AN EXPERT ADVISOR FOR THE FOREIGN EXCHANGE MARKET USING GATED RECURRENT UNIT(GRU)

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Dedication

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Abstract

A critical element of any financial decision making system is assessing the link between the nature of the stock market and the economy of a nation. Automated algorithmic trading systems, such as autobot, black boxes, and expert advisors, have evolved as institutional solutions in recent times. To demonstrate the effectiveness of these methods there has not been evidence or research to suffice. This dissertation outlines the stages involved in developing an Expert Advisor that uses a powerful neural network (GRU) used for time series prediction. It employs concepts in neural networks combined with the Bollinger Band and Stochastic RSI to buy and sell currency pairs based on the price fluctuations. As per the evaluations of this model , it uses the US Dollar and Canadian Dollar exchange rates as inputs and this technique is demonstrated to be beneficial and a minimum risk strategy.

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Acronyms

GRU - Gated Recurrent Unit

RSI - Relative Strength Index

FX - Foreign Exchange

OTC - Over the counter

LSTM - Long short term memor

SVM - Support vector machine

BPNN - Back propagation neural network

RNN - Recurrent Neural Network

OHLC - Open High Low Close

AI - Artificial Intelligence

GPU - Graphics processing unit

Introduction

The foreign exchange market is a decentralised or over-the-counter market that operates 24 hours a day globally for trading currencies. According to the 2019 Triennial Central Bank of Survey of FX and OTC derivatives markets the foreign exchange market is the world's largest market in terms of trade volume with a daily volume of 6.6 trillion and the most important method for a country's economy to grow. The monetary , credit , exchange and capital markets all contribute to it. It combines all exchange transactions and is shaped by a lot of various influences like inflation rates , interest rates , politics and financial crisis. This form of intervention offers a dynamic aspect to this market making it uncertain because of its volatility (which leads to profit loss) [Lund et al. 2012]. Trading takes place according to the four primary time zones : Australian , Asian , European and North American each of which has its own opening and closing hours. To have an impact on currency rates significant sum of money is required thus making it secure from scammers. Over the previous few decades forecasting the Forex market have been of huge interest to investors. Throughout the decision making process traders can adopt a variety of trading profiles (for example , fundamentalist, technical or momentum). A company's financial health is vitally significant for fundamentalists and technical analyst evaluates past price movements and attempts to find patterns in future price fluctuations [Lam 2004]. Algorithms based on neural networks have emerged to be the most effective for time series prediction. Many systems use various variants of neural networks for time series prediction because of its capacity to recall each and every piece of data throughout time as well as better forecasting accuracy employing the system's prior inputs. GRU is a reworked version of LSTM but the operation is pretty much identical. GRU employs considerably fewer parameters and hence needs fewer memory and is smoother than LSTM. GRU's train quicker and function better than LSTM on a smaller training dataset. Incase the system requires more input it is possible to easily provide multiple gates thus making it easier to adapt. This inspired us to create an Expert Advisor using GRU. The major goal of this study is to showcase how the Gated Recurrent Unit a powerful time series analyser and a buy/sell logic based on Bollinger Bands and Stoichastic RSI can be put together to forecast Forex currency prices. A model with GRU and a manually backtested buy/sell strategy specifically for this purpose has been created. We used our suggested algorithm to determine the closing price of major currency pairs and we projected the Forex price for the USD/ CAD pair for the 15minute timeframe as a prototype development. The following is a breakdown of this paper's structure : The second section provides the research conducted on various papers related to Forex price prediction using Artificial Neural Networks. Section 3 discusses the theoretical background and the working of the GRU to get a clear picture of how our expert advisor would work. Section 4 explains how our EA works and which strategy was utilised to develop it. The acquired results are then presented in Section 5, which includes a plot of the net profits and the Backtested results of our model. Section 6 concludes with conclusions , recommendations and finally the last section gives a brief discussion of future works that could be conducted.

Literature Review

Unexpected price variations induced by market uncertainties such as political conditions, regulatory policy shifts, changes in the economy, banking activities, and capital flows have made forecasting FX trends difficult. As a result experts have experimented with a variety of subjects in this subject.We examine and evaluate previous research in forex price prediction to determine the direction of our research and the effectiveness of our own model in producing trustworthy and legitimate findings. Artificial Neural Network solutions in the banking and financial sectors first appeared in the late 1980's. A comprehensive assessment of all Neural Network applications in financial markets is beyond the focus of this study. A quick examination of some of the topics is provided, though. In a nutshell, the studies fall into three categories: predicting, trading, and others. In Gerlein E. A. (2016) [1], Empirical approach based on technical indicators, nine features were created from original data (MA, RSI and WR).The efficiency of 6 basic neural network models was evaluated in order to predict a binary classification for price fluctuations (up or down) in the USD/JPY currency pair. Dingili's (2017) [2], research used 70 technical indicators as features extracted from technical analysis. He proposed an SVM to forecast future price trend directions. When it came to anticipating future price movements, the proposed model had an accuracy rate of 81 percent.The moving average is used as the neural network's input in Sharma and Sharma's [3], BPNN model carried out on MATLAB which used the USD/INR pair The dataset from the last 120 days is used to train the model. A total of 11 days' worth of data is used in the test with the goal of predicting the upcoming week's price.A. Baasher 2011 [4], used a neural network architecture to estimate future FX markets by integrating price and technical cues into it. A lot of studies are focused on forecasting. Some, on the other hand, will find it difficult to make trading judgments based on prediction outcomes. Some have discussed the automated trading system requirement. Being profitable by a stock market prediction model is the most essential factor for evaluation and hence we try to develop an expert advisor incorporated with GRU along with a manually backtested strategy of an accuracy of 60 percent for efficient and profitable trading.

Chapter 1

Theoretical Background

1.1 Gated Recurrent Unit

Early 2014 (J. Chung, C. Gulcehre, K. Cho, Y. Bengio, 2014) launched the Gated Recurrent Unit(GRU) which is the most effective recurrent neural network technique. Its primary goal is to solve the vanishing gradient problem that might occur in a regular recurrent neural network. It is deemed a variant of LSTM. Another intriguing feature of .GRU is that it lacks a distinct cell state C_t unlike LSTM and has only one hidden state H_t.Gates are used to control the flow of data. Update gate , reset gate and tank gate are the three layers in GRU. It employs update and reset gate for the vanishing gradient problem while also determining the output. In essence these two vectors determine what data should be sent to the output.They are unique in a way that they can be trained to retain knowledge from the past while not having to wash it away over time or delete information that is unrelated to the forecast.

1.1.1 Architecture

In appearance the GRU cell is comparable to an LSTM or RNN cell. Let us look at how the GRU works now.

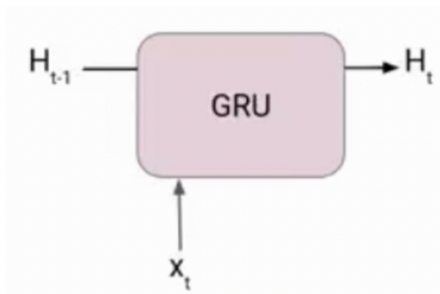

Figure 1.1: Architecture

It takes an input X_t and the hidden state H_{t-1} from the preceding timestamp t-1 at each timestamp t. It then returns a new hidden state H_t, which is sent to the next timestamp once more. In contrast to an LSTM cell, which has three gates, a GRU now has only two gates. The Reset gate is the first, while the Update gate is the second.

Reset Gate(Short term memory)

The network's short term memory is taken charge by the reset gate or hidden state H_t.The difference comes in the weights and the gate's usage.The reset gate aids the model in determining how much knowledge from the past should be forgotten.To determine the reset gate r_t at time-step t the following equation is used

$$r_t = \sigma(X_t * U_r + H_{t-1} * W_r)$$

X_t and H_{t-1} are multiplied by their respective weights and then added together. Because of the sigmoid function the value of rt will range from 0 to 1.

Update Gate(Long term memory)

The update gate assists the model in identifying what information from the previous time-step should be passed on to the next time-step. The equation is as follows,

$$u_t = \sigma(X_t * U_u + H_{t-1} * W_u)$$

X_t and H_{t-1} are multiplied by their weight and combined with each other in the calculation. The result is then transformed between 0 and 1 using sigmoid

1.1.2 Working

Let's have a look at how these gates work now. There is a two-step approach for finding the Hidden state H_t. To create the candidate hidden state is the first stage.

Candidate Hidden State:

$$\hat{H} = tanh(X_t * U_g + (r_t * H_{t-1}) * W_g$$

It delivers all the info to the tanh function after the input and hidden state from the previous timestamp t-1 are multiplied by the reset output gate r_t resulting in the candidate's hidden state as outcome. Crucial element of this formula is determining how the hidden state impacts the candidate state with the use of the reset gate's value. The information from the previous state H_{t-1} is taken into account when the value of r_t is 1 or will be excluded if it is 0.

Hidden State:

To produce the current hidden state the candidate state is utilised after obtaining it. Unlike LSTM we use a single update gate in GRU to manage both historical and fresh data. First term in the equation will disappear if u_t is close to 0 implying information from the prior hidden state will not be there in the new hidden state. The second portion, on the other hand, merges into one, implying that the hidden state at the present timestamp will only contain details from the candidate state.As a result, we deduce that the value of u_t in this formula is crucial varying from 0 to 1.

Chapter 2

Methodology

2.0.1 Design

Obtaining historical data from the forex currency pairs is the first step in the prediction process. The model is then trained, rates are predicted and the win/loss trade ratio are measured to look at the model's accuracy.

2.0.2 System Architecture

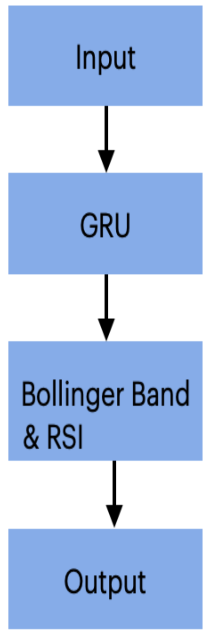

Figure 2.1: System Architecture

2.0.3 Data Collection

Figure 2.2: Data Collection

A historical data website can be used to obtain historical data for the currency pairs. We obtained data for a number of currencies however will be focusing on the USD/CAD currency pair here. From January 1, 2014, to December 31, 2020, we collected 7 years of historical 5minute time series data for our prediction model. The date and time, the high price, the low price, the open price, and the closing price are the five attributes of the dataset. These files contain OHLC (Open-High-Low-Close) time series data for every 5 minutes of the day.

2.0.4 Data Preprocessing

We check if the dataset has missing values and drop them so that we can avoid the error instead of filling them up with zero's because it might affect the model's accuracy. We have taken 10k data points.

2.0.5 Model Design

To begin with we create a GRU model for forex rate forecast using the USD/CAD currency pair. The GRU model is trained and tested with 10K data points.

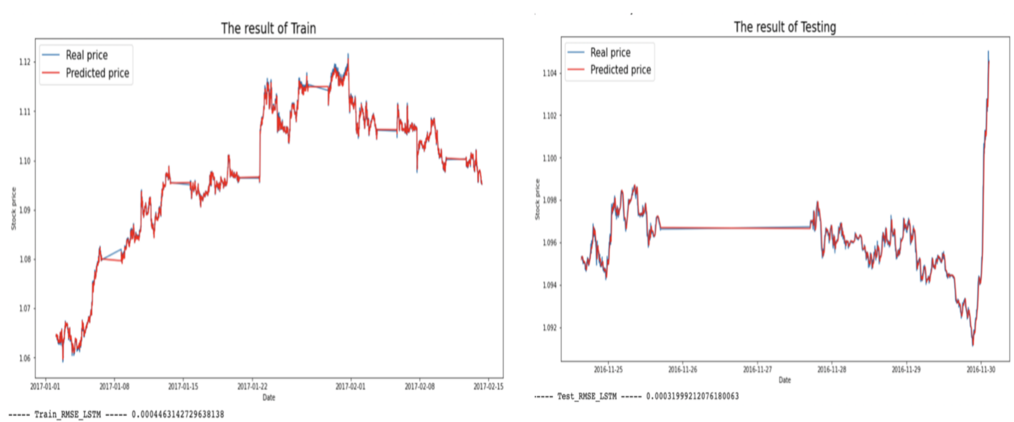

Figure 2.3: Train Test Results

Buy low sell high or sell high buy low is the core concept of profitable trading in the forex market. Our GRU model has four inputs (open ,high, low, close prices) and one output (close price). Here we use a manually backtested technical strategy to yield maximum profit and improve our accuracy rate. After the train and test of our model we setup our api connection for live trading with the FXCM web socket. However here we backtest using historical data. We have basically developed a manually backtested strategy based on the Bollinger Bands and the Stoichastic RSI [12].

Bollinger Bands (John Bollinger) which are a sort of a price envelope are drawn at a standard deviation level above and below the simple moving average. These bands respond to volatility fluctuations since the distance is directly proportional to standard deviation. Period and Standard deviation are the two parameters used.

Stoichastic RSI which ranges from 0 to 1 is a technical indicator calculated by applying the stoichastic oscillator formula to a collection of RSI values rather

than normal price values.
Our strategy works only if both the Bollinger Bands and Stoichastic RSI conditions are met. Here we first check if the candle either closes above or below the upper and lower Bollinger Bands respectively. If it does it returns a true value and our next condition is checked. Further we check if the two signal lines in the stoichastic RSI overlaps above or below the oversold or overbought region , we place a trade. Trades are taken only if both conditions are true.

Chapter 3

Result

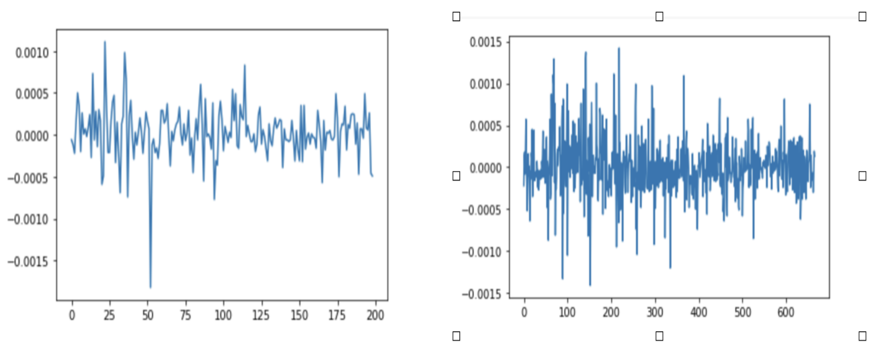

Figure 3.1: Long Short Net Profit Plots

The model was backtested on 10k datapoints and the result was obtained. Both long and short signals generated a positive net profit with a win rate of 44 percent and 52 percent respectively. We have plotted our net profit in the form a plot. The plots show Brownian movement. From which we can infer that even when the movement is random our model works well giving us a net profit however not consistent enough. This points that neural networks that have been optimised using historical data has a high predictive ability and can be further tuned to give consistent and profitable returns.

GRU and Strategy Backtest Result	Long	Short
Win Rate	44	52
Win/Loss	89/110	348/318
Net Profit	0.00523	0.0039599

Table 3.1: Backtest Results

Chapter 4

Future Works

The development of this proposed model is still in a preliminary stage. There are a lot of future enhancements which could be made to make this a very profitable alpha generating model. The major thing we should look at is the data we use to train , training it on a larger data will massively improve its performance. Something else we could do is enhancing our risk to reward ratio and employing the concept of partial profit booking while keeping our risk minimum. Further we could employ the concept of reinforcement learning to the model and analyse if it greatly improves its efficiency.

Chapter 5

Conclusion

Using advanced AI approach this study aims in developing an expert advisor incorporated with GRU along with a personalised buy/sell strategy to automate a profitable strategy and it has almost been successfully attained. While the findings thus far indicate that this blended process of developing a profitable trading strategy looks promising and the only major limitation we have to look at is the training of the model with a huge dataset to improve its performance and accuracy. This could not be achieved due to lack of time and the need for high end GPU's. However our research findings has shown lot of possibilities for further tuning the model's performance and automating trades based on this model. This research led us to the conclusion that automated trading offers promising prospects for the future of financial market activity, particularly in terms of the trader's techniques.

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