Journal of Information Systems and Informatics
Vol. 5, No. 4, December 2023 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v5i4.606 Published By DRPM-UBD

Prediction of Forex Prices on USD/NGN Using Deep Learning (LSTM and GRU) Techniques

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Abstract

The goal of the project is to develop a model to forecast the Foreign Exchange (FOREX) prices of United State Dollar to Nigerian Naira (USD/NGN), utilizing two machine learning algorithms, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These were chosen for this study because they have been found to be effective in previous studies that have been examined. The principles of machine learning and its applications, as well as the many machine learning techniques and algorithms will be covered in this study. Additionally, various extraction methods that will be used in the study will be presented. Data from the Investing.com dataset would be retrieved for this study's purpose and divided into training and test sets. Using the two machine learning techniques previously mentioned, the model would be trained and tested. Then, to measure the model's performance in terms of accuracy and precision, Mean Squared Error, Root Mean Squared Error, and Mean Absolute Error would be utilized. The results obtained showed that, GRU performed better than LSTM with a 0.950 Test R2 score and an adjusted R2 score of 0.122. The RMSE is way lower than LSTMs at 0.105 and MAE is even lower at 0.950.

Keywords: Forex, Deep Learning, Long Short-Term Memory, Gated Recurrent Unit.

1. INTRODUCTION

Barter trade was one of the most common ways of exchanging goods in the early cultures. A certain amount of goods is exchanged for a certain amount of another, and small tribes can only use this technique. As human societies grow, so does the need to exchange goods for money. Cash was a common item in these cities. In the Middle East, for example, barley was used as cash. In America, pearls were used as payment. In Herodotus' (440 BC) history, the Lydians were said to be the first to use silver coins [1]. As banks grew as a business, so did bank earnings as money. Most of Europe was on the gold standard from the 17th to the 19th centuries. The gold standard was a set and stable value for paper money in relation

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

to gold. After World War II, most countries agreed to use fiat backed by US dollars as it was the only stable currency with a value other than gold. In 1971, the United States unilaterally ended the Bretton Woods Treaty while Richard Nixon (1969 to 1974) was President of the United States. Since then, fiat money has replaced every other form of money. Global trade using many currencies has grown after World War II, and especially after the technology revolution. A country's currency, as we know it, refers to its entire monetary system. Because it is often used in a particular country, people began buying or selling currencies with the aim of exchanging them for another currency because of its intrinsic value or absolute value. All of these ideas contributed to the growth of the foreign exchange market (FX or currency market) [2].

The FOREX market is one of the biggest and most fluid marketplaces for traders and investors. It is an asset that can be exchanged for money (for example, currencies, stocks, bonds, and so on) [1]. The BOT (Bureau of International Settlement) estimates that the average daily volume on the foreign exchange market in April 2016 was $5.1 trillion. [2] An investor can buy or sell foreign currencies for this purpose using the underlying currency. The main commercial hubs are London (LME) and New York (NY), but there are other important hubs such as Tokyo (TYO), Hong Kong (HONG KONG), and Singapore. The participating banks are located all over the world.

Governments, Banks, Investors, and Traders would rather not trade or sell currencies randomly due to the difficulties mentioned above. They would consider the analysis and forecasts for the short and long-term volatility of the target currencies. They monitor several factors that affect market development. When prices are going up, they try to "buy low" and "sell high." An investor buys a currency in the expectation that it will appreciate over time. Because of the digital nature of the market, a single change in any single determining factor, like a government decision, can cause prices to move up or down in seconds [3]. A single government move, the addition of a new element of influence, or an abrupt change in pricing can all significantly affect the market. The history of the exchange rate data does not provide any information that can help participants or investors accurately predict the exchange rate in the long run. In addition, forecasting exchange rates is sometimes said to be pointless. It is widely believed that the exchange rate market is an efficient market [4].

The majority of dollar exchange rates already agree with Mussa's claim that forex is unpredictable and like a game of luck. However, this is not the only problem. Companies, investors, banks and almost all other entities that employ specialists, analysts and forecasters will include their predictions in their evaluations. Unless there's a dramatic change in the market, historical statistics can predict a market's slow growth or decline. Forex traders tend to benefit from forecasting, but it also depends on the accuracy of the prediction models because market movement is

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

dependent on experts' opinions [5]. Even though most market changes are repeatable patterns that have been repeated in the past, and even though they're happening fast, it's logical to be prepared for similar changes, even if historical data can provide that kind of knowledge. After some time, robotics, machine learning and artificial intelligence came into being. Many machine learning models were evaluated for forecasting Forex, and most of them provided accurate results, according to Mark. Regression was used in this study. The aim of the study is to predict forex prices of USD/NGN using Deep Learning algorithms such as Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM). The top forecast model will be selected after testing and comparing the two forecast models. The models used in the study are LSTM (Long Short-Term Memory) and GRU (Long-Term Recurrent Units) [6]. The five qualities and attributes that will be used from the datasets include: Open: Close; High: Low; Volume.

[46] created a forex prediction model that forecasts precise trading tactics with proper risk management; the most optimal model for EUR/GBP data at 15-minute timeframe. The study only used experimental data with 15-minute intervals without comparing them to longer time intervals. [47] made a model used to make predictions which uses two models, namely ANN and ANN-GA. One evaluation metric was used in Conducting evaluations, namely with RMSE which might not give out an accurate result in terms of prediction of forex prices. [48] With 80:20 data sharing, the best results were found in SGD/ USD. Here also, only RMSE was used in evaluating the models used.

This study will use higher timeframes like the 1day and 4-hour timeframe in predicting forex prices. And also, more evaluation metrics will be used, such as: RMSE, MAE and Adjusted R-squared. This research would further help in the prediction of forex prices over longer time intervals, which is deemed to be more accurate in predictions due to the fact that noises from prices on lower timeframes are greatly reduced. Also, the forex pair picked was just USDNGN, which would also help in increasing the accuracy of predictions because the model would be trained in order to forecast prices of just a single pair, USDNGN. Proper training and testing of the model could easily be carried out compared to models that are trained for multiple pairs, using multiple datasets, hence decreasing accuracy.

There are a few improvements left, like trying different combinations of hyperparameters in LSTM and GRU for improving the performance, you can use the Bi-directional LSTM algorithm and check whether it can be better than GRU and, and you can also use vanilla RNN and compare its performance with other algorithms for prediction of the foreign exchange rate.

Lastly, as we know, the foreign exchange rate stems on different factors like Balance of Payment of the country, Government debt, inflation, interest rates, current economic condition like recession, depression or boom, current political

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condition, etc. So, 09i86 we can use these in addition to the model which can be passed as input of the model for prediction of the foreign exchange rate in order to make more accurate predictions.

2. METHODS

Figure 1 is the proposed process of research design architecture.

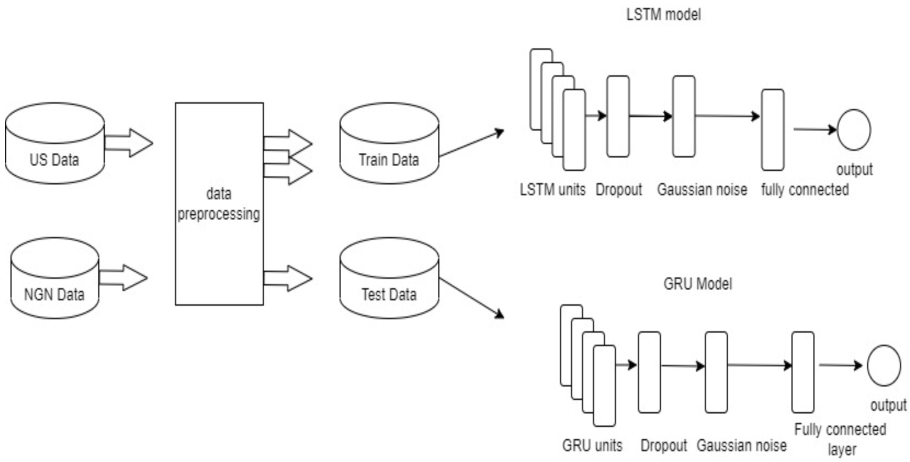

Figure 1. Proposed System Architecture

Figure 1 above shows a diagrammatic illustration of the proposed architecture of the model which will be used in the prediction of the forex prices. Firstly, the datasets of USDNGN will be collected, but before it can be used, it must undergo data preprocessing such as: data cleaning, filtering and data transformation. The data will further be split into training data and test data. The training data will be eighty percent (80 %), while the testing data will be twenty percent (20%). The training data will be passed to the LSTM units while the test data will be passed to the GRU units and conversely repeated. The LSTM unit is composed of a cell, and input gate and a forget gate. The LSTM units regulate the flow of data into and out of the cell. While the GRU units is also a gating mechanism used to control the flow of data into the model. The dropout is a method of regularization, where the input and recurrent connections to LSTM are removed from weight updates while training a model. It is used to reduce overfitting, which also increases model performance. The Gaussian noise is present in both the LSTM and GRU algorithm. It is a technique in deep learning which entails adding more weight and randomness to input data so as to represent many systems or scenarios that the model could be used on thereby increasing the robustness of model against the measurement of noise and its effects. Lastly, the fully connected layer is used to map output of LSTM layer into any desired output size.

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LSTM and GRU will be used in this research because they are more suitable for regression, which involves investigating the relationship between independent and dependent variables or outcome. It is used as a method for predictive modelling in machine learning in which an algorithm is used to predict continuous outcomes. And also, LSTM and GRU have proven to be accurate and successful algorithms in time series prediction.

2.1 Data Collection

The dataset was gotten from investing.com. Only dataset of US dollars and NGN (Nigerian naira) was gotten. Each data set is made up of five parameters: date and time, open price, high price, low price, and close price. The files have OHLC time series data at one-minute intervals every 24 hours.

2.2. Data Preprocessing

The dataset consisted of a large number of datasets and also included data from the 1-minute window. These calculations and data fusion were carried out after the transition of one OHLC dataset to a 10 minute or 30-minute datasets. These are:

a. Date and Time: There is a time lag of between 10 and 30 minutes between each instance of the data.
b. Open price: The open price at the start of the calculation for the 10-minute dataset for the first minute of the 10-minute time interval and the first minute of the 30-minute time period.
c. High price: The cost for each dataset that is incurred over the last ten to thirty minutes.
d. Low cost: The cost for each dataset that is realized between these 10 and 30 minutes at the lowest possible rate.
e. Close price: For the 10- and 30-minute datasets, this is the closing price of the final minute of the corresponding time durations (10 and 30 minutes). Examples of these attributes are hour, day, week, momentum, average price, range, and OHLC price. The computations for the attributes using the original dataset are listed below.
f.

Comparing the open and close prices yields the following results:

a. Opening and closing prices
b. The formula for average cost is (Low cost + High cost) / 2.
c. From high to low in price
d. The OHLC price is calculated using the formula (Open price + High price + Low price + Close price)/4.

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2.3 Models

The LSTM and GRU deep learning models were used in this research.

2.3.1 LSTM

Recurrent neural networks (RNNs) are a type of neural network commonly used in deep learning. However, the gradient vanishing problem (also known as gradient exploding) makes it very difficult to train conventional RNNs to handle long-term dependencies [4]. It was further developed by Gers et al. [5] and by Schmid and Huber [6]. The most basic part of the LSTM design is the LSTM unit. A LSTM unit consists of a collection of gates and cells working together to achieve a desired result. The forward pass of a LSTM unit is modeled in equations.

$$f\,t = \sigma\,(Wf\,.xt + Uf\,.h\,t\text{-}1 + bf\,) \tag{1}$$

$$i\,t = \sigma(Wi\,xt + Ui\,h\,t\text{-}1 + bi) \tag{2}$$

$$ct = tanh(W\,c\,xt + Uc\,h\,t\text{-}1 + bc) \tag{3}$$

$$ct = f\,t * ct\text{-}1 + it * \tilde{}ct\,, \tag{4}$$

$$o\,t = \sigma\,(W\,o\,xt + Uo\,h\,t\text{-}1 + bo) \tag{5}$$

$$h\,t = o\,t * tanh(ct\,), \tag{6}$$

Let's say we have the following equations: forget gate, input gate, input gate activation, output gate activation, cell input activation, cell state, HSTM output vector, biases vector, and HADAMARD product symbol. We'll start with cell state (ct), which has two types of data: old information (e.g., throw completely, keep completely) and new information (i, t, and ct) calculated using forget gate (2, 3). We'll then multiply the output value by 2. Finally, we'll use (5) to calculate a potential value, which will be based on the information in cell state (6). The cell state is the final calculation, so the LSTM works best when the information needs to be stored and used in the long run. Language modeling is a great example of this. The way the verb is formed in the middle and at the end of a phrase depends on what the subject is at the start.

2.3.2 Gated Recurrent Unit

Gated Recurrence Units (GRUs) were created in 2014 by Cho et al. to solve the issue of vanishing gradient in traditional recurrent networks. Just like LSTM, GRU uses information from the last state to get the range of values for intermediate

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gates, which then picks the output value. Eqs (7) to (10) describe the forward pass for a GRU unit.

$$zt = \sigma\, (W\, z\, .xt + Uz\, .h\; t\text{-}1 + bz\,) \tag{7}$$

$$rt = \sigma\, (Wr\, xt + Ur\, h\; t\text{-}1 + br \tag{8}$$

$$ht = tanh(W\, h\, xt + Uh(rt * h\; t\text{-}1) + bh), \tag{9}$$

$$h\; t = (1 - zt\,) * ht\text{-}1 + zt * h\; t \tag{10}$$

The activation vector for the update gate is zt, and the activation vector for the reset gate is rt. The output vector for the GRU is ht. The weights W and U are used, and the bias vector b is used. The Hadamard product is also used. Just like LSTM, we learn the weights and biases during training. Let's take a closer look at the equations to get a better understanding of how a GRU works. First, we calculate the first update gate using xt, the output of the previous h t 1 unit, and the activation function of the sigmoid. The reset gate works the same as the update gate, but it uses its own weights and biases. It also factors in the calculation of the candidate value, deciding how much information should be kept from the previous state. In fact, Eq. 9 shows that only the input value is taken into account when calculating candidate values. At the end, the output value is determined by comparing the new candidate output with the previous output. This is done using the update gate zt (where zt = 1 creates a new output no matter what the old output was, and zt = 0 copies the previous output). There are some similarities between the two, since both LSTMs and GRUs use some sort of intermediate gating mechanism, which is then used later to calculate the output value. When it comes to sequential data, the LSTM is usually stronger and more efficient. For example, Chung et al. (10) showed that GRU outperformed LSTM in many tasks, and Chen L. (11) found that GRU was better at many tasks than LSTM, except for language modeling. Shewalar et al. (12) found that LSTM was better at the voice recognition test than GRU, but they admit that GRU is faster. Faster optimization is one of the advantages of GRU over LSTM because it has fewer parameters.

2.4 Model Validation

The Mean Squared Error, RMSE, and Mean Absolute Error (MAE) metrics were used to measure how well our system is performing. The error of each data point is squared in MAE and RMSE before determining the average, so these two metrics give the higher error more weight. MAE can be really helpful when a big error is really bad, like it is for predicting forex on the other hand, MAE is not as tolerant of outliers. But it's better to measure performance using continuous data,

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which is what we're doing here. When these matrices go down, the model does better. R squared (R2) on the other hand, is a measure of how well a model fits the dataset. It can range from 0 to 1. A value of 0 means the model doesn't match the input data, while a value of 1 means it does well. Another important R2 interpretation that's used a lot in the financial industry is R2. Investors use this to evaluate their current and future investments. A value of R2 of 1 means the movement of the benchmark fully accounts for the movement in the underlying financial instrument (in this case the FOREX price). On the other hand, a score of 0 means the benchmark doesn't support the movement in the asset.

3. EXPERIMENTAL RESULTS

3.1 LSTM

The result after fitting the LSTM model is shown below:

Table 1. LSTM performance after fitting

	Train set	Test set
R2	0.958	0.974
MAE	0.180	0.974
RMSE	0.204	0.110
Adjusted R2	0.958	0.234

The Test R2 score of 0.974 is lower than the GRU's R2 score and the adjusted R2 score is also lower than 0.322. The RMSE of the test is 0.105, while the test MAE is 0.974.

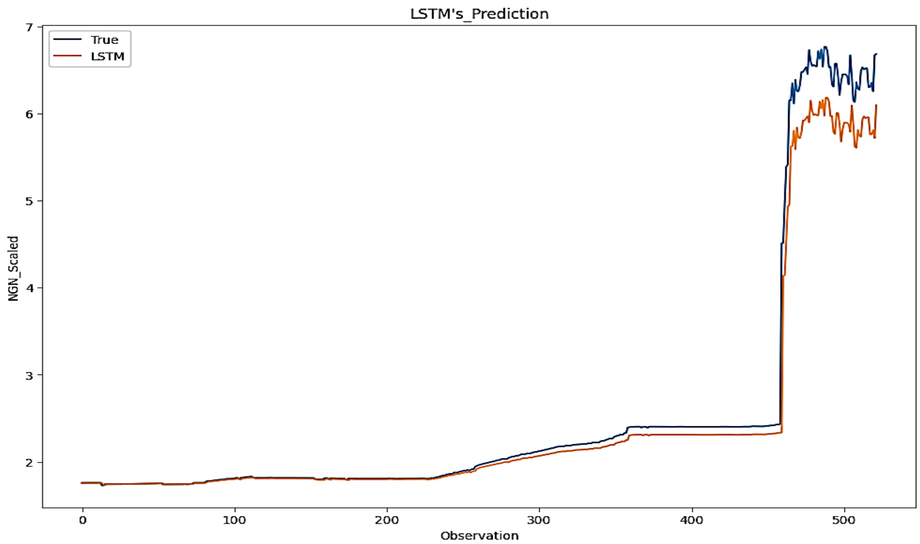

Figure 2. LSTM Prediction

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The graph above shows how good the LSTM is for the first observations. We'll then make a GRU model to see if it can beat the LSTM.

3.2 GRU

The result after fitting the GRU model is shown below:

Table 2. GRU performance after fitting

Performance metrics	Train set	Test set
R2	0.950	0.989
MAE	0.085	0.950
RMSE	0.104	0.105
Adjusted R2	0.989	0.122

The GRU is doing really well compared to LSTM - it's got a 0.950 Test R2 score and an adjusted R2 score, which is way better than LSTM. The RMSE is way lower than LSTM's, at 0.105, and the MAE is even lower, at 0.950. In a nutshell, the GRU did way better than LSTM networks when it comes to predicting currency rates.

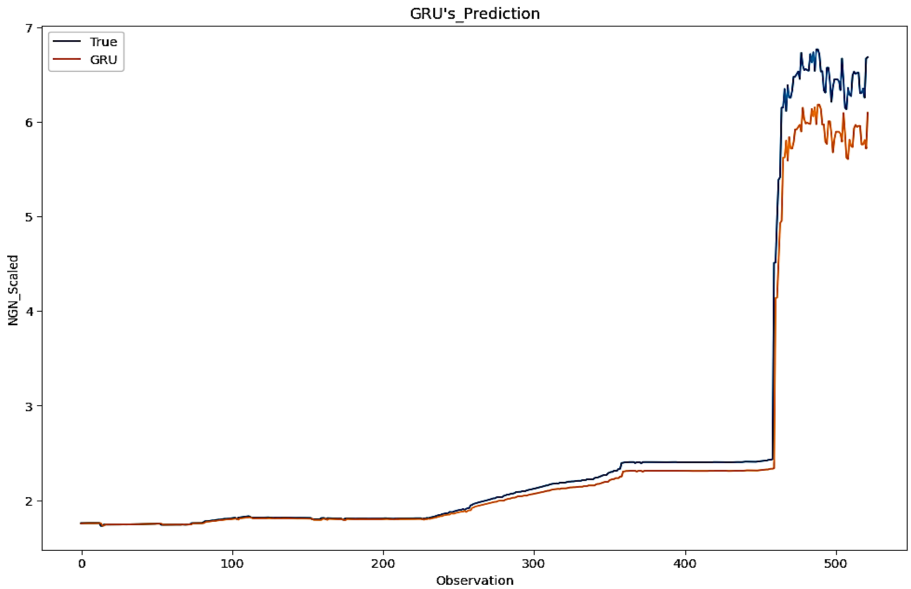

Figure 3. GRU Prediction

GRU is a good choice for predicting foreign exchange rates, since it's pretty accurate. After 400 observations, the difference between its forecast and the actual price is much smaller than the difference between LSTM and GRU. We also did an inverse transformation of the predicted and actual values, since we adjusted the actual values when normalizing.

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3.3 Discussion

After inverting the predicted and actual numbers, which are shown in the chart below, we're now building a data frame for the pandas, which includes the date, the actual price, the predicted price, and the RMSE. We did this to make a comparison of the expected and the actual numbers. The stats for the data frame are summarized in the chart below.

Table 3. GRU performance

	Price	GRU Prediction	RMSE
Count	499.000000	499.000000	16.000000
Mean	469.716092	476.889160	0.069021
Std	111.297434	131.599274	0.059742
Min	408.760000	408.757263	0.053874
25%	414.630000	414.503387	0.053874
50%	421.080000	420.528687	0.053874
75%	459.940000	460.610229	0.054139
Max	791.820000	870.665771	0.293047

The GRU model performed better at predicting forex prices, since it has a really close relationship between the actual price and the GRU prediction price. You can use it to see price trends and decide if it's worth buying or selling a currency at a certain point in the future, since the predicted prices have usually been pretty close to the real ones. We've also plotted the prediction result of the dataframe with dates on the x axis.

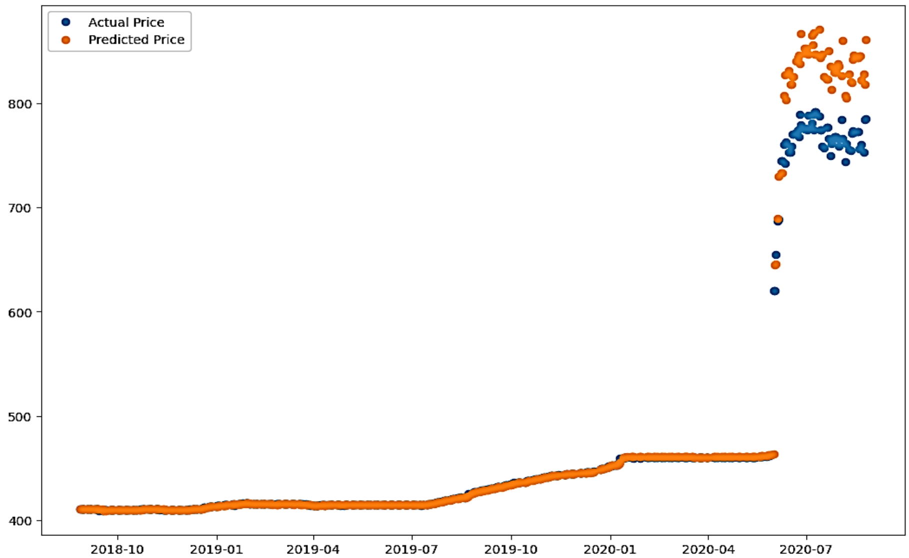

Figure 3. GRU Plotted Prediction

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4. CONCLUSION

In this research, forex market data was analyzed from the past 10 years. After necessary preprocessing, we used the LSTM as our base model, and further applied GRU. The results of the two models were compared and GRU is predicted the best compared to LSTM with a 0.950 Test R2 score and an adjusted R2 score of 0.122, which is way better than LSTM. The RMSE is way lower than LSTM's, at 0.105, and the MAE is even lower, at 0.950. In a nutshell, the GRU did way better than LSTM networks when it comes to predicting currency rates.

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