_t) \tag{4}$$

Where: W_{hh} = RN weight, W_{xh} = input weight

$$y_t = W_{hy}h_t \tag{5}$$

Where: y_t = output

W_{hy} = output layer weight

2.3 *LSTM-Long Short Term Memory Network*

As seen in Figure 3, Recurrent Neural Network (RNN) that has been tweaked to make it simpler to recall previous data in memory. It is used to get around RNN's vanishing gradient issue. LSTM networks use memory blocks connected by layers in place of neurons. For training, back propagation is employed. A LSTM network contains three gates [13] [15] [19]. This is a diagrammatic illustration of the gates.

- o Input Gate – Input values.

$$i_t = \sigma(W_i.[s_{t-1}, a_t] + b_i) \tag{6}$$

$$\widetilde{C_t} = \tanh(W_C[s_{t-1}, a_t] + b_C) \tag{7}$$

Where: σ = sigmoid activation function

s_{t-1} =previous state

a_t = input state

Tanh = activation layer function

C_{t-1}, C_t = cell state

W_C, W_i = weight matrix of input associated with hidden state

b_c, b_i = biases

- o Forget gate – Information to be deleted from the memory.

$$f_t = \sigma \tag{8}$$

- o Output gate:

$$o_t = \sigma(W_o.[s_{t-1}, a_t] + b_o) \tag{9}$$

$$h_t = o_t * \tanh(C_t) \tag{10}$$

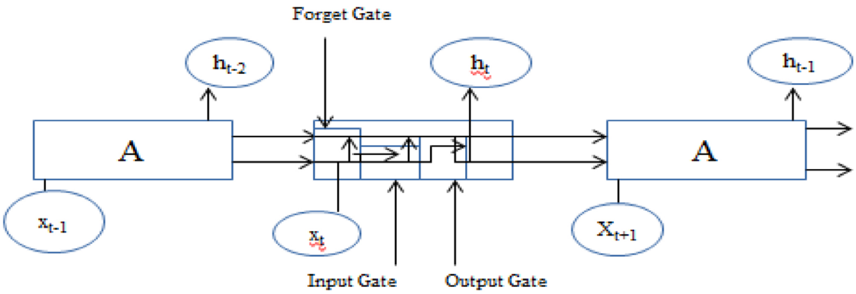

Figure 3

Architecture of LSTM

2.4 *GRU-Gated Recurrent Unit*

The Gated Recurrent Unit, as depicted in Figure 4, is the most recent accumulation to the order modelling approaches, following RNN and LSTM. Hence, it provides an increase in efficiency over LSTM and RNN. GRU is an improvement over the common RNN and a condensed form of LSTM [12] [20]. Gated recurrent units, such as LSTM, use several gates to govern information flow.

Where: St = hidden state,
A_t = input
S_{t-1} = previous state

Compared to an LSTM, a GRU has two gates. Reset gate and Update gate are the first two. The network's hidden state is controlled by the short term memory. The reset gate's equation is provided below,

$$r_t = \sigma(A_t * U_r + S_{t-1} * W_r) \quad (11)$$

Here $U_r \wedge W_r$ are weight matrices.
Update gate – For long term memory and the equation is given below,

$$u_t = \sigma(A_t * U_u + A_{t-1} * W_u) \quad (12)$$

Here $U_u \wedge W_u$ are weight matrices.

3. Discussion

To create the forecast model, we gathered the investing.com exchange rate dataset and examined daily data from January 2011 to January 2021 (10 years). There are two sections of the data. The first 80% of the data, which covers the period from January 2011 to January 2019, is used to

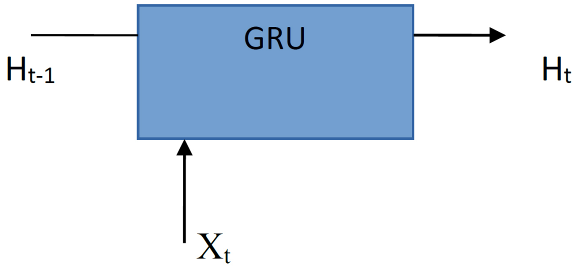

Figure 4

Architecture of GRU

train the models, while the final 20% is utilized to test the models. Exchange rate forecasting is done using a loss and prediction function in each of the three models (ANN, LSTM and GRU). To compare the definite and predicted values, the relevant graphs for the three models are being developed. To determine each model's effectiveness, the RMSE (Root Mean Square Error), MAE (Mean Absolute Error), R2 rate, and attuned R2 rate have been determined. We noted that the R2 value of the GRU (0.987 for the training set and 0.849 for the testing set) is superior to both ANN's and LSTM's (0.628 for the testing set and 0.990 for the training set, respectively) (0.982 for training set and 0.816 for testing set). This demonstrates that GRU has a lower error than the simulations. Similarly, the R2 rate of GRU, which is 0.849, is nearly 1, indicating that the model's forecast is much more accurate than others. Hence, we may say that GRU performed better than ANN and LSTM [2], [17].

4. Results

We have graphically displayed our findings and analysis in this part. A time plot is essentially a line plot that depicts how a time series has changed over space and time. We are using year as the x-axis and data points as the y-axis here [5]. One of the early pre-processing procedures we need to perform is seen in this plot, where we partition our modelling dataset into training and testing samples [6]. INR-scaled is taken into account in this graphic observation. Here, we are taking into account year-by-year observations in the x axis and values for INR-Scaled exchange rates on the y axis [7, [9]]. In order to employ them on our sequence prediction problem, we created the LSTM and GRU models in this work [8].

Time-series forecasting is the process of fitting a model to previous data and utilizing the results to forecast future observations. We have

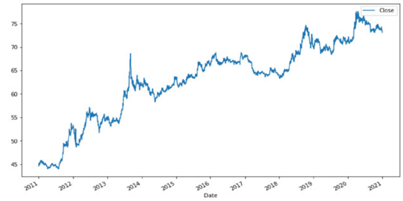

Figure 5
Prices change over time

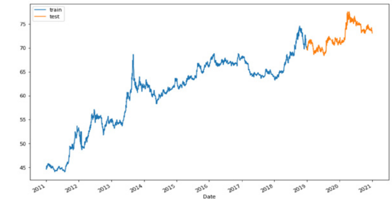

Figure 6
Splitting the data set

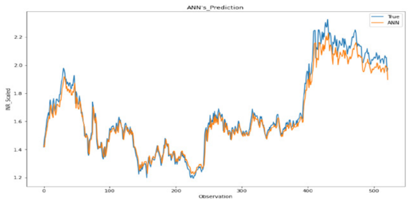

Figure 7
ANN prediction

Figure 8
LSTM prediction

Figure 9
GRU prediction

displayed year-by-year observations using Indian exchange rates in Figures 5 through Figure 9.

Where,

MAE – Mean Absolute Error

Root Mean Square Error (RMSE)

In this part, the stream flow data from historical observations are compared to the streamflow computed using ANN, LSTM and GRU. A network aims for the highest degree of accuracy while making predictions. The effectiveness of the ANN, LSTM, and GRU models is shown in Table 1. We discovered from the analysis that the GRU model outperforms the ANN and LSTM model.

Table 1

Comparison of three models

NAME OF THE MODEL	TRAINING SET				TESTING SET			
	R^2 Value	MAE	RMSE	Adj. R^2 Value	R^2 value	MAE	RMSE	Adj. R^2 Value
ANN	0.990	0.081	0.102	0.990	0.628	0.253	0.281	0.628
LSTM	0.982	0.122	0.136	0.982	0.816	0.104	0.135	0.815
GRU	**0.987**	**0.074**	**0.101**	**0.987**	**0.849**	**0.094**	**0.123**	**0.849**

5. Conclusion and Future Scope

Here, the assumption is based on the supplied dataset and the studied time period. Though, the outcomes may vary depending on the bazaar, the time frame of the training, and the exchanges used to calculate the conversation rate. The study's ends are therefore arbitrary. Despite the fact that their working methods are very similar, GRU has been proven to be the most accurate and successful process for time series prediction. Moreover, GRU is faster than LSTM because it employs fewer training parameters and so needs less memory. The models could be skilled for a short-term prediction with a small dataset as a potential future extension. This analysis can be expanded further to forecast the exchange rates of additional nations.

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