Predicting Exchange Rate Changes in Sri Lanka Using the LSTM-based Deep Neural Network Model

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Abstract

The exchange rate is a significant macroeconomic variable reflecting a country's economic position and directly impacts the economic condition through its fluctuations. Therefore, improved prediction of exchange rates would be immensely valuable for key economic stakeholders to make the right decisions on economic activities. Therefore, accurate exchange rate prediction is crucial for policymakers, especially for decision making based on economic forecasts.

Various macroeconomic and global market factors contribute to fluctuations in the exchange rate, while political, economic, and social sentiments can also influence its movements. Therefore, accurate prediction of exchange rates is widely acknowledged as a challenging task. This study identifies the most appropriate macroeconomic variables and global market factors for exchange rate prediction in Sri Lanka, including oil price, Dow Jones Industrial Average (DJIA) stock market index, interest rates, and secondary market treasury bill rates. In addition, this study considers public sentiment through news headlines to understand the impact of socioeconomic and political factors on exchange rate fluctuations. Input sequences for the deep learning model were generated from text features extracted from Tweets related to the foreign exchange market and the most appropriate macroeconomic and global market factors for exchange rate prediction in Sri Lanka.

This paper suggests a Long Short Term Memory (LSTM)-based Deep Neutral Network (DNN) model to predict the exchange rate, incorporating macroeconomic and global market factors with financial sentiments. The Mean Absolute Percentage Error (MAPE) value achieved for the model is 0.6693%.

Key Words: *Exchange rates, LSTM, Keras, Deep Learning, Machine learning, Text Analytics*

[1] The views presented in this paper are those of the author and do not necessarily indicate the views of the Central Bank of Sri Lanka

1. Introduction

The exchange rate is a crucial indicator in open economies that reflects the country's economic condition. It represents the price of one currency in relation to another currency. Due to economic globalisation, the foreign exchange market has expanded significantly. Further, exchange rate fluctuations directly affect the decisions of policymakers, entrepreneurs, and investors. Due to the exchange rate's high volatility, policymakers must predict the exchange rate accurately to make the necessary decisions to enhance the country's economic condition.

The complicated and volatile nature of the foreign exchange market makes exchange rate prediction difficult. According to Yasir et al. (2019), macroeconomic and volatile global market variables affect exchange rate fluctuations. In addition, Xing et al. (2021) confirm the predictive power of high-frequency news sentiment for exchange rate prediction. Meanwhile, machine learning and deep learning techniques have been successful in the field of finance. Thus, various researchers have used them to predict the exchange rate.

Moreover, since numeric factors with public sentiment collectively affect exchange rate fluctuation, it is necessary to incorporate machine learning techniques to predict the exchange rate more accurately with numeric and text features. This study proposes a novel hybrid model to predict the exchange rate in Sri Lanka. It incorporates macroeconomic and global market factors such as crude oil and gold prices and political sentiment derived from public opinion data. This study examines text analytics and deep learning techniques to improve the accuracy of exchange rate predictions.

2. Literature Review

2.1 Introduction

The exchange rate is one of the most important economic variables that reflects the economy in the long run, especially for export-oriented countries (Chang & Chien, 2017). Exchange rate prediction is significant for decision making parties such as policymakers, bankers, and investors (Henríquez & Kristjanpoller, 2019). It is a very complicated and challenging task since the foreign exchange market is a multivariable non-linear system (Shen et al., 2015). Yasir et al. (2019) claim that the exchange rate is affected by several factors, including socioeconomic and political factors. In addition, they emphasise the importance of an accurate exchange rate prediction mechanism. Therefore, as claimed in the above cited literature, forecasting exchange rates is a challenging task that should be performed accurately to make right decisions.

2.2 Exchange rate forecasting in Sri Lanka

The managed float exchange rate regime was introduced in Sri Lanka in November 1977 (Weerasinghe, 2018). Several studies have been conducted to identify the behaviour of exchange rates in Sri Lanka. Jayasuriya and Perera (2016) have identified that the net foreign assets, trade balance, and workers' remittance can be used to predict the exchange rate successfully. The exchange rate has a relationship between inflation, interest rate, remittances, terms of trade, and foreign purchases (Rajakaruna, 2017). Nanayakkara et al. (2014) claimed that Artificial Neural Network has performed better than the GARCH model for forecasting the exchange rate with higher accuracy. Nanthakumaran and Tilakaratne (2018) have introduced a hybrid model using empirical mode decomposition (EMD) and feedforward neural networks (FNN). According to the above-cited literature, the exchange rate in Sri Lanka can be predicted by macroeconomic variables such as inflation, interest rate remittances, etc.

2.3 Use of macroeconomic variables and global market factors to predict the exchange rate in other countries

Numerous studies have examined the factors influencing exchange rate movements in various countries. A study about Pakistan identified current balance, inflation, and Foreign Direct Investment as negatively correlated with the exchange rate, while GDP is positively correlated (Mohsin et al., 2018). Further, Malaysian research shows that commodity prices affect exchange rates. Meanwhile, prices of crude oil, palm oil, rubber, and gold have been found to influence fluctuations in exchange rates (Ramakrishnan et al., 2017; Mensah et al., 2017). In addition, Yasir et al. (2019) emphasise the use of oil and gold prices for exchange rate prediction.

2.4 Use of text analytics to predict exchange rate

As suggested by Khadjeh Nassirtoussi et al. (2015), Jin et al. (2013), Chen et al. (2019), and Yono et al. (2019), unstructured textual information in the news, forums, social media, and tweets have been used to determine economic sentiment index for several economic research areas including sentiment analysis for exchange rate prediction and stock market prediction. Accordingly, it is evident that public opinions that derive from unstructured textual information can influence the direction of the foreign exchange market based on the public's financial activities.

Natural language processing, text analysis, and computational linguistic techniques are used to conduct the sentiment analysis using unstructured textual information (Komariah et al., 2016). Mainly, two primary methods exist for conducting sentiment analysis based on supervised and unsupervised algorithms.

A lexicon-based approach is an unsupervised approach that uses positive and negative opinion words such as "good", "amazing", "worse", and "lose", which express the polarity of the sentiment for deriving the sentiment score for a sentence or phrase. There are three main lexicon based approaches: manual, dictionary based, and corpus based. The manual approach is known as a very time-consuming method (Shuhidan et al., 2018). There are some drawbacks associated with the lexicon based approach. The effectiveness of the lexicon based approach highly depends on the lexical resource. In addition, a huge disadvantage is the inability to determine the sentiment value of a word when it has several meanings based on its use and context. Seifollahi and Shajari (2018) have obtained 91.67% accuracy in predicting price movements in the FOREX market using an improved Word Sense Disambiguation (WSD) method.

The supervised learning approach uses a training dataset and its corresponding output values to predict the sentiment polarity. The algorithm has enhanced predictive accuracy for specific domains regarding unknown data. According to Kirchner (2019), the supervised learning approach has outperformed the lexicon based method. Naive Bayes Classification, Support Vector Machines (SVM), and Maximum Entropy (ME) are widely used supervised learning algorithms.

Yasar and Kilimci (2020) developed a powerful method to predict the US Dollar/Turkish Lira exchange rate by combining financial sentiment and time series analyses. They used separate models for analysing financial sentiment and time series, and then combined them for prediction. Word embeddings (including Word2Vec, GloVe, and fastText) and deep learning models (CNN, RNN, and LSTM) were used for sentiment analysis. The combination of LSTM and GloVe word embeddings achieved the highest performance in the study

2.5 Exchange rate forecasting using machine learning and deep learning techniques

Numerous studies have explored using machine learning and deep learning techniques to predict exchange rates. Dautel et al. (2020) have found that LSTM and GRU algorithms offer the best predictions for exchange rates compared to other deep learning models tested in their study. It emphasises the potential of LSTM for accurate exchange rate forecasting. Meanwhile, Samarawickrama and Fernando (2019) found that Multivariate Regression, SRNN, and LSTM have outperformed the other GRU and CNN models in multi-step exchange rate prediction. They have shown the potential of applying deep learning techniques for accurate exchange rate forecasting. Moreover, Ranjith et al. (2018) have identified the LSTM as the most effective model compared to SRNN and GRU models.

3. Methodology

Table 1 presents input data identified by a combined analysis of literature and industry expert interviews. The data set for this study was gathered from 01 January 2014 to 15 December 2020.

Table 1: Details of input data for the study

Data		Description
Numeric Data		
Indicative US Dollar SPOT Exchange rate		The weighted average rate of USD/LKR SPOT transactions conducted in the previous business day
Global market factors	Oil price	Global production of crude oil data
	Gold price	Daily gold price
	Dow Jones Industrial Average (DJIA) Index	DJIA is a stock market index that representing the performance of companies registered under the stock exchange in the United States.
	USA Treasury Bill Rates	Following USA treasury bill rates were considered for the study. ▪ USA Treasury Bill Rate BD 4 weeks ▪ USA Treasury Bill Rate CE 4 weeks ▪ USA Treasury Bill Rate BD13 weeks ▪ USA Treasury Bill Rate CE 13 weeks ▪ USA Treasury Bill Rate BD26 weeks ▪ USA Treasury Bill Rate CE 26 weeks ▪ USA Treasury Bill Rate BD52 weeks
Macro-economic factors	Interest rates	The following interest rates in Sri Lanka, which directly involve the Sri Lankan monetary policy, were considered for the study. ▪ Average Weighted Call Money Rate ▪ Inter-Bank Call Weighted Average Rate ▪ Market Repo Weighted Average Rate
	Sri Lanka Secondary Market Treasury Bill Rate	Following Sri Lankan, secondary market treasury bill rates were considered for the study. ▪ Secondary Market Yield Rate – 091 days ▪ Secondary Market Yield Rate – 182 days ▪ Secondary Market Yield Rate – 364days
Text Data		
News headlines		Tweets of Bloomberg tweet account

3.1 Pre-processing tweet data set

Several key steps are associated with the tweet-text preprocessing task such as removing empty values, HTML tags, URLs, user mentions, and special characters, lowercasing all text, and expanding contractions. These preprocessing steps are essential for preparing the data for further analysis and natural language processing tasks. In addition, empty and duplicate tweets were removed to ensure data quality. The most relevant tweets for the financial domain were identified using a pre-trained language model called FinBert (Araci, 2019). Each tweet was classified as positive, negative, or neutral. Then, each day's positive and negative tweets were concatenated to acquire the most relevant financial text. In addition, lemmatization and stop word-removing processes were employed to concatenated text of tweets before getting text features. Further, if the previous business day were a holiday, then the text features of the holiday were also concatenated with the text features of the considering day.

3.2 Preprocessing numeric data set

This study aims to forecast the exchange rate in Sri Lanka for only Sri Lankan business days. The Last Observation Carried Forward (LOCF) method was employed to address the missing values of global market factors. Data normalisation was implemented to standardise the range because of the variations in scales of numerical variables. The Minmax scaler method converted each variable into a standardized range between 0 and 1. The formula of the Minmax scaler is as follows:

$$MinMaxScaler(x_i) = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

3.3 Identify the most effective factors for exchange rate prediction

The Granger causality test, a statistical method for analysing the potential causal relationships between financial time series, was employed in this study. The purpose of applying this test is to identify the financial series that can effectively contribute to predicting the exchange rate. Due to the non-stationary nature of the time series variables, logarithmic transformations were employed prior to applying the Granger causality test. It was conducted for fifteen lags, and lag three produced the best results.

The null hypothesis was rejected for probabilities below the significance level of 0.05. The macroeconomic and global financial variables in Table 2 cause exchange rate values for lag 3. Therefore, these variables and the previous day's exchange rate offer potential for predicting future exchange rates.

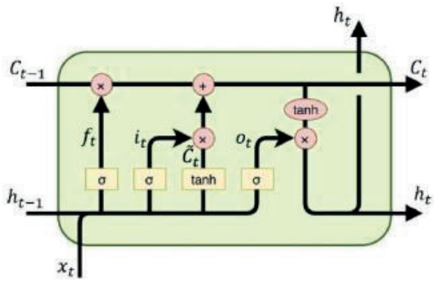
Table 2: Most suitable variables to predict the exchange rate

Macroeconomic and global factors	
Oil price	
DJIA stock market index	
Interest rates	Average weighted call money rate
	Inter-Bank Call Weighted Average Rate
	Market Repo Weighted Average Rate
Secondary market Treasury Bill rates	Secondary Market Yield Rate – 182 days
	Secondary Market Yield Rate – 364 days

3.4 Long Short Term Memory (LSTM) architecture

LSTM was created as a solution to the vanishing gradient problem that exists with the RNN (Hochreiter & Schmidhuber, 1997). It can capture the long term dependencies in long sequences without suffering optimisation. It is mostly used for the sequential data domains. As per Fischer and Krauss's (2018) study, LSTM has outperformed statistical models.

Figure 1: LSTM cell



The LSTM cell is composed of three main gates such as input gate(i_t), output gate (o_t), and forget gate(f_t). These three gates connect to the cell state C_t as depicted in Figure 1. Cell state is updated by the input gate using the current input value. Subsequently, the concatenated value of the input and the output of the hidden state is processed by the tanh activation function.

Further, the sigmoid function is applied to the input. Pointwise multiplication is applied for the output values of tanh and sigmoid functions (Hassanien et al., 2018). Forget gate determines the information which should be eliminated. The hidden state for the next input is determined by the output gate. The equations related to the LSTM cell are as follows:

$$i_t = \sigma(W_i .[h_{t-1}, x_t] + b_i) \tag{2}$$

$$f_t = \sigma(W_f .[h_{t-1}, x_t] + b_f) \tag{3}$$

$$o_t = \sigma(Wo.[h_{t-1}, x_t] + b_o) \tag{4}$$

$$\tilde{C}_t = tanh(W_c .[h_{t-1}, x_t] + b_c) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

$$h_t = o_t * \tanh (C_t) \tag{7}$$

where i_t represents input gates, f_t represents forget gate, o_t represents output gates, C_t represents cell state at time step t, $\tilde{C}_t$ represents a candidate for cell state at time step t and h_t represents hidden state vector.

3.5 Create Deep Neural Network (DNN) model using Keras

Keras is a deep learning API that runs on top of the TensorFlow machine learning platform. It provides an interface for addressing research issues effectively. Keras consists of two main model creation methods: the sequential API and the functional API. Functional API facilitates the creation of complex models with multiple inputs and outputs or shared layers without having a sequential layering scheme.

The inputs for the deep learning model in this study consist of text and numeric values. Keras Functional API is well suited for handling multiple inputs in the deep learning model to accommodate these distinct input categories. Therefore, Keras Functional API was used in this research to develop the deep learning model.

3.6 Implementation of the LSTM-based Deep Neural Network (DNN) model

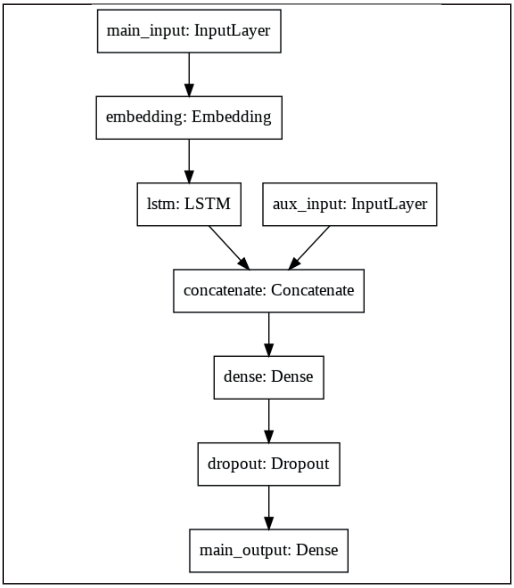
This study employed the GloVe model, a standard pre-trained word embedding model, and 100-dimensional word embedding of tweets were used. The dataset was divided into training/validation (80%) and testing (20%) sets. The training/validation set was further divided into 80% for training and 20% for validation. Keras Functional API was employed to construct an LSTM-based deep neural network model. Hyperparameter optimisation was conducted to identify the best parameters for the model. Table 3 includes the best parameters for the model.

Table 3: Best parameters identified through the hyper-parameter training process

Parameter Name	LSTM based DNN Model
lstm/gru	150
first_activation	Linear
main_activation	Linear
first_neuron	150
drop_out	0.01
batch_size	32

The main input of the model was an input sequence derived from tweet text features. The LSTM- based deep neural network will process it through the created embedding layer. In addition, numerical variables were provided as the auxiliary input for the model, as depicted in Figure 2. Afterward, the output of the LSTM deep neural network was combined with the auxiliary input, and a deep, densely connected network was stacked onto the top of the created layers. The exchange rate for the next three days was the main output of the model.

Figure 2: LSTM based model architecture



4. Evaluation measures

Mean Squared Error (MSE)

MSE is used to measure the average squared difference between predicted values and observed values. MSE is measured by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{8}$$

where x_i are the observations, $\hat{x}_i$ are predicted values and n is the number of observations.

Root Mean Square Error (RMSE)

RMSE is used to measure the difference between predicted values and observed values. The standard deviation of the residuals is represented by RMSE. RMSE is measured by

$$RMSE = \sqrt{\frac{\sum_{i-1}^{N}(x_i - \hat{x}_i)^2}{N}} \tag{9}$$

where x_i are the observations, $\hat{x}_i$ are predicted values and N is the number of observations.

Mean Absolute Error (MAE)

MAE represents the average value of all absolute errors. MAE is measured by

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |x_i - \hat{x_i}| \tag{10}$$

where x_i are the observations, $\hat{x_i}$ are predicted values and N is the number of observations. It indicates the error that we can expect from the prediction process.

R-Squared

It represents the proportion of the variance in the dependent variable. Moreover, it measures the strength of the dependent variable and the model using 0 to 1 scale. R-squared is measured by

$$R^2 = 1 - \frac{RSS}{TSS} \tag{11}$$

where RSS is the sum of squares of residuals and TSS is the total sum of squares. The closer to 1 indicates that the dependent variable is predicted accurately.

Mean Absolute Percentage Error (MAPE)

It is used as a loss function for regression problems specially in machine learning. MAPE is measured by

$$M = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{x_i - \hat{x_i}}{x_i}\right| \tag{12}$$

where x_i are the observations, $\hat{x_i}$ are predicted values and n is the number of observations.

5. Results

Table 4: Model accuracy

Measurement	LSTM based DNN
Root Mean Squared Error (RMSE)	1.8002
Mean Squared Error (MSE)	3.2406
Mean Absolute Error (MAE)	1.2405
Mean Absolute Percentage Error (MAPE)	0.6693%
R-squared Value (r_score)	0.74047

Table 4 provides the testing accuracy received for the LSTM-based DNN model. The LSTM-based DNN model was implemented as per the parameters obtained from the grid search function, which was conducted for the hyperparameter optimization process. As per the results shown in Table 4, r_squared value is 74.047%. Therefore, it ensures that the model correctly fits the data to predict the exchange rate. As per the values of RMSE, MSE, MAE, MAPE, and r_score, the LSTM-based DNN model has achieved an acceptable level of accuracy in predicting the exchange rate.

Figure 3: Training/Validation loss curves for LSTM based DNN model

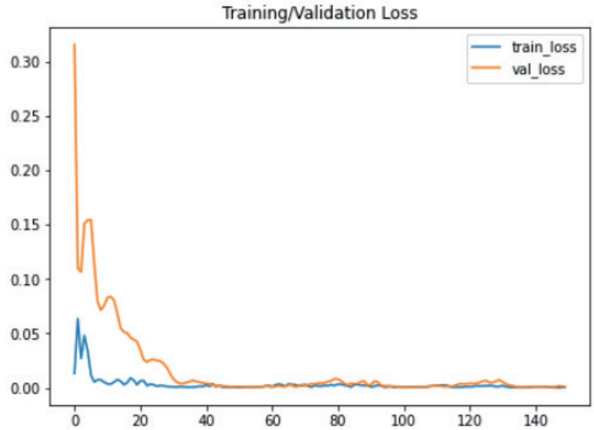


Figure 3 shows the training validation loss curves for the LSTM-based DNN model which ensures the right fitting of the model.

6. Conclusion

Due to the high volatility nature of exchange rate movements, it is a very challenging task to predict exchange rates accurately. Several studies have been conducted to predict the exchange rate in Sri Lanka using macroeconomic variables. However, according to existing literature, financial sentiment factors have not been considered for the exchange rate prediction in Sri Lanka. Therefore, this study proposes a novel hybrid model by integrating highly influential macroeconomic and volatile factors with financial sentiments to predict the exchange rate more accurately. Thus, it is a significant contribution to the field of financial economics. Furthermore, the proposed hybrid model incorporates the most appropriate factors for exchange rate forecasting in Sri Lanka. Another specialty associated with this study is extracting the most relevant news headlines for the financial domain to obtain the text features for the DNN model. To gain a deeper understanding of financial sentiment's impact on exchange rates, this study has incorporated text features in addition to numerical sentiment factors.

Furthermore, expanding the research to consider other exchange rates in addition to the USD/LKR rate will be more beneficial. This study has used a single source for news headlines, and it would be more helpful to consider the multiple data sources related to the foreign exchange market. In addition to the current LSTM-based DNN model, exploring alternative architectures, such as GRU, CNN, TCN, and Bidirectional LSTM, would be advantageous to obtain more accurate results.

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