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Foreign exchange currency rate prediction using a GRU-LSTM hybrid network

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ABSTRACT

The foreign exchange (FOREX) market is one of the biggest financial markets in the world. More than 5.1 trillion dollars are traded each day in the FOREX market by banks, retail traders, corporations, and individuals. Due to complex, volatile, and high fluctuation, it is quite difficult to guess the price ahead of the actual time. Traders and investors continuously look for new methods to outperform the market and to earn a higher profit. Therefore, researchers around the world are continuously coming up with new forecasting models to successfully predict the nature of this unsettled market. This paper presents a new model that combines two powerful neural networks used for time series prediction: Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM), for predicting the future closing prices of FOREX currencies. The first layer of our proposed model is the GRU layer with 20 hidden neurons and the second layer is the LSTM layer with 256 hidden neurons. We have applied our model on four major currency pairs: EUR/USD, GBP/USD, USD/CAD, and USD/CHF. The prediction is done for 10 minutes timeframe using the data from January 1, 2017 to December 31, 2018, and 30 minutes timeframe using the data from January 1, 2019 to June 30, 2020 as a proof-of-concept. The performance of the model is validated using MSE, RMSE, MAE, and R^2 score. Moreover, we have compared the performance of our model against a standalone LSTM model, a standalone GRU model and simple moving average (SMA) based statistical model where the proposed hybrid GRU-LSTM model outperforms all models for 10-mins timeframe and for 30-mins timeframe provides the best result for GBP/USD and USD/CAD currency pairs in terms of MSE, RMSE, and MAE performance metrics. But in terms of R^2 score, our system outperforms all compared models and thus proves itself as the least risky model among all.

1. Introduction

The foreign exchange (FOREX) market is the world's biggest currency exchange market [1]. Traders trade trillions of dollars per day [2]. The FOREX market is very complex, volatile, and often compared with the black box because of the nature of high fluctuation in currency rates [3]. The FOREX market is open 24 hours a day [4], but the trading occurs based on the four major time zones: Australian zone, Asian Zone, European Zone, and the North American Zone [5] where each of these zones has its own opening hours and closing hours. A huge amount of money is needed to make an effect on currency rates, which makes the market safe from scammers [6]. Along with other fields, predicting the FOREX market has been a key interest of researchers over the last few decades. One of the most important mechanisms applied to the market is leverage. As opposed to regular markets such as the stock market, there's no need for the foreign exchange market to have a huge amount of money. In its simplest definition, leverage allows opening positions on any currency pair having only partial capital protection. Such an approach is considerable facilitation for persons with small capital. Moreover, it is also one of the most important features of the FOREX market that attracts small and private investors.

The FOREX market can be predicted using the fundamental analysis and the technical analysis [7]. Fundamental analysis considers many different factors, like the economic and industrial condition of the company and the country as well; where the technical analysis solely predicts the FOREX market based on previous time-series data. Recent years have seen a lot of researchers using fundamental analysis for FOREX prediction [8]. Technical analysis has also been used in a lot of researches in recent years [9–11]. Researchers used different types of approaches previously for predicting FOREX currency rates [12]. Among these ap-

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proaches, methods based on neural networks have proven to be one of the best reliable algorithms for time series prediction. Not only are reliable, but they also adapt according to the situation and provides a good result [13–15].

Nowadays most of the systems are using different implementations of RNN (Recurrent Neural Network) for time series prediction because of its capability to remember each and every information through time and also for improved prediction ability using the previous inputs of the system. LSTM has proven to be the most accurate and successful algorithm in time series prediction closely following by GRU [16]. GRU is a revised version of LSTM but the working procedure is quite similar. GRU requires less memory as it uses less training parameters thus its faster than LSTM. Though LSTM is a bit of time-consuming, it is more accurate as it uses longer sequences. This motivated us to build a hybrid model based on two of the most promising neural networks and to combine the power of these two models into a single one.

The main aim of this research is to demonstrate the combined power of two of the most powerful time-series analyzers: Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM), to predict FOREX currency price. For this purpose, we have developed a hybrid model that has a GRU at the front layer and LSTM at the back. We applied our proposed model to predict the closing price of four major FOREX currency pairs: EUR/USD, GBP/USD, USD/CAD, and USD/CHF. As a proof of our concept, we have predicted the FOREX price for 10 minutes and 30 minutes before the actual time. Although many researches have been conducted to predict foreign exchange currency in the past, but still researchers are trying to come up with new models to predict the nature of this market. While there are many machine learning and deep learning approaches used in finance, there is a constant competition where traders look for new techniques to outperform the market. This makes the novel approaches more demanding as their uniqueness helps traders to meet their desire in a particular way.

The rest of the article is organized as follows. Section 2 presents the related works in recent years, Section 3 briefly discusses about the GRU and LSTM models, Section 4 explains our proposed methodology. Section 5 discusses the results of our model and compares the model against other models. Finally, Section 6 concludes the present study and also discusses future research direction.

2. Related works

Previous years have seen a lot of different techniques that have been applied to predict the FOREX market. A variety of methods were tested where most of the methods are based on machine learning techniques. Some of these are models include only one processing technique whereas some researchers incorporated a combination of two or more techniques. Recent years have seen a lot of machine learning techniques like regression techniques, decision trees, trading rule methods, fuzzy logic, support vector machine, etc. that have been applied for foreign exchange market prediction. A hybrid model based on the regression technique was developed by Said, Omar, and Aziz who used a combination of regression techniques with the cuckoo search algorithm [17]. Their model was inspired by the autoregressive moving average (ARMA) model and they prepared their dataset with historical data of USD/EUR currency pair. Support vector regression (SVR), multiple linear regression (MLR), CRT regression tree, and partial least squares (PLS) regression methods were used to train their dataset. The weights that were generated by these four algorithms were used as the inputs of the Cuckoo search algorithm. The experiment was done with two years of historical data. Multiple linear regression (MLR) provided better results than SVR, PLS, and CRT. Their model outperformed other regression algorithms [18] [19]. Another hybrid model was developed by Paponpat, Kosin and Nattapol [20] for statistic inspection and prediction that's supported compressed vector autoregression. They used a random compression technique to decrease an outsized number of FOREX data into a reduced form. Then the Bayesian model averaging (BMA) technique was accustomed to the load of every random compressed data to get the intersecting parameters. The currency pairs they used had a high mean squared error due to the predictors used for forecasting were four lagged dependent variables alongside random compression of other forex currency pairs. Their proposed model proved to possess an efficient result for 6 currency pairs: EUR/TRY, CAD/CHF, EUR/DKK, CAD/JPY, EUR/MXN, and AUD/JPY and outperforms the prevailing benchmark of Bayesian Autoregression. A similar approach was employed by other researchers [21,22] for predicting FOREX currencies.

Recent years have also seen many researchers trying to create predictive models that were based on trading rules. Trading rules define a trader's entry, exit, and money management criteria. These rules are necessary for calling a trade successful or poor. Such a rule-based model was proposed by Jia, Yang, Xiao, Changqin, Gansen, and Yong [23] for FOREX online prediction that used the weighted majority (WM) algorithm for selecting experts. It was challenging for them to maintain a good prediction rate when the system does continuous prediction. So, as a solution, they took online website suggestions into account and predicted according to the suggestions. The website was selected based on the result of the average error rate and average earned profits. WM algorithm with adapting empirical risk minimization was used to select a set of suitable experts that have good average profit and less average error. Two sets of experts were evaluated based on the mistake and profit as well as union and intersection. The result analysis showed that the intersection method achieves better accuracy in the 20 days prediction which is 30% higher than the baseline. Many other researchers also performed the prediction using trading rules [24,25].

Decision tree models have also seen some usage but not as widely as other algorithms. Using a decision tree, Juszczuk, Kozak, and Trynda [26] created a model that can generate datasets from real-world FOREX market data. These datasets are then transformed into decision tables which had buy, sell or wait attributes. The CART algorithm and C4.5 algorithm was also used for testing the quality of the classification. They used three currency pairs and three datasets of each currency pair for the system development. They found that most of the data (86-98%) were assigned to the wait class which made it harder to analyze the data. So, they used algorithms for analyzing the result. After analyzing the result of the accuracy of the classification and the size of the decision tree, the CART algorithm provided the best result. This method was also used by Dadabada and Vadlamani [27].

Another popular technique for statistical prediction was the support vector machine (SVM). SVM was implemented in both individual and hybrid systems with prediction capabilities. Thuy and Vuong [28] proposed a model for foreign exchange prediction using SVM. They used the EUR/USD currency pair for their models implementation. They used the cross-validation method for their data-set and divided the results into two categories positive output and negative output. They used accuracy rate, positive, negative, macro averaging, and micro averaging for comparing the performance. Their result showed a big difference (29.5%) between training sets and test sets in the Gaussian RBF method. But only a little difference was found in the polynomial model. According to the result kernel function taken from polynomial provided high performance. They compared the normal transaction method with SVM transactions and found that the profit rate was tripled when using an SVM model. SVM was used by many researchers as well [29,30].

Natural language processing is another subfield that has seen interests from researchers in recent years. Like any other field foreign exchange has also seen natural language processing-based systems that were used to predict the exchange rates. Apart from text-based problems, NLP has surprisingly shown great results in prediction as well [31,32].

One of the favored algorithms that has attracted the researchers are Optimization Techniques. Such a hybrid model that mixes the Jaya optimization technique with extreme learning machines was proposed by Smruti, Debahuti, and Minakhi [33], which is capable of predicting currency exchange rates. They used two currency pairs, USDEUR and

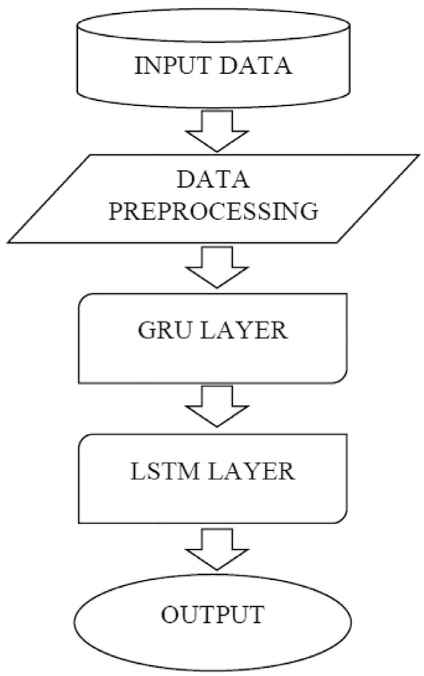

Fig. 1. Simple architecture of our proposed pipeline.

USDINR. They tested their model against other models supported by ELM, NN, and FLANN. They found that between ELM, NN, and FLANN, ELM shows the most effective optimization. Consistent with their evaluation data, for MAPE evaluation ELM DE provides rock bottom error. For MAE, ARV, and Theils U models ELM TLBO, ELM PSO and ELM Jaya provided the most effective result respectively. For FOREX trading strategy optimization, a genetic algorithm was employed by Galeshchuk and Mukherjee [34] to evolve a special set of profitable trading rules inspired from a weighted moving average method. For generating rules, their Genetic algorithm significantly returns above the exhausted search. Another hybrid Machine learning framework was proposed by Smruti, Debahuti, and Minakhi [35]. Their proposed model was matched with the ELM-Jaya and ELM and their model can forecast the currency prices of both exchange rate using technical indicators, statistical measures, and mixing both of them. Other researchers [36] [37] also used optimization techniques as well.

Chaos theory has attracted many researchers in recent years [38]. By employing a new hybrid forecasting approach that involving Chaos theory (Chaos) and multivariate adaptive regression splines (MARS), exchange rates were predicted by Dadabada and Vadlamani [39]. They tested their system with differing types of chaos-based forecasting models for 3 major FOREX currencies: JPY/USD, GBP/USD, EUR/USD, and got the highest accurate predictions for these currencies by Chaos + MARS approach. A chaotic interval type-2 fuzzy neuro-oscilattory network (CIT2-FNON) was proposed by Raymond [40], for worldwide financial prediction. The CIT2-FNON was constructed by a Chaotic discrete-time neural oscillator namely Lee-Oscillator which is transient fuzzy input neurons of the recurrent networks. The Chaotic Type-2 Transient fuzzy logic(CT2TFL) proposed in their model to provides a very Type-2 Fuzzy Logic Systems (T2FLS) with Chaotic transient fuzzy property to resolve the complexity problem. More models [41] [42] were developed using chaos theory to predict FOREX price.

Another popular method was the pattern-based model. Such a model was developed by Erik and Richard [43], who proposed multidimensional string models which may be used for statistic forecasting. They enhanced the 1-endpoint open string model with a 2-endpoints open string model combined with D2-brane. They showed how the statistics of the predictors are often changed by the new object properties and use them to model a spread of time series systems. They used four different currency pairs real demo simulations for evaluating their system. They found that higher efficiency for the string models is often achieved by using longer string lengths. Paponpat and Nattapol [44] proposed a model to predict the forex rate of exchange using dynamic model averaging (DMA) and transformed models of general DMA. They applied this model on 3 currency pairs JPY-USD, EUR-USD, and GBP-USD. 70 percent of the total data is employed for training the model and the rest 30 percent is employed for the evaluation. consistent with the results of their proposed model they found that autoregression with four lags also referred to as AR(4) and time-varying autoregression with four lags, referred to as TVP-AR(4) model gives best USD-JYP prediction result. For EUR-USD data-set parsimonious model provides good results. They assumed that models that use stochastic process which evolves coefficients are best to use for this prediction. They found reliable consistency for DMA and DMS. Similar methods was employed by other researchers also [45,46].

Dadabada and Vadlamani [47] provided an overview of the FOREX rates prediction. They studied and reviewed 82 hybrid systems that were used for currency exchange rate prediction in the duration of 1998 to 2017. They noticed that artificial neural network-based hybrid systems

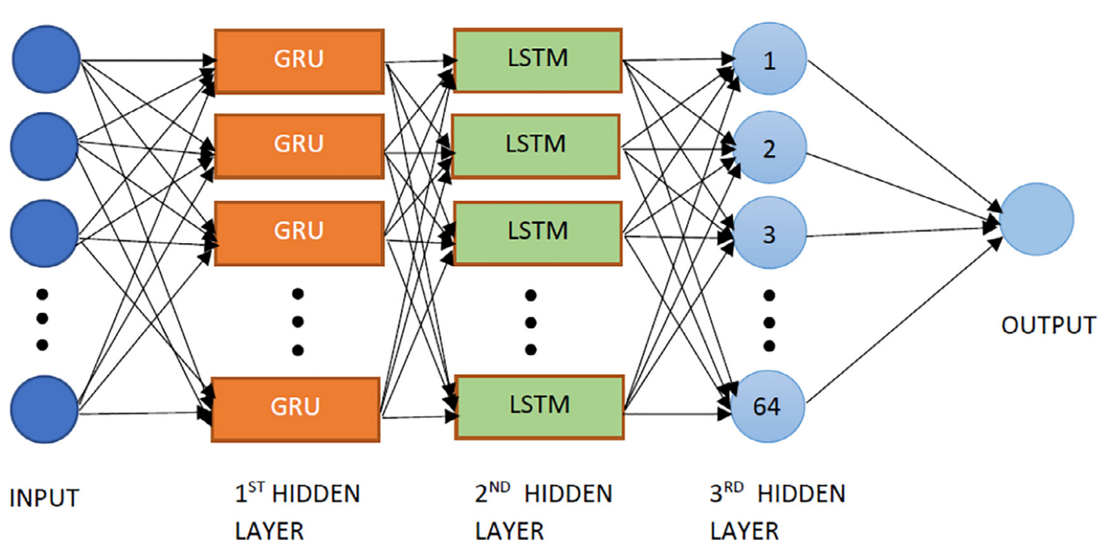

Fig. 2. Internal structure of hidden layers.

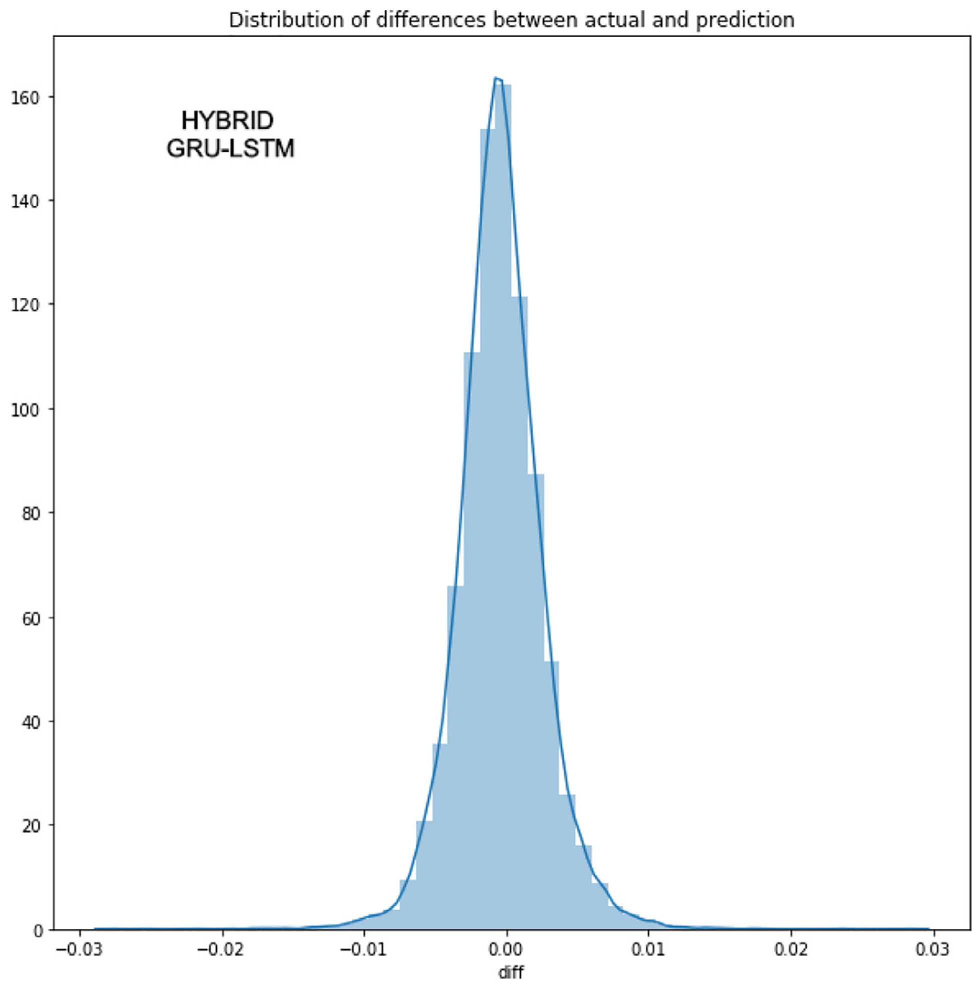

Fig. 3. Distribution of differences between actual and predicted curve for EUR/USD 10-mins timeframe.

provided more stability and accuracy in predicting the rates. The analysis showed that hybrid models performed better than stand-alone models. Hybrid models provided more accuracy and also reduced uncertainty. This also motivates us to use a combination of GRU and LSTM to predict FOREX price. After studying the artificial neural network-based hybrid models, they found that deep learning architecture was the less used algorithm for currency exchange forecasting. Although, recent years has seen plenty of researches based on neural network [48–50]. A new hybrid system C-RNN method was employed by Lina et. al [51] for the prediction of time series of the forex. C-RNN was the mixture of recurrent neural network (RNN) and convolutional neural network (CNN). They used the data-driven technique to look at the changing characteristics of the forex market. The model was compared with algorithms that were based on long short term memory (LSTM) and convolutional neural network (CNN). Using RMSE performance evaluation they found that the proposed C-RNN model provided fewer errors than LSTM and CNN based models. Jacek and Piotr [52] used the neural network and genetic algorithm-based system for forex trading. This model was applied for the EUR/USD closing values. They used other models like: NGD, NGW, MACD, MA and continue to compare with their proposed model. They proposed two different methods one with weight and another with direction. They found that after averaging the 20 total experiments, their weighted version performed best with 111% profit while the direction version showed a 56% profit. Another hybrid model was developed by Rajashree [53] who used the mixture of an improved shuffled frog leaping (ISFL) and computationally efficient functional link artificial neural network (CEFLANN) for prediction. The improved shuffled frog leaping was used for reducing the error rate of the system. She used three different currency pairs USD/CAD, USD/CHF, and USD/JPY for her proposed system. to check the performance of the system, two different algorithms Shuffled frog leaping algorithm and Particle Swarm optimization algorithm were used. The result showed that this proposed model performed better than both of the compared algorithms. For RMSE the error rate for USD/CAD and USD/JPY currency pairs was between 0.04–0.05 and for USD/CHF the range was between 0.03–0.04. Similar approach was also taken by other researchers [54–56]. A performance analysis of various ANN algorithms was done by Svitlana [57]. She used three different currency pairs USD/EUR, JPN/USD, and USD/GBP for her evaluation for the most effective model that would predict exchange rates. She optimized and preprocessed the raw input file to be used with neural network models. For training the model, she used the backpropagation algorithm. She predicted three different stages daily, monthly, and quarterly for all three currency pairs and used a multilayer perceptron with a 5-10-1 structure with one step prediction mode. A deep learning method was employed by Jerzy and Marcin [58] who proposed a system which will forecast financial statistic and which may be used as an agent within the A-Trader system. They analyzed the performance of both neural networks and deep learning methods. They used 4 hidden layers with 78, 64, 87, and 63 neurons respectively for his or her system. For the performance evaluation, MLP agent and B&H benchmark were used. They divided their results into three different periods. For the primary and second periods combined, their proposed system performed better. Sitty, Indrabayu, and Sofyan [59] compared statistical methods against machine learning. They experimented with the open, close, high and low variable. For 1 and 1 to five days prediction ASTAR provided better results for high and close variables where GA-NN provided an im-

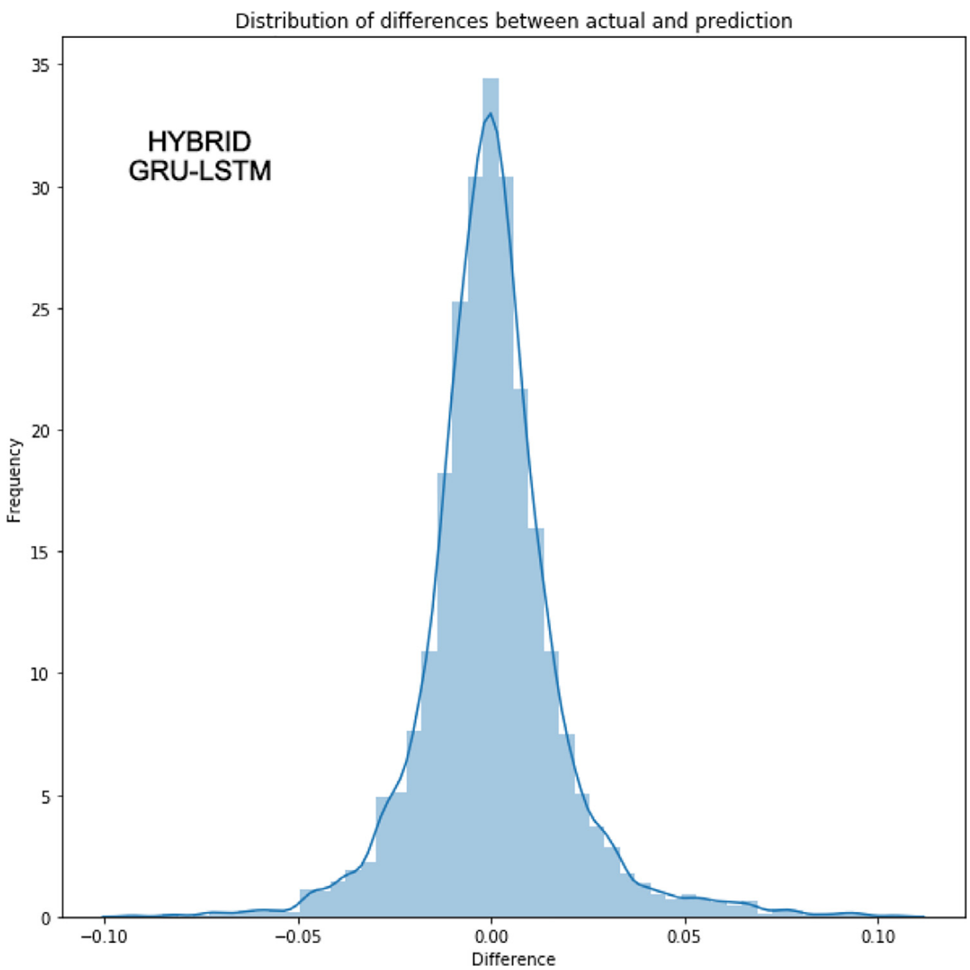

Fig. 4. Distribution of differences between actual and predicted curve for EUR/USD 30-mins timeframe.

proved result for open and low. But for longer-term prediction (whole month) the result changed where GA-NN provided a higher result for open and high and for the remainder ASTAR was better result provider while SVM always provided a mean value of GA-NN and ASTAR. Many other systems supported neural network was implemented in these previous years as well [60,61].

3. An overview of GRU and LSTM

In this section, we have briefly discussed the two powerful variations of Recurrent Neural Network (RNN): GRU and LSTM, which are used in this research. They are more effective and more popular among the researchers especially for time series analysis.

3.1. Gated Recurrent Unit

Gated Recurrent Unit (GRU) was first introduced by Cho et al. [62] in 2014, and has become one of the most promising algorithms of recurrent neural network (RNN). The main task of GRU is to deal with vanishing gradient problem which occurs in a standard recurrent neural network. GRU is considered as a variation of LSTM because both of these algorithms can provide excellent results for some cases. GRU has three sigmoid layers: update gate, reset gate, and tanh layer. GRU uses the update gate and reset gate for vanishing gradient problem and also decides what will be the output.

3.1.1. Update gate

The data processing starts with the update gate. Firstly, the calculation of the update gate zt at timestep t is done by using the following formula:

$zt = \sigma(wz.[h(t-1), xt])$

In the calculation, xt and h(t-1) is multiplied by its weight and is added together. Then a sigmoid activation is used to convert the result between 0 and 1. Update gate helps the model to determine how much of the past information needs to be passed along to the future timestep.

3.1.2. Reset gate

The calculation of the reset gate rt, at timestep t is calculated using the following equation:

$rt = \sigma(wr.[h(t-1), xt])$

Calculation starts with the multiplication of xt and h(t-1) by its weight and is added together. Then a sigmoid activation is used to convert the output between the value 0 and 1. Reset gate helps the model to determine how much of the past information needs to be forgotten.

3.1.3. Current memory content

This is involved with the reset gate. This starts with introducing a new memory content that will use the reset gate and store the relevant information from the past. The mathematical equation is as follows:

$ht = tanh(w.[rt * h(t-1), xt])$. The calculation starts with the multiplication of the input xt with its weight. Then the element-wise multiplication is done to the reset gate rt and the previous output ht-1. This allows to only pass the relevant past information. Then both of the calculated results are added together and a tanh function is applied.

3.1.4. Final memory at current time step

Finally, the unit has to calculate the ht vector which holds information for the current unit and it will pass the information further down to the network. The update gate zt plays a key role in this.

Fig. 5. Actual value vs predicted value curve for EUR/USD 10-mins timeframe.

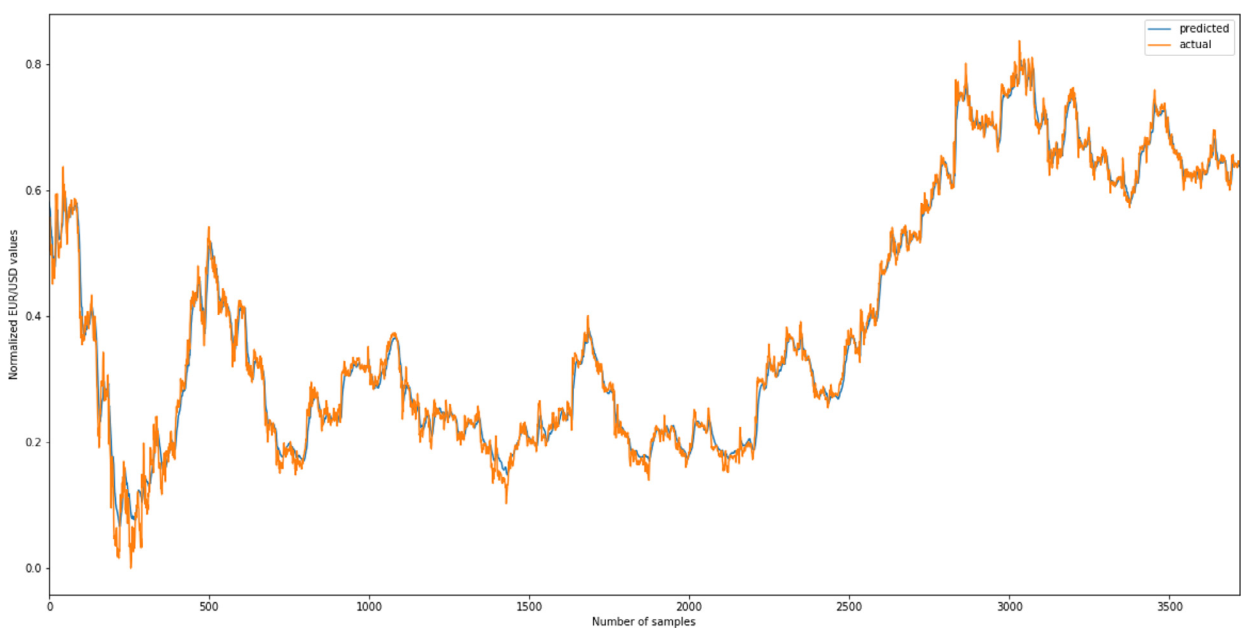

Fig. 6. Actual value vs predicted value curve for EUR/USD 30-mins timeframe.

The mathematical equation for this is: $ht = (1 - zt) * h(t - 1) + (zt * ht)$. From the calculation, if the vector zt is close to 0, a big part of the current content will be ignored since it is irrelevant for the prediction. At the same time, since zt will be close to 0 at this time step, 1-zt will be close to 1, allowing the majority of the past information to be kept.

3.2. Long short term memory

An LSTM is another variation of recurrent neural network which can be trained using an optimization algorithm like gradient descent on a set of the training sequence. LSTM was first introduced by Hochreiter and Schmidhuber [63] in 1997 as an updated version of RNN for addressing the problems like vanishing gradient and later were simplified or refined [64]. The LSTM is combined with backpropagation through time for computing the gradients needed during the process of optimization. This is done to change all the weights of the LSTM network in proportion to the derivation of the error rate concerning the corresponding weight. LSTM is capable of learning long term dependencies. They are capable of remembering for a long period of time using a memory unit. Normal RNN has only one layer (tanh) while an LSTM has four layers. The key component of the LSTM is the cell state. It runs straight down the entire timesteps with only minor but important interactions. LSTM can add or remove information from the cell state using several gates. Each gate is made of a sigmoid neural network layer. These sigmoid layers produce output numbers between 0 and 1, which represents how much information each component should be let through. 0 represents “let nothing through” whereas 1 represents “let everything through”. 3 layers out of the four are used to control the cell state.

The workflow of an LSTM can be described in three steps. First step of an LSTM is to decide which information is to deduct from the cell state. The sigmoid layer which is also known as the “forget gate” makes

Fig. 7. Actual value vs predicted value curve for GBP/USD 10-mins timeframe.

Fig. 8. Actual value vs predicted value curve for GBP/USD 30-mins timeframe.

this decision. It looks at the previous timestep ht-1 and xt, and produces the output between 0 and 1. The mathematical equation of this process is:

$ft = \sigma(wf.[h(t-1), xt] + bf)$

The second step is to decide what new information is going to be stored in the cell state. A sigmoid layer called the "output gate" first decides which values will be updated. Then a tanh layer creates a new vector of candidate values Ct, that could be added to the cell state. The equations of this steps are:

$$it = \sigma(wi.[h(t-1), xt] + bi)$$

$$Ct = tanh(wc.[h(t-1), xt] + bc)$$

Then old cell state Ct-1 needs to be updated into the new cell state Ct. The mathematical equation for this is:

$Ct = ft * (Ct - 1 + it * Ct)$

The final step is to decide what will be the output of the system. The output is based on the cell state but a filtered version of it. First the sigmoid layer decides which parts of the cell state are going to be presented as output. Then the cell state is put through the tanh function to convert the values between -1 and 1. Then it is multiplied with the sigmoid layers output to get only the desired output. Mathematically this is done by using these two equations:

$$ot = \sigma(wo.[h(t-1), xt] + bo)$$

$$ht = ot * tanh(Ct)$$

4. Proposed scheme

The prediction process starts from acquiring the datasets for EUR/USD, GBP/USD, USD/CAD and USD/CHF currency pairs. Then training the system, predicting rates and lastly acquire the performance

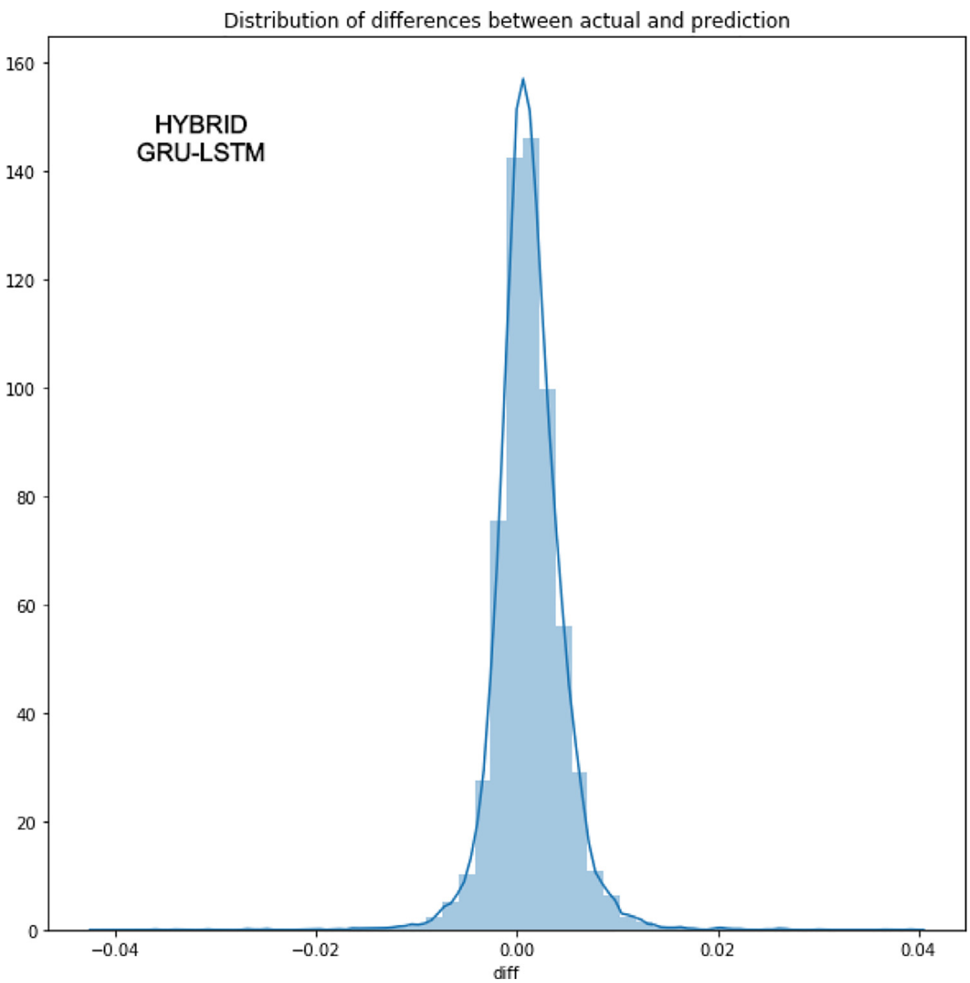

Fig. 9. Distribution of differences between actual and predicted curve for GBP/USD 10-mins timeframe.

of the model using MAE, MSE, RMSE, and R^2 score. Fig. 1 presents the system architecture of our proposed system.

4.1. Data collection

The dataset was collected from Histdata [65] website. Data was collected for four major currency pairs: EUR/USD [66], GBP/USD [67], USD/CAD [68], and USD/CHF [69]. We have collected two years of historical time series data from 1st January, 2017 to 31st December, 2018 for our 10 minutes prediction model and from 1st January, 2019 to 30th June, 2020 for the 30 minutes prediction model. Each dataset contains a total of 5 attributes: *Date and Time, Open price, High price, Low price*, and *Close price*. These datasets contain OHLC (Open-High-Low-Close) time-series data for a 1-minute interval of the entire 24 hours each day.

4.2. Data preprocessing

Each of the collected datasets didn't have any missing values, therefore we didn't have to deal with that. However, the dataset contained the 1 minute interval data values and was huge in size as well. We converted these 1 minute OHLC datasets into 10-mins and 30-mins datasets where we have calculated and combined the data values in the following manner.

- *Date and Time*: 10 minutes and 30 minutes time interval between each instance of the data
- *Open price*: The open price of the first minute of the 10 minutes time interval when the calculation starts for 10 minutes dataset and the first minute of the 30 minutes time interval when the calculation starts for 30 minutes dataset.
- *High price*: The highest price value that is reached between these 10 minutes and 30 minutes for respective datasets.
- *Low price*: The lowest price value that is reached between these 10 minutes and 30 minutes for respective datasets.
- *Close price*: The close price of the last minute of the 10 minutes and 30 minutes time interval when the calculation ends for 10 minutes and 30 minutes datasets respectively

For getting a better relation between the data and for getting a better training result, we have added some additional attributes to our datasets. These attributes are: *Hour, Day, Week, Momentum, Average price, Range,* and *OHLC price*. The attributes are calculated from the original dataset as follows.

- Momentum = Open price – Close price
- Average price = (Low price + High price) / 2
- Range = High price – Low price
- OHLC price = (Open price + High price + Low price + Close price)/4

4.3. Model Design

Our proposed hybrid model is built using four layers, where the first layer contains GRU with 20 hidden neurons and the second layer contains LSTM with 256 hidden neurons. The third layer and fourth layers are dense layers with 64 and 1 hidden neurons respectively. We have trained this model using the 10 minutes and 30 minutes interval data which we have processed from the original 1-minute interval data. The

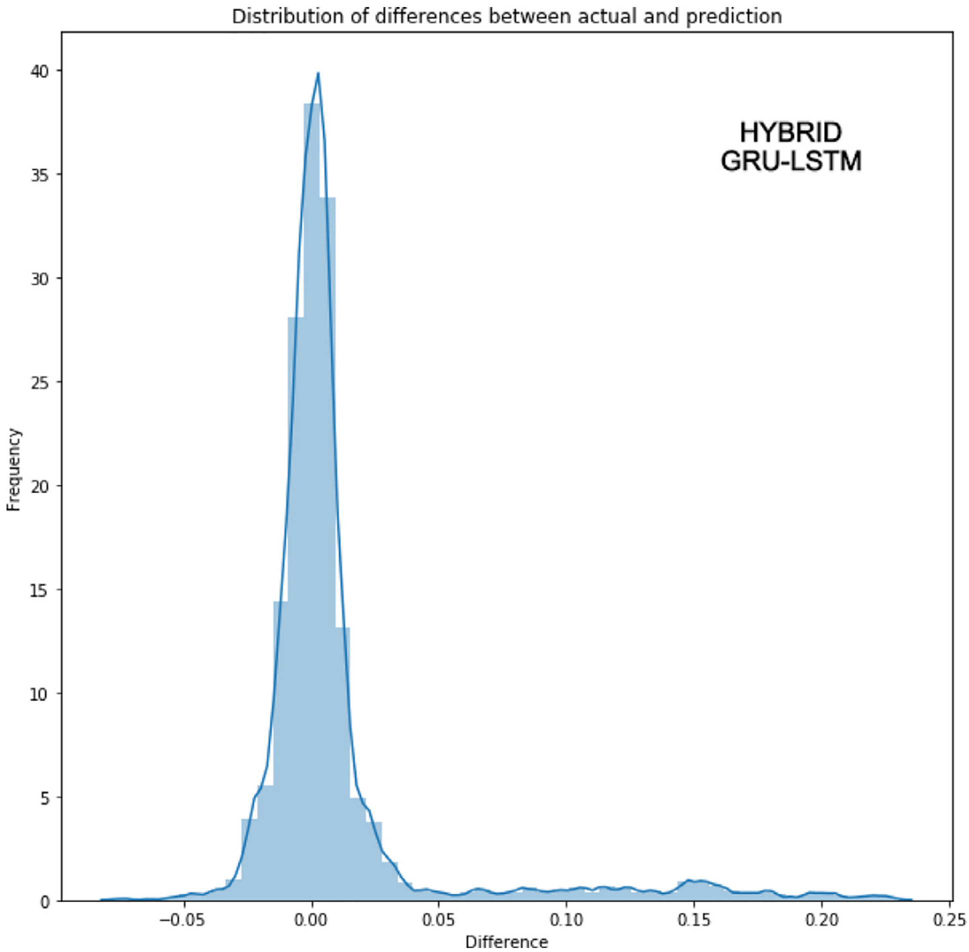

Fig. 10. Distribution of differences between actual and predicted curve for GBP/USD 30-mins timeframe.

percentage of training data and testing data are 80% and 20% respectively. In numbers, training data is approximately slightly larger than 60000 on average for 10 minutes prediction model and approximately slightly larger than 14800 on average for 30 minutes model while testing data is approximately slightly larger than 14000 on average for 10 minutes model and is slightly larger than 3700 on average for 30 minutes prediction model for all currency pairs. Fig. 2 shows the internal structure of different hidden layers in the proposed system.

At first, all the attributes of the dataset is used as the input of the GRU layer. GRU is our first hidden layer. Each GRU neurons collect the data and along the path, a weighted value is generated. Data is then passed from the GRU layer to the LSTM layer which is our second hidden layer. Again a weighted value is generated along the path from the GRU layer to the LSTM layer. Similarly, data is then passed to the Dense layer which is the third hidden layer. A weighted value is generated from LSTM to Dense layer. The dense layer is a normal neural network layer that we have used to produce the output. From the third hidden layer, the data is then passed to the output neuron and weight is generated correspondingly. The output is then compared with the original value to find out the error function. The weighted values are then updated according to the difference of the actual value and predicted value until it reaches the minimum point of the cost function and weights are then saved for future predictions. Based on the saved weighted values, the future predictions for 10 minutes and 30 minutes are done and the system's performance is measured.

4.4. Model validation

Validation is an important step that is used to check the performance of the system by comparing the actual data with predicted data. Here we have used MSE (Mean Squared Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and R-squared (R^2) value for measuring the performance of our system. Among them in MSE and RMSE, the error of each data point is squared before taking the average. This implies that these two metrics puts more weight on the larger error. MSE and RMSE can be very useful when a large error is very much undesirable which is true for FOREX prediction as well. On the other hand, MAE takes the average of absolute error of all data points. MAE is not too sensible to outliers comparing to MSE or RMSE. But it's useful when the performance is measured on continuous data which is also true in our case. The smaller the values these matrices have, the better is the model.

On the other hand, higher values of the R^2 metric, also known as the coefficient of determination, indicates better fitness of the model. R^2 value indicates how good a model fits the dataset. R^2 can have the value between 0 and 1 where 0 implies that the model doesn't fit the given data whereas 1 indicates that the model fits perfectly to the given dataset. There is another important interpretation of R^2 that has been used widely in the finance. R^2 is also used as a risk-adjusted return ratio which helps investors to assess existing and potential investment. R^2 value 1 means that the movement of the financial asset (FOREX price in this case) is perfectly justified by the movement in the benchmarked index. 0, on the other hand, indicates the movement of the asset is not justified at all by the benchmark.

5. Results and discussion

In this section, we validate the performance of our proposed system for the four major currency pairs we have used: EUR/USD, GBP/USD, USD/CAD, and USD/CHF. We have applied our model to predict the

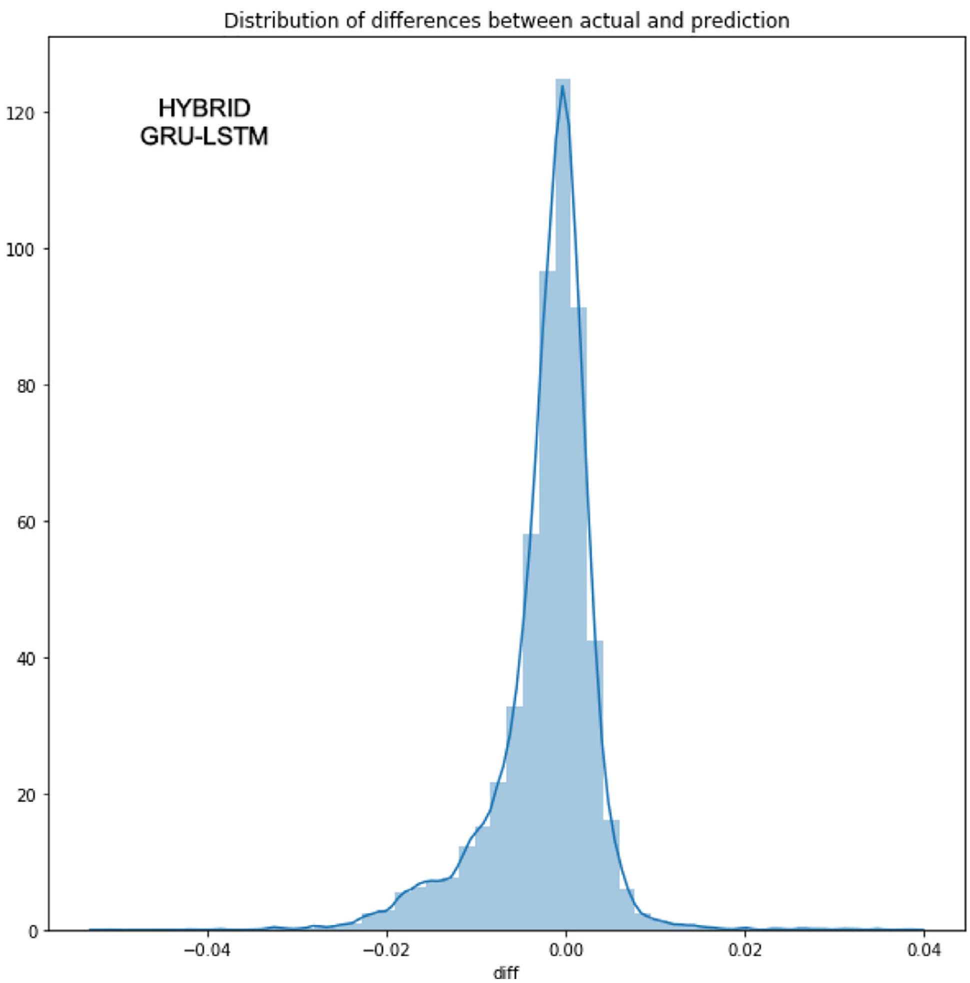

Fig. 11. Distribution of difference between actual and predicted curve for USD/CAD 10-mins timeframe.

closing price of each currency pair before 10 minutes and 30 minutes than the actual time. Also, we have compared our proposed models against a standalone GRU, a standalone LSTM, and a statistical model that is based on the moving average technique.

5.1. Performance evaluation

For each currency pair, our model was trained using the 20-256-64 formation of the hidden layers and was run for 100 times. The prediction was then done on the 20% of the total data. Then the performance was measured using the performance matrices MSE, RMSE, MAE, and R^2 score which compares the difference between actual and predicted values and provided a result between 0 and 1. We chose the performance matrices MSE, RMSE, and MAE to check the error rate our model provides as the quality of any regression model can be understood by its error rate. The R^2 score is chosen for measuring the risk of using our model. To compare the efficacy of our proposed model, we chose standalone GRU model and standalone LSTM model as we wanted to see if our proposed model improves the overall performance and can outperform any of these algorithms as the whole experiment will be meaningless if the system provides same performance or worse than the individual models and its not possible to understand the difference without proper comparison. Another reason for choosing these two models is their performance, which is better than other deep learning approaches [16] in time series prediction. Both of the GRU and LSTM model were trained using the same data- sets, same hidden layer formation and was run 100 times each as our proposed model. Moreover, this proposed model is also compared against a simple statistical model that uses the moving average of the previous 20 days closing price to predict future prices. The following 4 subsections discuss the results of four major currency pairs we have used in this research.

5.1.1. EUR/USD

For the EUR/USD currency pair, we validated the model against 14886 samples for our 10-mins model and 3723 samples for our 30-mins model that is 20% of our total data respectively. The model is trained using the rest of the data. Figs. 3 and 4 present the distribution of differences between actual and predicted curve provided in Figs. 5 and 6, respectively. The x-axis represents the difference between the actual and predicted value and the y-axis represents the frequency of scores for each value.

Figure 5 and 6 show the actual value vs predicted value curve for EUR/USD pair for 10-mins and 30-mins models respectively. Here, the x-axis indicates the number of samples we have used for validation, which in this case is 14886 and 3723 for 10-mins and 30-mins, respectively. The actual closing values of the currency pair are marked by a yellow color, and the model predicted closing values are marked by blue color. The y-axis indicates the unit value of this pair which in this case is the normalized closing price of EUR/USD currency pair. The fluctuation in the curve indicates the ups and downs of the closing prices.

The graphs clearly show how accurate the predictions are: actual and predicted values almost overlap with each other. The MSE, RMSE, and MAE scores of our model for EUR/USD 10-mins pairs are 0.00001, 0.00301, and 0.00224 respectively. For 30-mins pair, the MSE, RMSE, and MAE scores are 0.00032, 0.01790, and 0.01233 respectively. These values also verify the high accuracy of the predictive model for both large and small timeframes. In terms of R^2 score, we got 0.99678 for 10-mins pair and 0.99205 for 30-mins pair. This implies that the pre-

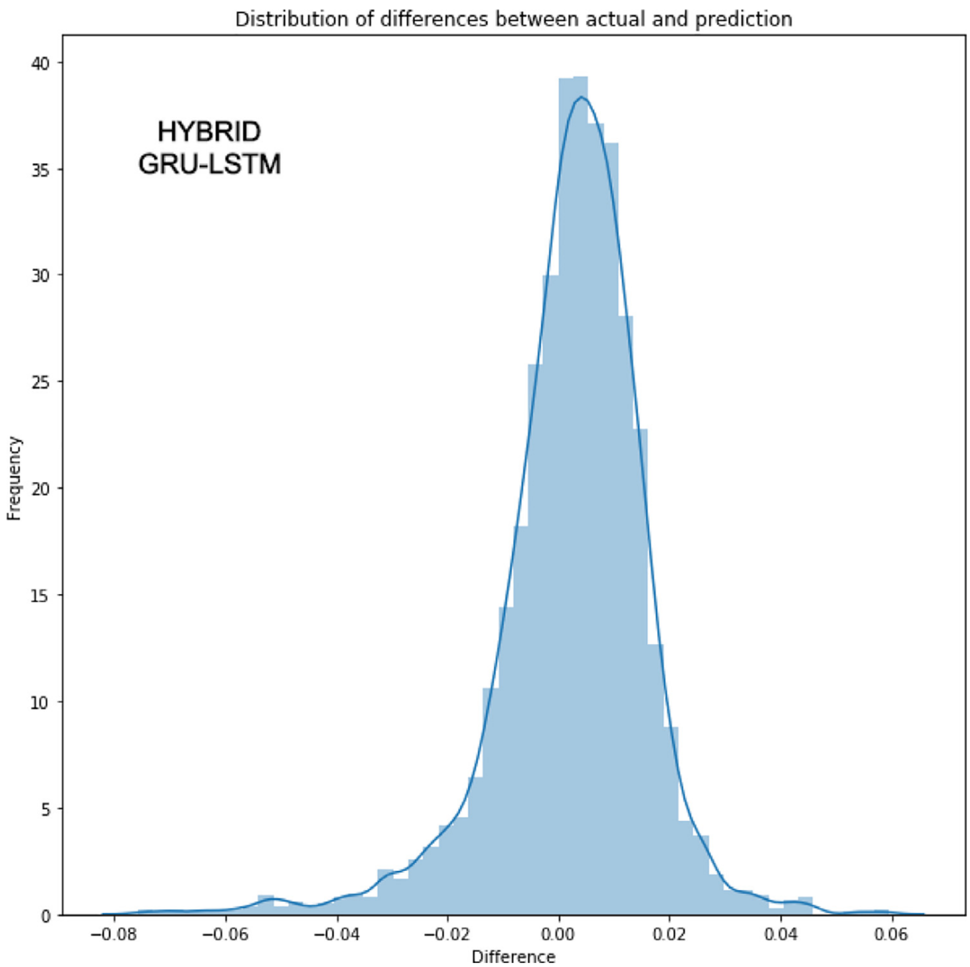

Fig. 12. Distribution of difference between actual and predicted curve for USD/CAD 30-mins timeframe.

dicted price movements of the currency pair are almost perfectly justified the benchmarked index data. Therefore the model has a negligible risk-adjusted with financial return.

5.1.2. GBP/USD

The proposed orientation of the GRU-LSTM model wasn't providing the results as we have expected. However, once we altered the formation of the two layers (LSTM-GRU), the performance of the model increased. The MSE, RMSE, MAE and R^2 scores for GBP/USD 10-mins model are 0.00001, 0.00357, 0.00253 and 0.99509, respectively. And for 30-mins model, these values are 0.00084, 0.02895, 0.01448 and 0.93690 respectively. The actual vs predicted value curves are provided in Figs. 7 and 8.

The x-axis indicates the number of test samples (14871 for 10-mins model and 37224 samples for 30-mins model) that have been used for prediction. The actual closing values of the currency pairs are marked by yellow color and model predicted closing values are marked by blue color. The y-axis indicates the normalized closing price of the GBP/USD pair. The fluctuation in the curve indicates the ups and downs of the closing prices.

Figs. 9 and 10 present the distribution of differences between actual and predicted curve provided in Figs. 7 and 8, respectively. The difference of output and the frequency of the differences are represented by the x-axis and y-axis respectively.

5.1.3. USD/CAD

For the USD/CAD currency pair, we have tested our model for 14685 samples for a 10-mins timeframe and 3740 samples for 30-mins timeframe. The MSE, RMSE, MAE and R^2 scores we got for 10-mins are 0.00004, 0.00597, 0.00387 and 0.99510, while for 30-mins timeframe, these values are 0.00018, 0.01358, 0.00998 and 0.99287 respectively. The actual vs predicted value curves are presented in Figs. 13 and 14. The *x*-axis indicates the number of testing samples and the y-axis indicates the normalized closing price of USD/CAD pair.

Figs. 11 and 12 present the distribution of differences between actual and predicted curves provided in Fig. 13 and 14, respectively. The *x*-axis and *y*-axis similarly represent the differences and the frequency of differences for each value, respectively.

5.1.4. USD/CHF

Finally, we have validated our proposed model against 14805 USD/CHF samples for a 10-mins timeframe and 3727 samples for 30-mins timeframe. Like the other three currency pairs, the model produces a very low prediction error. The MSE, RMSE, and MAE values for 10-mins timeframe are 0.00001, 0.00362, and 0.00261 while for 30-mins timeframe, we got 0.00020, 0.01422, and 0.01015 respectively. In terms of R^2 score, we got 0.99880 for 10-mins timeframe which is the best among our four tested currency pairs for 10-mins interval. But for 30-mins timeframe, the R^2 score we got is 0.98159. The actual vs prediction value curves are shown in Figs. 15 and 16. The x-axis indicates the number of test samples and the y-axis indicates the normalized closing price of the samples. The actual closing values of the currency and model predicted closing values are marked by yellow and blue color respectively. The fluctuation in the curve represents the ups and downs of the closing prices.

Figs. 17 and 18 presents the distribution of difference between actual and predicted curves provided in Figs. 15 and 16. Like before, the x-axis

Fig. 13. Actual value vs Predicted value curve for USD/CAD 10-mins timeframe.

Fig. 14. Actual value vs Predicted value curve for USD/CAD 30-mins timeframe.

represents the differences between actual and predicted values while the y-axis represents the frequency of scores for each value.

5.2. Performance comparison

To determine how good a model is, we have compared our hybrid GRU-LSTM model against a standalone GRU model, a standalone LSTM model, and a simple statistical model where we have used simple moving average (SMA) of previous 20-days closing price. Moving average is used for filtering out the noise and smoothing the price trend. We have considered a 20-days moving average for analyzing the performance as a 20-days moving average is proven to provide the best result [70].

Tables 1–4 show the comparison for 10-mins timeframe in terms of MSE, RMSE and MAE values for all the four currency pairs. For every currency pair, our proposed model outperforms the other models.

Table 1
EUR/USD 10-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	**0.00001**	**0.00301**	**0.00224**
LSTM	0.00002	0.00468	0.00365
GRU	0.00005	0.00739	0.00624
SMA	0.00008	0.00930	0.00722

Table 2
GBP/USD 10-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	**0.00001**	**0.00357**	**0.00253**
LSTM	0.00004	0.00601	0.00449
GRU	0.00002	0.00391	0.00275
SMA	0.00016	0.01301	0.01064

Fig. 15. Actual value vs predicted value curve for USD/CHF 10-mins timeframe.

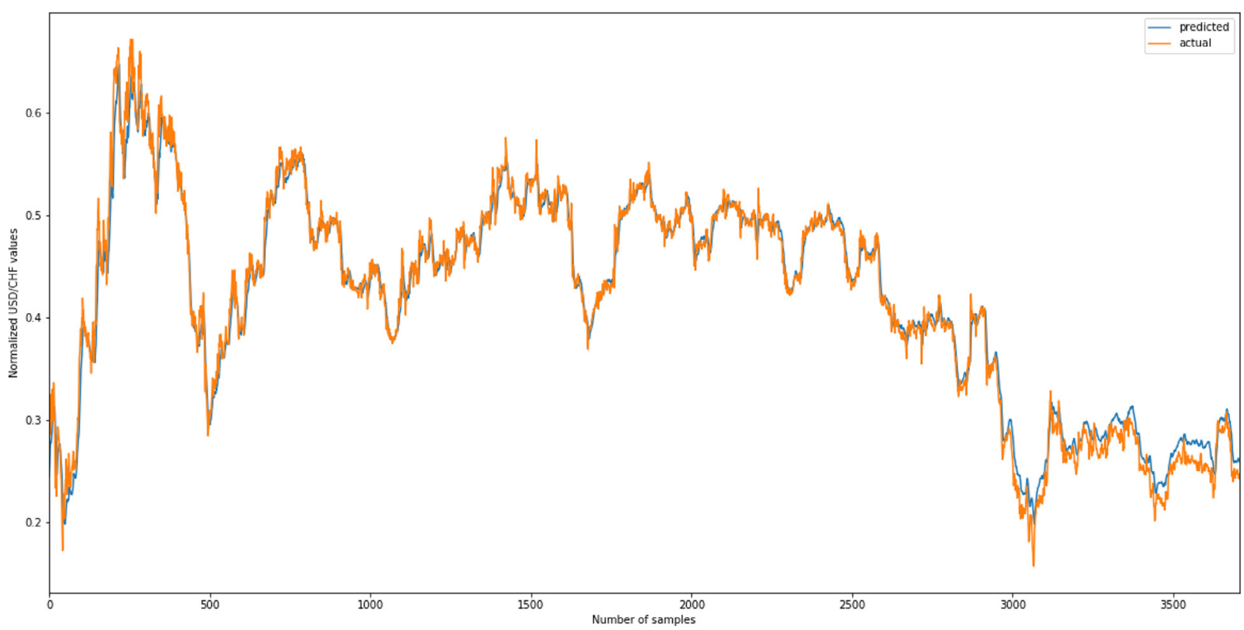

Fig. 16. Actual value vs predicted value curve for USD/CHF 30-mins timeframe.

Table 3
USD/CAD 10-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	**0.00004**	**0.00597**	**0.00387**
LSTM	0.00005	0.00686	0.00464
GRU	0.00041	0.02024	0.01721
SMA	0.00008	0.00936	0.00788

Table 4
USD/CHF 10-mins performance comparison.

Model	MSE	RMSE	MAE
Proposed Model	**0.00001**	**0.00362**	**0.00261**
LSTM	0.00001	0.00385	0.00281
GRU	0.00036	0.01888	0.01516
SMA	0.00006	0.00825	0.00649

Table 5
EUR/USD 30-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	0.00032	0.01790	0.01233
LSTM	0.00066	0.02573	0.01816
GRU	0.00038	0.01955	0.01334
SMA	**0.00021**	**0.01459**	**0.01066**

Table 6
GBP/USD 30-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	**0.00084**	**0.02895**	**0.01448**
LSTM	0.00097	0.03121	0.01920
GRU	0.00419	0.06473	0.06324
SMA	0.00105	0.03246	0.02232

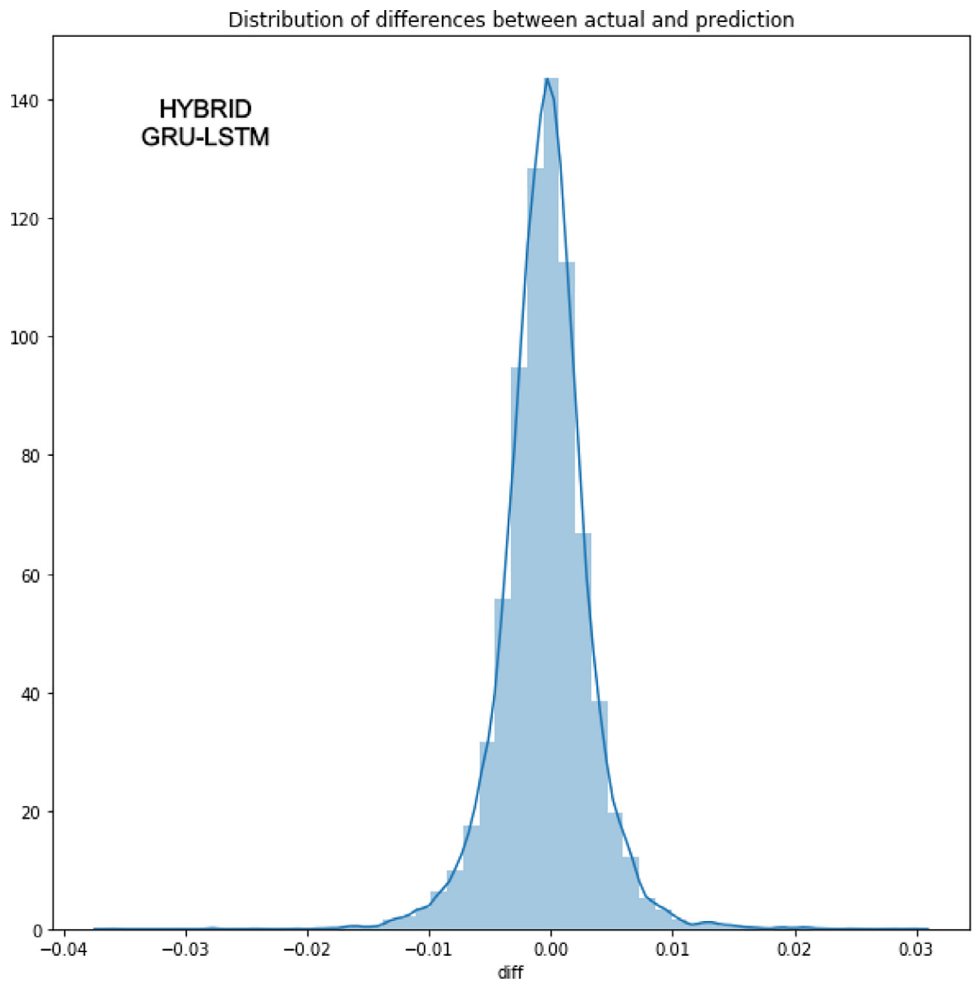

Fig. 17. Distribution of difference between actual and predicted curve for USD/CHF 10-mins timeframe.

Table 7
USD/CAD 30-mins performance comparison.

Models	MSE	RMSE	MAE
Proposed Model	**0.00018**	**0.01358**	**0.00998**
LSTM	0.01043	0.10211	0.10082
GRU	0.00247	0.04965	0.03703
SMA	0.00056	0.02374	0.01376

Table 8
USD/CHF 30-mins performance comparison.

Model	MSE	RMSE	MAE
Proposed Model	0.00020	0.01422	0.01015
LSTM	0.01435	0.11981	0.11777
GRU	0.00022	0.01478	0.01093
SMA	**0.00009**	**0.00959**	**0.00681**

Tables 5–8 show the 30-mins timeframe comparison for the currency pairs.

Analyzing the result, we can see that the proposed model produces less MSE, RMSE, and MAE, for 10-mins timeframe thus ensures better accuracy for all of the four currency pairs. For 30-mins timeframe, our proposed system provides better results for 2 currency pairs: GBP/USD and USD/CAD while for EUR/USD and USD/CHF currency pairs SMA provides the best MSE, RMSE, and MAE score. But while considering the risk-adjusted with the returns of these models, our proposed model shows its superiority over every model. Though SMA provides less error for EUR/USD and USD/CHF pairs, it has the lowest R^2 values (0.39487 and 0.21750, respectively) among all the models and thus have a huge risk associated with it. Table 9 and 10 show the comparison of the models in terms of R^2 scores for 10-mins and 30-mins timeframe respectively. Our proposed model produces higher R^2 scores than both of the standalone models and SMA for all currency pairs in both 10-mins and 30-mins timeframes. Since R^2 score is a risk analysis metric, we can say that our model is more reliable and safe than the compared models.

Table 9
R^2 score performance comparison for 10-mins timeframe.

Model	EUR/USD	GBP/USD	USD/CAD	USD/CHF
Proposed Model	**0.99678**	**0.99509**	**0.99510**	**0.99880**
LSTM	0.99415	0.99007	0.98414	0.99614
GRU	0.95929	0.99500	0.89748	0.90488
SMA	0.53698	0.48313	0.82412	0.58618

Table 10
R^2 score performance comparison for 30-mins timeframe.

Model	EUR/USD	GBP/USD	USD/CAD	USD/CHF
Proposed Model	**0.99205**	**0.93690**	**0.99287**	**0.98159**
LSTM	0.98358	0.92664	0.59762	0.30702
GRU	0.99052	0.68449	0.90486	0.98010
SMA	0.39487	0.05839	0.01325	0.21750

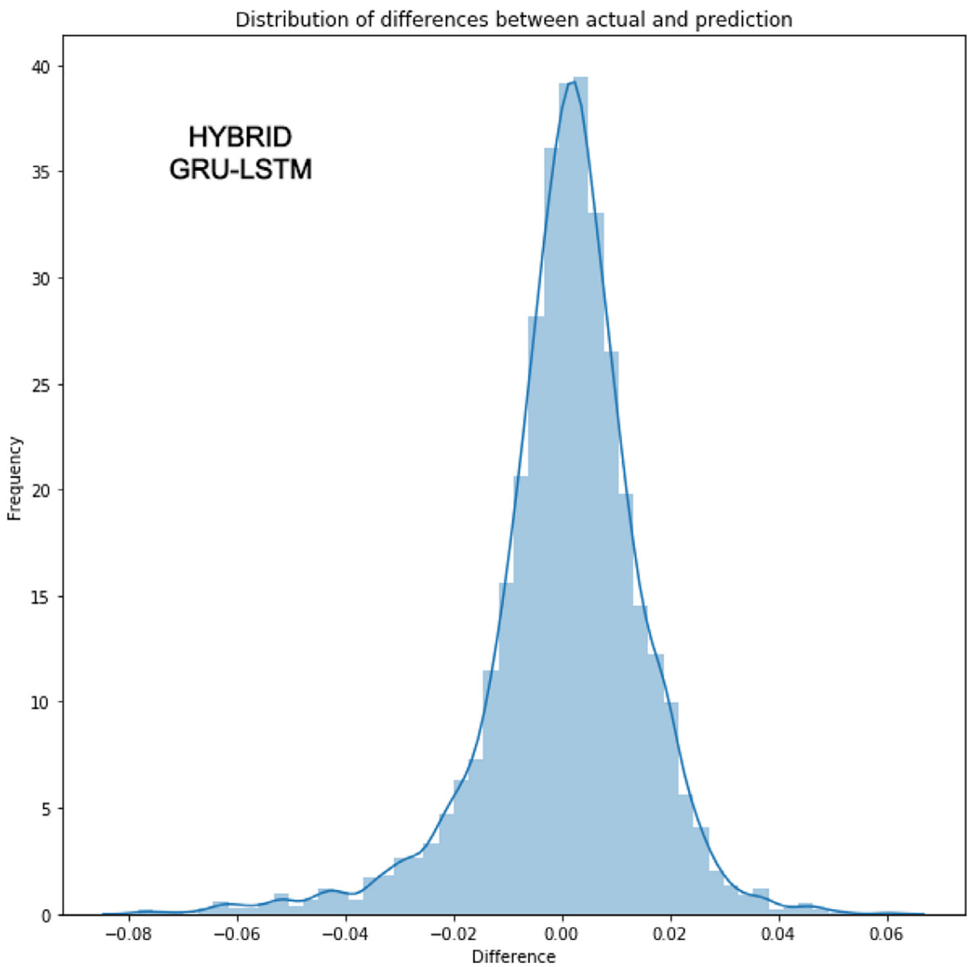

Fig. 18. Distribution of difference between actual and predicted curve for USD/CHF 30-mins timeframe.

6. Conclusion

In this research, we have demonstrated the power of a hybrid model combining GRU and LSTM to predict FOREX currency prices. We have performed this research on EUR/ USD, GBP/USD, USD/CAD and USD/CHF major currency pairs. We have predicted the price of 10 minutes and 30 minutes before the actual time as a proof-of-concept. We have collected a 1-minute interval dataset from the histdata website and converted them into 10 minutes and 30 minutes interval datasets. Then we have inserted the data into a GRU model where it generates a weighted value and then passes the data to the LSTM network. LSTM calculates another weight value and passes the data to the dense layer. Dense layer produces the overall model output and then passes the result to the output layer. In the output layer, the system generated output is compared against the actual output and weighted values are optimized so that the value of the loss function minimizes. The experimental results show that the GRU-LSTM hybrid model predicted prices on the FOREX currencies more accurately than two of the most popular and reliable time series analyzers: LSTM and GRU. We have also compared our proposed hybrid model against a simple statistical model that uses the simple moving average of the previous 20-days closing price. Although, this model produces less error for EUR/USD and USD/CHF in 30-mins timeframe, but it has a very high risk associated with it. In terms of risk associated with the return, the proposed model maintains its superiority among all the models for both timeframes. Although the proposed model has a good predictive capability, it sometimes suffers when the closing price increases or decreases suddenly. As we can see in Fig. 13 where the USD/CAD closing price maintains an incremental flow from intervals 12,000 to 14,000 and in Fig. 8 where the GBP/USD 30-mins price suddenly decreases between 0 to 500 intervals. Also, the combination of the first two hidden layers needed to be altered for the GBP/USD pair for obtaining good performance. This provides us the opportunity for further research.

This proposed model is still in a relatively early stage of development. There are few other improvements still need to be explored, since the model offers a promising and potentially fruitful area of research. In future, we will apply our model to all the remaining major currency pairs and will evaluate the accuracy of our proposed model for 5 minutes and 15 minutes prior to the actual time.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

M.S. Islam: Conceptualization, Methodology, Resources, Validation, Data curation, Formal analysis, Writing - original draft, Visualization, Writing - review & editing. **E. Hossain:** Conceptualization, Methodology, Validation, Writing - original draft, Investigation, Supervision, Project administration, Writing - review & editing.

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