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Divine Currency Exchange using Repetitive Brain Network

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ABSTRACT : An exchange rate is the rate at which one currency may be exchanged for another between countries or economic zones. Because it is used to evaluate the value of various currencies in relation to one another, it is useful in analysing trade and capital movement trends. Predicting the value of a currency while exchanging is a challenging issue for many experts and even average business people. Successful worldwide businesspeople are particularly interested in forecasting future currency price and share declines. Business analysts and analysts can use good and effective prediction models to forecast currency prices in the future. Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models were proposed in this research. In this work by expanding the Epochs and group size of brain organization, the precision of expectation is more. In proposed strategy, we are utilizing a test information that is utilized to foresee which gives results that are more exact with the test information. The proposed technique is fit for following and expectation of cash esteem and the forecast will deliver higher and precise outcomes.

KEYWORDS: Currency value prediction, Recurrent Neural Network (RNN), Long Short Term Memory (LSTM),

I. INTRODUCTION

The currency exchange rate represents the purchase price between two currencies. Our research is a recurrent neural network that uses machine learning to estimate currency value at the moment of cross-border exchange. Many investors are particularly interested in anticipating future currency value ups and downs in order to make a profitable business. Individuals in the business world can utilize great and viable expectation models to gauge the future worth of a cash. In this review, I proposed a Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) model for anticipating trade rates using Machine and Deep Learning models. There are different strategies for foreseeing the conversion scale right now, however they are less solid.

II. METHODOLOGY

Here we are using two methods. That are,

- i. RNN (RECURRENT NEURAL NETWORK)
- ii. LSTM (LONG SHORT TERM MEMORY)

RNN is intermittent in nature since it executes similar capacity for every information input, and the current info's result is reliant upon the past estimation. The output is replicated and transmitted back into the recurrent network when it is created. It evaluates the current input as well as the output it has learnt from the prior input when making a decision. RNNs, unlike feed forward neural networks, can process sequences of inputs using their internal state (memory). So here we need one memory place for long time [LSTM]. Each of the contributions to other brain networks are free of each other. In a RNN, in any case, every one of the data sources are associated with each other.

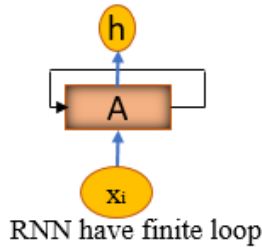
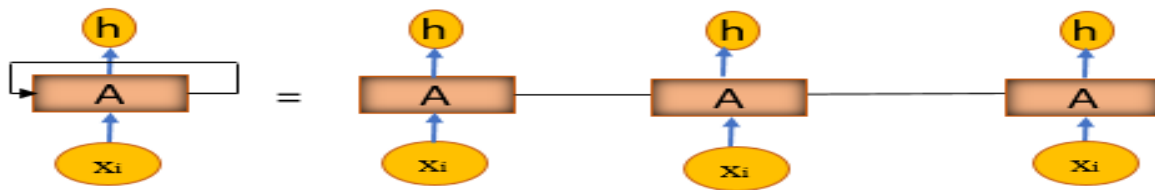


Fig.1. RNN with loop

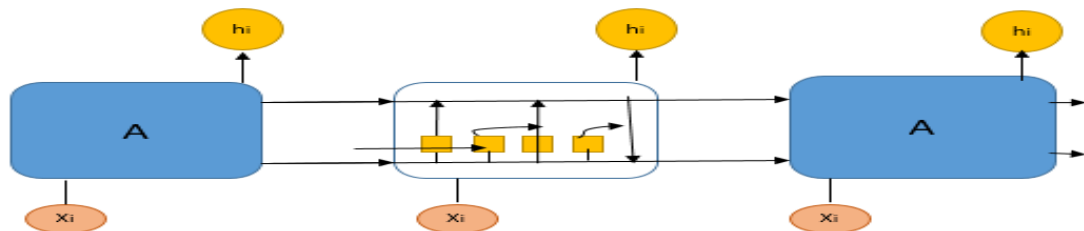


RNN structure for unrolled concept

Fig.2 Working model of RNN

(i) LSTM (LONG SHORTTERMMEMORY)

The default nature of LSTMs is to recall data for expanded timeframes Investigate the chart underneath, which shows that each LSTM module will contain three doors: a neglect entryway, an info entryway, and a result



entryway.

Fig.3 LSTM working model

2.2.1INPUT

Find which esteem from the information ought to be used to change the memory with an info door. The sigmoid capacity figures out which numbers are permitted to go through 0,1.The andtanh work relegates weight to the things provided, deciding their relative significance from - 1 to 1.

2.2.2FORGET

Forget about the gate; figure out which details should be removed from the block.The sigmoid function determines this.For each number in the cell state Ct1, it looks at the previous state (ht-1) and the content input (Xt) and produces a number between 0 (omit this) and 1 (keep this).

2.2.3OUTPUT

The output of an output gate is determined by the input and memory of the block. The Sigmoid capacity figures out which values to permit by means of 0,1, and the tanh work appoints weightage to the qualities that are passed, going from - 1 to 1, and is duplicated by the result of the Sigmoid capacity

III. DATA THAT IS USED IN THE MODEL

Here we choose currency exchange between the US dollar and Indian Rubee.In the Model Two types of data are being used. They are

(i)Train Data

Train data from the last four years of USD/INR historical data is utilised in the model.Our model will be trained using this data.To improve accuracy, we utilise epochs of around 200.



(ii) Test data

Data from a year of USD/INR historical data is utilised to test our data in the Model Test. This information is needed to verify the correctness of our model.

Date =	Price =	Open =	High =	Low =	Change % =
Mar 16, 2022	76.399	76.302	76.694	76.294	-0.01%
Mar 15, 2022	76.410	76.470	76.683	76.297	-0.03%
Mar 14, 2022	76.430	76.663	76.715	76.445	-0.07%
Mar 11, 2022	76.483	76.372	76.715	76.249	0.25%
Mar 10, 2022	76.290	76.256	76.505	76.056	-0.09%
Mar 09, 2022	76.355	76.915	77.004	76.317	-0.70%
Mar 08, 2022	76.890	76.984	77.187	76.715	-0.09%
Mar 07, 2022	76.960	76.675	77.173	76.658	0.72%
Mar 04, 2022	76.410	75.935	76.451	75.935	0.61%
Mar 03, 2022	75.943	75.652	76.020	75.603	0.44%
Mar 02, 2022	75.611	75.912	75.940	75.569	-0.19%
Mar 01, 2022	75.752	75.289	75.816	75.260	0.34%
Feb 28, 2022	75.493	75.760	75.790	75.282	0.58%
Feb 25, 2022	75.060	75.428	75.488	75.075	-0.71%
Feb 24, 2022	75.600	74.692	75.848	74.657	1.30%
Feb 23, 2022	74.630	74.625	74.730	74.532	0.01%
Feb 22, 2022	74.620	74.697	74.994	74.616	0.17%
Feb 21, 2022	74.495	74.584	74.741	74.343	-0.23%
Feb 18, 2022	74.670	75.075	75.105	74.479	-0.57%
Feb 17, 2022	75.100	74.993	75.238	74.953	0.10%
Feb 16, 2022	75.022	75.175	75.297	74.947	-0.17%
Highest: 77.187	Lowest: 74.343	Difference: 2.843	Average: 75.744	Change %: 1.663	

Table 1. Example Dataset

4. Result

The GUI Interface in the model project in the Python environment comprises of three buttons. I Open the Training file, (ii) Open the Test file, and (iii) Press the Get button. The graph shows the model's outcome, the graph of the anticipated future 30 days, and the close value of the forecasted 30 days. In the Python environment, each button is expressed as a function declaration. The first button opens the train data, the second button opens the test data, and the third button runs the RNN and LSTM and fits the model to the RNN.

```

# Visualization
plt.figure(figsize=(50,50))
plt.subplot(231)
plt.plot(y_test, color = 'red', label = 'Real Google Stock Price')
plt.plot(y_pred, color = 'blue', label = 'Predicted Google Stock Price')
plt.title("Result of the model of Prediction")
plt.xlabel('Time')
plt.ylabel('Google Stock Price')
plt.legend()

plt.subplot(233)
lst_output=scaler.inverse_transform(lst_output)
plt.plot(day_pred,lst_output)
plt.title("Graph of predicted Stock Price of future 30 days")
plt.xlabel('Time')
plt.ylabel('Google Stock Price')

df3=inputs.values.tolist()
df3=scaler.inverse_transform(df3).tolist()
df3.extend(lst_output)
plt.subplot(235)
plt.title("Graph of predicted Stock Price")
plt.xlabel('Time')
plt.ylabel('Google Stock Price')
plt.plot(df3[1:])
plt.show()

for i in range (0,30):
    print("The Close Price of day",i+1,"is:",lst_output[i])
    
```

Fig.5. Plotting the graph

In addition, the code is built to forecast the coming year. There is included code for visualising the graph of the model's output, as well as a graph of expected close and open prices for the next year.

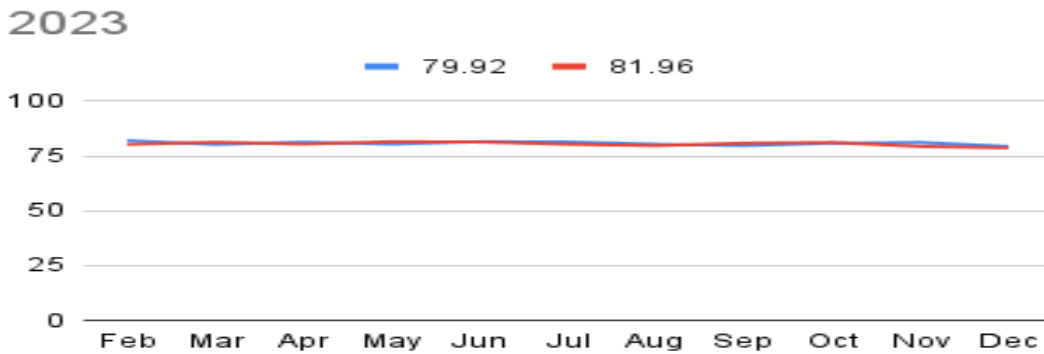


Fig.6 graph model for future currency value

The model has forecasted the currency value more accurately, as shown in the graph above. The findings were more precisely anticipated by the model. The actual exchange value is compared to the anticipated currency value in this graph, and we can see that the model has forecasted the currency value more correctly.

VI. CURIOSITY OF THE PROPOSED MODEL

The advantage of being new in my venture is that my trade Price expectation model is more precise than other existing models, and my undertaking is additionally novel in that I made a Graphical User Interface (GUI) where we can transfer Train and Test Data and come by the model's outcome as well as trade costs. In my project, I produced a result graph that includes the Future 365 days Predicted Close currency values. A distinctive feature of the model is that it may present the near values of the expected future 30 days.

Month	Open	Low-High	Close	Mo,%	Total,%
2023					
Jan	79.92	79.92-83.19	81.96	2.6%	8.6%
Feb	81.96	79.06-81.96	80.26	-2.1%	6.3%
Mar	80.26	80.04-82.48	81.26	1.2%	7.6%
Apr	81.26	79.19-81.61	80.40	-1.1%	6.5%
May	80.40	80.29-82.73	81.51	1.4%	8.0%
Jun	81.51	80.14-82.58	81.36	-0.2%	7.8%
Jul	81.36	79.11-81.51	80.31	-1.3%	6.4%
Aug	80.31	78.52-80.92	79.72	-0.7%	5.6%
Sep	79.72	79.59-82.01	80.80	1.4%	7.0%
Oct	80.80	79.90-82.34	81.12	0.4%	7.4%
Nov	81.12	78.15-81.12	79.34	-2.2%	5.1%
Dec	79.34	77.49-79.85	78.67	-0.8%	4.2%

Table 2.future Indian currency value

VII. BACKGROUND OF THEPROPOSED MODEL

The cash esteem expectation model is more exact than other current models, and my venture is one of a kind in that I planned a Graphical User Interface (GUI) where we can include Train Data, Test Data, and get the model's outcome along with a chart of future days expected trade values. In my project, I built a result graph that includes the Future 365days Predicted Close Exchange Prices. In my app, the user may obtain forecasted exchange currency values for the next 365 days. In addition, a USD-INR dataset is incorporated in the model.



VIII. BENEFIT OF THE MODEL

The key benefit is that the model's forecast of currency value will be more accurate because it incorporates RNN, LSTM, Machine Learning, and Deep Learning models. On addition, the algorithm can forecast future stock prices for the next 30 days and display them in a graph. The model may also provide an average currency value for each month in 2023, which is a key function.

IX. CONCLUSION

There are various methods for forecasting currency value at the moment, however they are less accurate. We suggested a more accurate model that employs RNN and LSTM to forecast the trend in currency prices. In the buried layer of the network, LSTM adds the memory cell, a computational unit that substitutes typical artificial neurons. The accuracy of prediction is improved in this study by increasing the Epochs and batch size. The suggested technique is capable of tracing and predicting currency value predictions, and it will produce more accurate and reliable results. We are receiving accurate findings with our above model, which will be more valuable to currency value experts, business analysts, and stock market investors. We use a test in the proposed technique.

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