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Machine learning for exchange rate forecasting: a case study on SAR/PKR, SAR/IDR, and USD/IDR

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Abstract: Exchange rate prediction is essential in industries such as travel, finance, and religious tourism, particularly to Indonesia and Pakistan as the sources of Umrah and Hajj pilgrims to Saudi Arabia. This paper compares machine learning models, namely, Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Multi-layer Perceptron (MLP), in predicting SAR/PKR, SAR/IDR, and USD/IDR rates based on historical data. While prior research noted LSTM's utility during periods like the COVID-19 pandemic, its precision remained limited. This work evaluates models using key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared.Results identify LSTM as the most effective for the SAR/PKR pair, achieving an MSE of 26.814, RMSE of 5.178, MAE of 3.370, and R-squared of 0.8685. However, for the SAR/IDR and USD/IDR pairs, the SVR model demonstrated superior performance with lower errors. For SAR/IDR, it recorded an MSE of 768.295, RMSE of 27.718, MAE of 20.788, and R-squared of 0.9768. For USD/IDR, metrics were an MSE of 17752.818, RMSE of 133.239, MAE of 108.761, and R-squared of 0.9631.The findings validate SVR's reliability for forecasting these specific currency pairs. This analysis provides valuable insights for travelers, investors, and pilgrimage stakeholders, enabling better currency risk management in religious tourism and related financial activities.

1 Introduction

In the fast-changing world of international travel and finance, accurate projection of foreign currency rates is crucial especially in Saudi Arabia which is a major tourist, investment and expatriate labour destination. Millions of people visit the Kingdom, especially the Indonesians and Pakistanis to the sacred activities of Umrah and Hajj. Such religious excursions are marked with high financial dealings and hence, exchange rates of Saudi Riyal (SAR) to the US Dollar (USD) are the key to the tourist and the travel agencies who engage in such exchange [1].

The exchange rates reflect the rate at which one currency can be exchanged with another and proper projections are essential in the global trade and free movement of capital across the borders. The uncertainty of the exchange rates may lead to financial uncertainty in relation to Hajj and Umrah, especially on the pilot agencies and pilgrims. This research paper investigates the application of machine learning models as predictors of foreign exchange rates in terms of providing valuable information to the travel agencies to make sound decisions on currency transactions regarding travel arrangements and pilgrimage costs [2].

Precise currency projections are essential in maximizing financial planning especially to the travel agencies which might be faced with a situation of knowing when to buy SAR or USD. Inadequate reference data may impede the strategic decision making on the currency acquisition resulting in inefficient financial decision making. Use of pilgrimage funds in Indonesia is an example of Hajj Fund Management Agency (BPKH), which handles large amounts of money and the management of this money is quite dependent on the precision of currency forecasts. By matching these forecasts with the Sharia principles, BPKH aims at providing lucrative profits and facilitate the expectations of the potential pilgrims [3].

This paper intends to evaluate the performance of three common machine learning algorithms namely, Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), and Support Vector Regression (SVR) to predict exchange rates with the use of Python. The main goals are to compare the performance measures of all the algorithms and which model is the most effective in the forecast of the target currency pairs: SAR/PKR (Saudi Riyal/Pakistani Rupee), SAR/IDR (Saudi Riyal/Indonesian Rupiah), and USD/IDR (US Dollar/Indonesian Rupiah) [4] [5].

The study is of great importance to the economy of Saudi Arabia particularly tourism and financial sectors. Proper forecasts of SAR/PKR, SAR/IDR and USD /IDR rates will enable the travel agencies, investors, expatriate workers and pilgrims to make better financial decisions. This will further help to make the currency exchange operations more efficient and stable hence affecting the economy of the Kingdom as a whole. Moreover, the results of this research may also be used to make future projections of SAR with respect to other currencies and enable expansion of investment opportunities, financial management planning, and individual finances [6].

2 Literature review

A foreign currency price is the cost of one currency in relation to the other [4]. It is really the trade rate among two currencies. To illustrate, when the foreign currency rate stands at 1 USD = 100 JPY then one US dollar can be exchanged to 100 Japanese yen [7].

Machine learning is a field of artificial intelligence which enables computers to learn by the data and improve their performance in specific tasks without being directly programmed. The computer devices help identify patterns and relationships in the information to prove projections or decisions, instead of applying particular regulations [8][9]. The analysis and implementation of three supervised learning algorithms with the use of data on three different currency pairs were a part of this project.

Long Short-Term Memory (LSTM) is a type of recurring neural networks (RNN) specifically made to effectively model and discover time-series or sequence data. The main elements consist of the architecture are normally an input layer, an LSTM layer or a series of LSTM layers, and an output layer. The appropriate activation functions, such as sigmoid and tanh, are used in each layer to control the flow of information [10].

The LSTM network addresses the vanishing gradient problem in traditional RNNs by incorporating a memory cell and three gates—input gate, forget gate, and output gate—which regulate the flow of information through the network [11].

At each time step t, the LSTM updates its internal cell state c_t and hidden state h_t using the following equations:

- Forget gate (1):

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (1)$$

- Input gate (2):

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

- Cell candidate (3):

$$\widetilde{C_t} = tanh(W_C[h_{t-1}, x_t] + b_C) \quad (3)$$

- Cell state update (4):

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (4)$$

- Output gate (5):

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (5)$$

- Hidden state update (6):

$$h_t = o_t * tanh(C_t) \quad (6)$$

Where:
σ is the sigmoid activation function,
tanh is the hyperbolic tangent activation function,
o denotes element-wise multiplication.

Key components and the roles:

- Forget gate: Determines how much of the previous cell state to forget.
- Input gate: Determines how much of the new cell candidate to update into the cell state.
- Cell candidate: Computes a potential new value for the cell state.
- Cell state: Stores information over time.
- Output gate: Determines how much of the cell state to output as the hidden state [8].

SVR with a Radial Basis Function (RBF) kernel is a popular combination used in machine learning for regression tasks. The RBF kernel introduces a nonlinear transformation to the data, allowing SVR to handle complex relationships that may not be linearly separable [12].

Radial Basis Function (7):

$$\varphi(x) = exp\left(-\left||x-c|\right|^2/2\sigma^2\right) \tag{7}$$

Where:
x is the input vector,
c is the center or prototype of the function,
σ is a parameter that controls the width of the RBF,
MLP (Multilayer Perceptron).

A multilayer perceptron (MLP) comprises interconnected neurons known as perceptrons [13]. The fundamental notion of a single perceptron was presented by Rosenblatt in 1958. A perceptron produces a singular output from many numerical inputs by computing a linear combination of its input weights, perhaps including a nonlinear activation function to the outcome. This process may be expressed numerically as follows (8) [14]:

$$y = f(\Sigma(w_i * x_i) + b) \tag{8}$$

Where:
x_i are the input values,
w_i are the weights associated with each input,
b is the bias term,
f is the activation function (e.g., sigmoid, ReLU, etc.).

For an MLP with one hidden layer, the calculations can be generalized as follows:
1. First layer (9):

$$h = \varphi(W^1 * x + b^1) \tag{9}$$

Where:
W_1 is the weight matrix of the first layer,
x is the input vector,
b_1 is the bias vector of the first layer,
φ is the element-wise nonlinear activation function.

2. Second layer (Output) (10):

$$y = W^2 * h + b^2 \tag{10}$$

Where:
W^2 is the weight matrix of the second layer,
b^2 is the bias vector of the second layer.

Evaluation metrics:
- Mean Squared Error (11):

$$MSE = (1/n) * \Sigma(y_i - \hat{y}_i)^2 \tag{11}$$

Where:
y_i are the true values and $\hat{y}_i$ are the predicted values.

- Root Mean Squared Error (12):

$$RMSE = \sqrt{((1/n) * \Sigma(y_i - \hat{y}_i)^2)} \tag{12}$$

- Mean Absolute Error (13):

$$MAE = (1/n) * \Sigma|y_i - \hat{y}_i| \tag{13}$$

- R-squared (14):

$$R^2 = 1 - (RSS/TSS) \tag{14}$$

Where:
RSS is the sum of squares due to regression (explained sum of squares),
TSS is the total sum of squares.

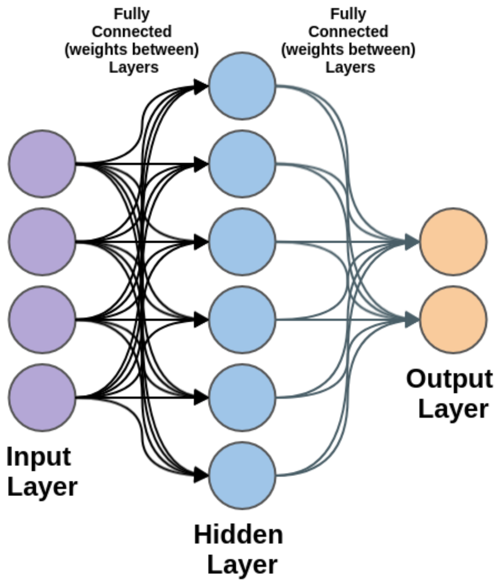

Figure 1 Signal-flow illustration of an MLP (austingwalters)

Permana et al. [15] using the Markov Chain approach to predict the exchange rate between the SAR and IDR monetary units. The research used time series data obtained from Bank Indonesia's official website to predict future currency rates. The study used a model that combines Fuzzy Time Series and Markov Chain techniques to predict the exchange rate. The research results demonstrate that the model displays a negligible error, with an AFER of 0.827% and an MAE of Rp32.96. In 2019, Mohammadi concentrates on forecasting currency exchange rates using four machine learning models: LSTM (Long Short-Term Memory), RBF (Radial Basis Function), Backpropagation, and SVR (Support Vector Regression). Three currency pairs, EUR/USD, USD/JPY, and USD/TRY, were constructed and trained in Python with datasets from the Swiss Dukascopy banking group. The study aimed to predict the following day's currency values based on real data from the FOREX market. The algorithms were trained, assessed, and analyzed to ascertain their strengths and weaknesses. Statistical performance metrics, such as MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error), were used to determine the ideal model. The results indicated that SVR outperformed the other approaches, whereas Backpropagation had the least effectiveness in forecasting currency exchange rates [16]. Researchers [17] attempted to forecast USD/IDR exchange rates during the COVID-19 pandemic. Their findings indicate that the LSTM model is the most effective for long-term forecasts, notwithstanding the omission of COVID-19 events. The model predicted a decline in the value of the Rupiah against the US dollar, exacerbated by the repercussions of the epidemic[18]. The RMSE achieved a lower value of 271 during the testing phase, using an algorithm with 7 epochs and 5 neurons. The ideal result is attained with the use of the LSTM algorithm. The restriction of this model is its applicability just during the COVID-19 era [19]. Yarham [20] in his thesis (2024) demonstrates that SVR models consistently outperform both LSTM and MLP models in predicting exchange rates for USD/IDR, SAR/IDR, and SAR/PKR with manual hyperparameter optimization (Figure 1). The RBF kernel of the SVR model produced a significant reduction in RMSE for USD/IDR (61.223) compared to previous LSTM research, which indicated an RMSE of 271. For SAR/IDR, SVR reduced the MAE by 70%, attaining a value of 9.417 compared to 32.96 in prior experiments using the Markov Chain Method. The SVR Model exhibited enhanced performance for SAR/PKR, achieving a mean squared error of 1.046 and an R-squared value of 0.9934. The findings underscore the SVR model's superior accuracy and robustness in forecasting financial time series compared to other models, establishing it as a crucial tool for stakeholders in alleviating currency exchange concerns [21].

3 Methodology

3.1 Peer review process

This study uses a methodology where it predicts foreign exchange rates based on three machine learning algorithms, which are Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Multilayer Perceptron (MLP). The models will aim to forecast the SAR/IDR currency pair, SAR/PKR currency pair and the USD/IDR currency pair exchange rates. The method includes data collection, preprocessing, model training via automated grid search, and evaluation, especially the performance measures that evaluate the accuracy of prediction [22]. These features are High, Open, Low and Price as the target. LSTM, SVR, and MLP models are the models that we use, and the selection of these models is due to the previous studies that have shown that they are effective when it comes to forecasting various currency exchange rates. The LSTM model has demonstrated successful performance when used with USD/IDR exchange rate [23]. The SVR algorithm has demonstrated exceptionally good performance when used with USD/TRY, EUR/USD and USD/JPY exchange rates [24]. MLP model has demonstrated lower error rates as compared to other models [25]. In this analysis, we make use of Python through Google Colab where we have imported many libraries such as NumPy, Pandas, Matplotlib, Scikit-Learn, and Keras.

The relevant historical exchange rates data of the given currency pairs (SAR/IDR, SAR/PKR and USD/IDR) are acquired through the authoritative sources like investing.com. The variables that are typically involved in the dataset are Open, High, Low, and Price. This information is the basis of the time series forecasting activity. Table 1 presents the data within a specific period of time. The training and validation data will be 80 percent and the testing will be 20 percent. The exchange rate of the respective currency pairings are shown in Tables 2, 3 and 4.

Table 1 Data summary [26]

Currency Pair	Time	Data	Percentage (%)	Total Data
SAR/PKR	Training: January 05th, 1998 to May 08th, 2019	5550	80	6937
	Testing: May 09th, 2019 to Agustus 30th, 2024	1387	20	
SAR/IDR	Training: January 04th, 2000 to May 03th, 2019	5145	80	6431
	Testing: May 06th, 2019 to Agustus 30th, 2024	1286	20	
USD/IDR	Training: January 03rd, 2000 to July 26th, 2019	5102	80	6377
	Testing: July 29th, 2019 to Agustus 30th, 2024	1275	20	

Date	Price	Open	High	Low	Change %
1998-01-05	11.7334	11.7337	11.7334	11.7337	0.0001
1998-01-06	11.7336	11.7340	11.7336	11.7340	0.0000
1998-01-07	11.7325	11.7331	11.7325	11.7331	-0.0001
1998-01-08	11.7271	11.7287	11.7271	11.7287	-0.0005
1998-01-09	11.7333	11.7349	11.7333	11.7349	0.0005
...	...	...	...	...	...
2024-08-26	74.2800	74.2600	74.3900	74.1900	0.0018
2024-08-27	74.2600	74.3250	74.4100	74.1650	-0.0003
2024-08-28	74.1500	74.3100	74.4100	74.1800	-0.0015
2024-08-29	74.1500	74.2500	74.4100	74.2050	0.0000
2024-08-30	74.3000	74.2500	74.4000	74.1850	0.0020

6937 rows × 5 columns

Table 2 SAR/PKR exchange data

Date	Price	Open	High	Low	Change %
2000-01-04	1910.41	1904.00	1910.41	1904.00	0.0155
2000-01-05	1907.80	1901.23	1907.80	1901.23	-0.0014
2000-01-06	1934.49	1927.90	1934.49	1927.90	0.0140
2000-01-07	1907.77	1901.18	1907.77	1901.18	-0.0138
2000-01-10	1910.56	1903.95	1910.56	1903.95	0.0015
...	...	...	...	...	...
2024-08-26	4126.24	4104.69	4126.64	4080.27	0.0053
2024-08-27	4125.77	4126.24	4145.21	4116.93	-0.0001
2024-08-28	4109.00	4129.50	4139.50	4109.50	-0.0041
2024-08-29	4106.00	4110.50	4117.00	4095.00	-0.0007
2024-08-30	4117.00	4107.50	4127.50	4107.50	0.0027

6431 rows × 5 columns

Table 3 SAR/IDR exchange data

Date	Price	Open	High	Low	Change %
2000-01-03	7055.0	7065.0	7105.0	6875.0	0.0097
2000-01-04	7165.0	7045.0	7175.0	7005.0	0.015600000000000001
2000-01-05	7155.0	7125.0	7245.0	7105.0	-0.0014000000000000002
2000-01-06	7255.0	7145.0	7255.0	7135.0	0.013999999999999999
2000-01-07	7155.0	7265.0	7285.0	7150.0	-0.0138
...	...	...	...	...	...
2024-08-26	15425.0	15341.0	15435.0	15295.0	-0.39%
2024-08-27	15490.0	15480.0	15545.0	15460.0	0.42%
2024-08-28	15420.0	15517.5	15532.5	15420.0	-0.45%
2024-08-29	15410.0	15420.0	15447.5	15367.5	-0.06%
2024-08-30	15450.0	15450.0	15490.0	15437.5	0.26%

6377 rows × 5 columns

Table 4 USD/IDR exchange data

A. Data preprocessing

Here, cleaning and transformation of the data is done to match the needs of machine learning algorithms. This involves dealing with missing values, eliminating any outliers, and putting the data into the form of a time series, in which the target variable (the Price) will be predicted. The features chosen are Open, High, and Low, whereas the unnecessary columns are removed to simplify the model. This measure will make the data uniform and devoid of anomaly.

B. Data splitting

The cleaned data is subsequently divided in training and testing sets. In this case 80 percent of the data is utilized in training and 20 percent is being utilized in testing. The machine learning models are trained on the training set and tested on the testing set.

C. Data scaling

In order to standardize the data, a Min-Max scaler is used. The technique normalizes the features between 0 and 1, which is particularly valuable to models such as LSTM and SVR which are sensitive to the size of the input data. Scaling also makes sure that there is no feature domination relating to the difference in scale and models converge more effectively in training.

D. Algorithm implementation with Python

In this research we did automatic grid search to find the best hyperparameter with 30 days for lookback window.

- LSTM: The architecture involves input layers, hidden LSTM layers, and an output layer, trained to predict future values based on past exchange rates. Tables 5, 6 and 7 present the results of the automated grid search used to identify the best model.

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 30, 150)	92,400
dropout_2 (Dropout)	(None, 30, 150)	0
lstm_3 (LSTM)	(None, 200)	280,800
dropout_3 (Dropout)	(None, 200)	0
dense_1 (Dense)	(None, 1)	201

Total params: 1,120,205 (4.27 MB)
Trainable params: 373,401 (1.42 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 746,804 (2.85 MB)

Table 5 The best model summary for SAR/PKR

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 30, 150)	92,400
dropout_2 (Dropout)	(None, 30, 150)	0
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Trainable params: 373,401 (1.42 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 746,804 (2.85 MB)

Table 7 The best model summary for USD/IDR

- SVR: Support Vector Regression is a powerful regression technique that fits the data by finding a hyperplane that best represents the relationship between the input features and the target variable. SVR is well-suted for capturing non-linear patterns in the data (Table 8, Table 9, Table 10).

Table 8 Best hyperparameters from grid search SAR/PKR with SVR model

Hyperparameters	Value
Prediction Days	30
Kernel	rbf
Gamma	0.005
Epsilon	0.0001
C	150

Table 9 Best hyperparameters from grid search SAR/IDR with SVR model

Hyperparameters	Value
Prediction Days	30
Kernel	rbf
Gamma	0.005
Epsilon	0.0001
C	150

Table 10 Best hyperparameters from grid search USD/IDR with SVR model

Hyperparameters	Value
Prediction Days	30
Kernel	rbf
Gamma	0.005
Epsilon	0.0001
C	150

- MLP: Multilayer Perceptron is a fully connected feedforward neural network with multiple hidden layers. It utilizes backpropagation to minimize the prediction error during training, making it effective for regression tasks like predicting exchange rates (Table 11, Table 12, Table 13).

Table 11 Best hyperparameters from grid search SAR/PKR with MLP model

Hyperparameters	Value
Prediction Days	30
Hidden layer sizes	150
Activation function	tanh
Initial learning rates	0.001
Alpha	0.001

Table 12 Best hyperparameters from grid search SAR/IDR with MLP model

Hyperparameters	Value
Prediction Days	30
Hidden layer sizes	50
Activation function	relu
Initial learning rates	0.1
Alpha	0.001

Table 13 Best hyperparameters from grid search USD/IDR with MLP model

Hyperparameters	Value
Prediction Days	30
Hidden layer sizes	100
Activation function	relu
Initial learning rates	0.01
Alpha	0.0001

4 Results and discussion

4.1 Results

This section presents the evaluation results of the models used to predict exchange rates. Table 14 shows the performance of the three models in predicting the SAR to PKR, SAR to IDR, and USD to IDR exchange rates. The models tested include Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Multi-Layer Perceptron (MLP). Each model was evaluated using several metrics, namely MAE, MSE, RMSE, and R^2, to assess the accuracy of the models in predicting these exchange rates.

Table 14 Evaluation metrics

Model	Metric	SAR/PKR	SAR/IDR	USD/IDR
LSTM	MAE	3.370	21.159	110.331
	MSE	26.814	947.537	18278.84
	RMSE	5.178	30.782	135.199
	R^2	0.8685	0.9714	0.9620

SVR	MAE	4.573	20.788	108.761
	MSE	46.253	768.295	17752.818
	RMSE	6.800	27.718	133.239
	R2	0.7731	0.9768	0.9631
	MAE	7.871	22.140	126.417
	MSE	103.993	1001.426	24006.745
	RMSE	10.197	31.645	154.941
	R2	0.4900	0.9698	0.9501

4.2 Discussion

In all models, SVR demonstrated mimumum prediction error (RMSE of 27.72) and maximum explanatory power (R-squared of 0.9769). This is why SVR was the most appropriate model used to predict the SAR /IDR exchange rates in this research. The LSTM model was also quite effective and especially in the extent of modeling the temporal dependencies, but it was poorer than the SVR. Although effective in certain applications, MLP presented the worst error and the least R -squared value and thus it is not as applicable in this task of forecasting a financial time series.

LSTM model provided the best predictive power in SAR/PKR exchange rates. It also had the lowest MAE (3.37) and RMSE (5.18) and the highest value of R-squared (0.8685) which depicts a good ability to represent the trends and fluctuations of the exchange rate. With the currency pair prediction, LSTM was superior to SVR that had been performing well in the preceding forecasts. The bigger errors in SVR (RMSE of 6.80 and R-squared of 0.7732) indicate that it might not have been as useful to capture the specific complexities of SAR/PKR. The MLP model was unsatisfactory, and its error measures were high and the R-squared was only 0.4900, which means that it could not evidentiate more than half of the data.

The SVR produced the minimum MSE (17,752.82), RMSE (133.24) and MAE (108.76) and the highest value of R-squared (0.9631) gave the best results on predicting USD/IDR exchange rates. The potential of SVR to use non-linear relationships and its high effectiveness in regression processes qualifies it as a good predictor of the USD/IDR exchange rate. The LSTM model, although a little less precise, followed closely after, showing a good ability to deal with the sequential time-series data with R-squared value of 0.9620. Nevertheless, MLP lost to both LSTM and SVR with much higher error rates and lower R-squared value (0.9502), which means that it was not as effective in the modeling of exchange rate dynamics.

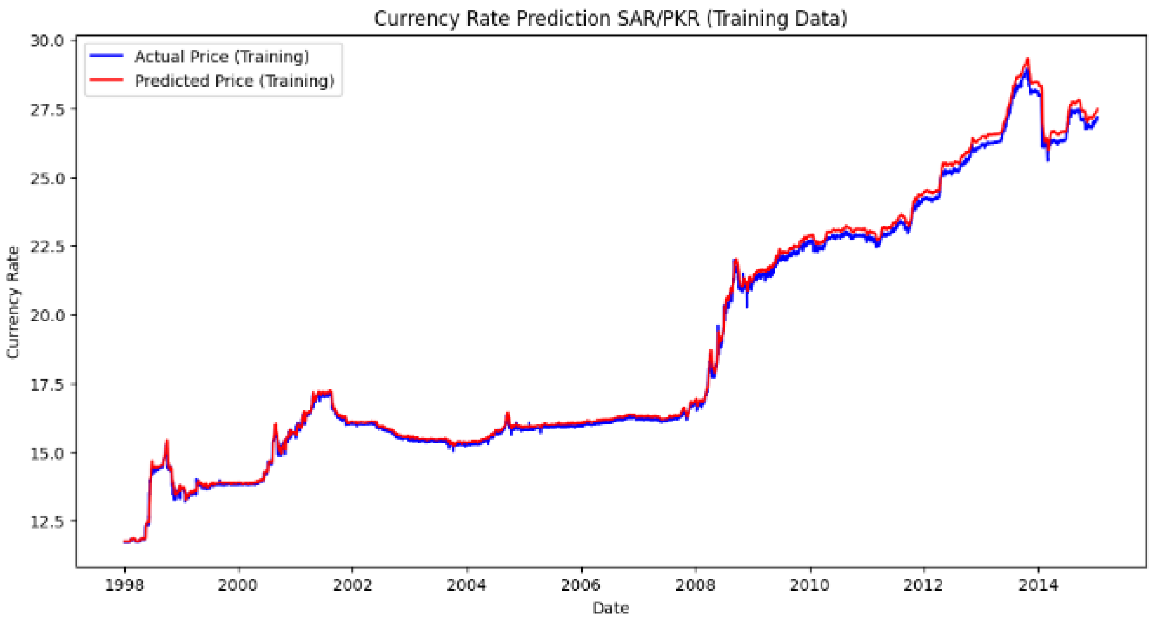

Figure 2 SAR/PKR training predicted using LSTM model

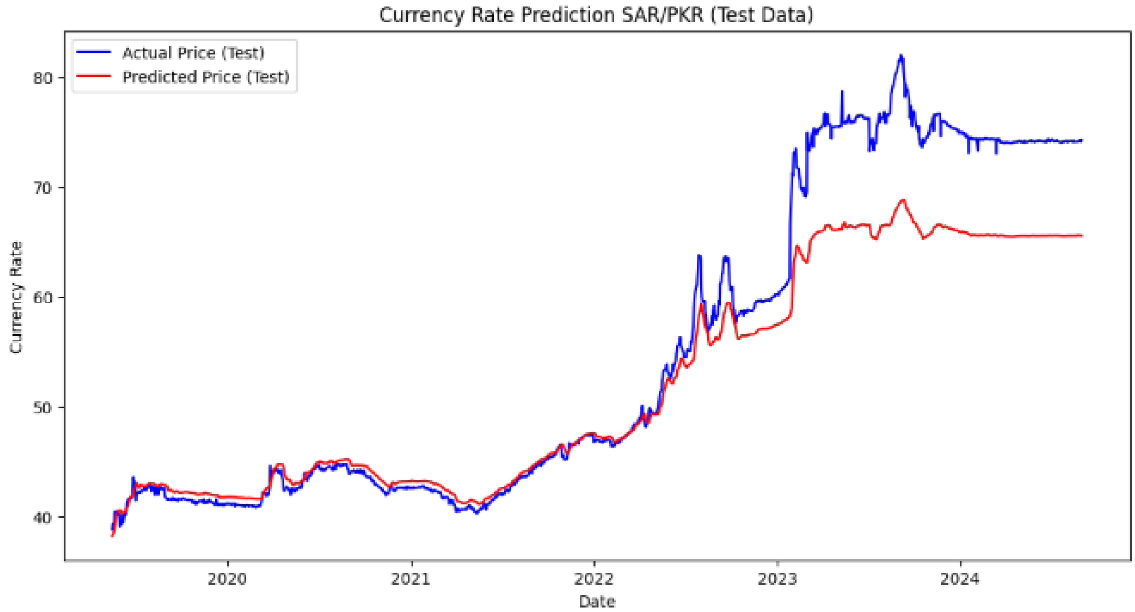

Figure 3 SAR/PKR testing predicted using LSTM model

Figure 2 indicate that The LSTM model is not bad and the predictions are almost perfect in terms of accuracy during the training process. Figure 3 depict the model as effective in capturing short-term trends but with severe changes such as the enormous spike in 2023. This points to the challenge of forecasting large and unpredictable happenings or changes in currency markets through historical data only.

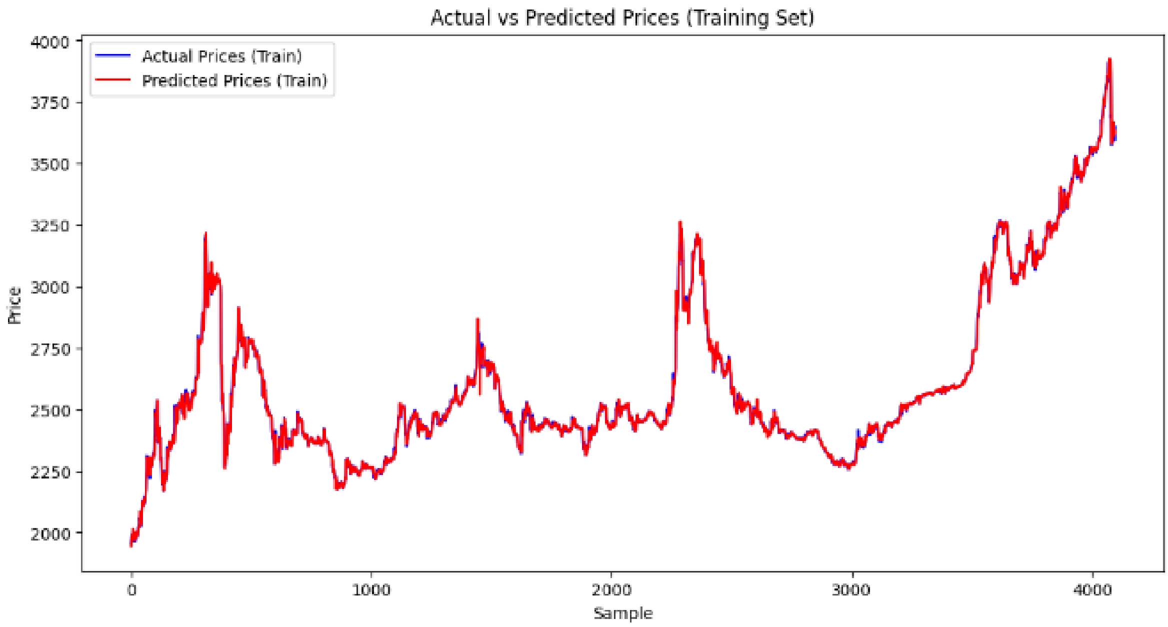

Figure 4 SAR/IDR training predicted using SVR model

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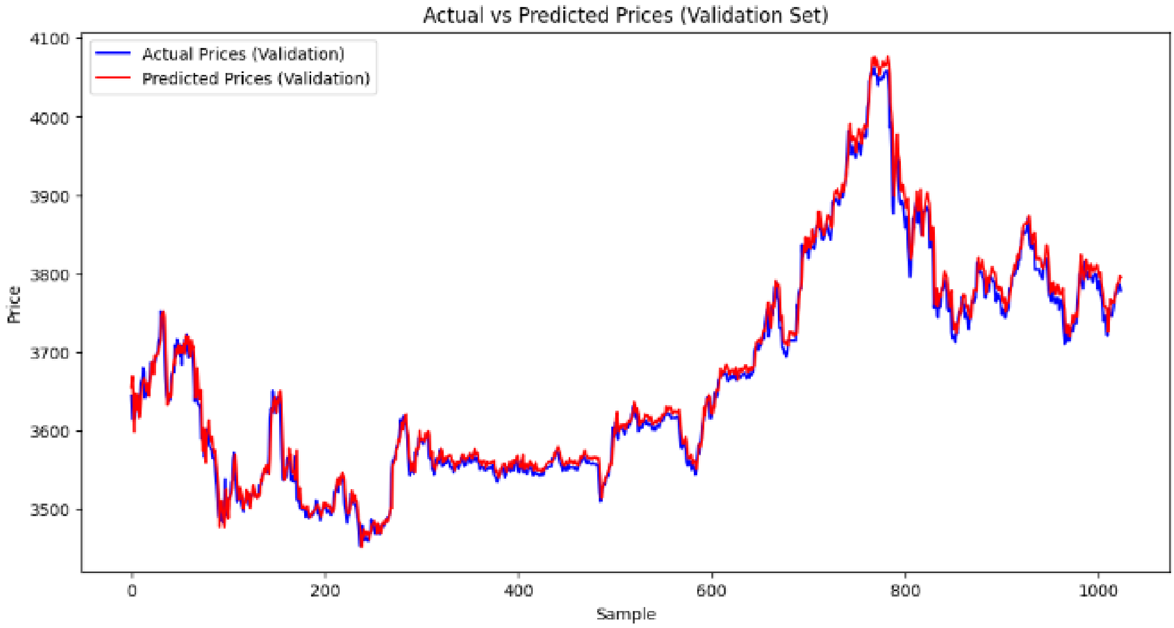

Figure 5 SAR/IDR validation predicted using SVR model

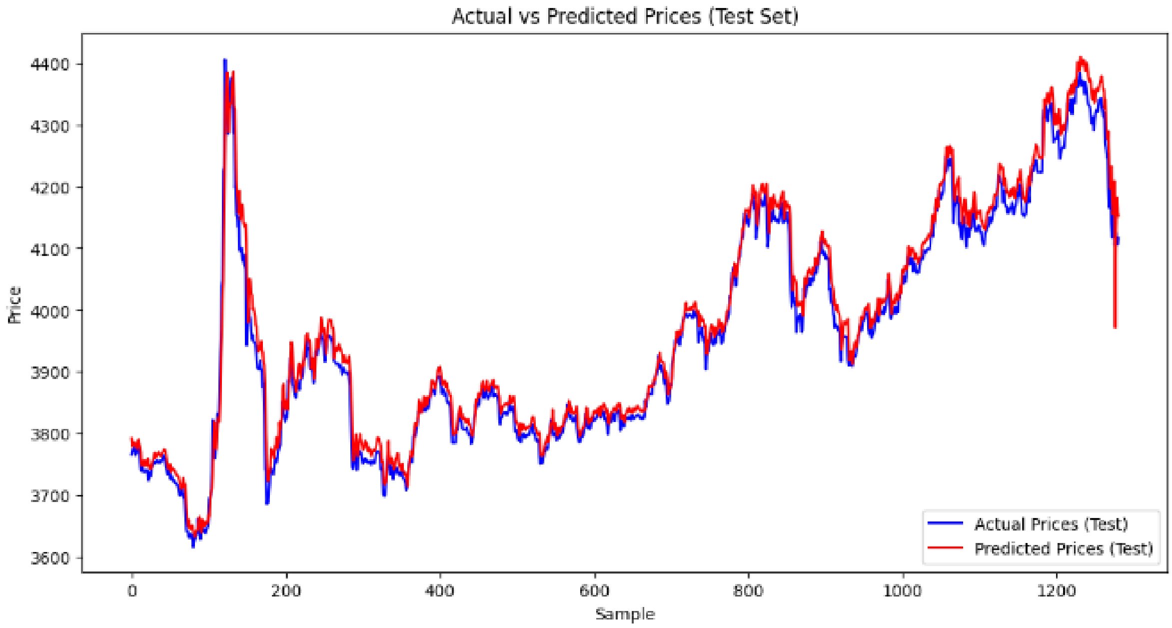

Figure 6 SAR/IDR testing predicted using SVR model

Figures 4, 5 and 6 indicate that the model is very consistent in its work with both training, validating and testing datasets. This consistency means that this model has a high generalization capacity and is not overfitting to the training data.

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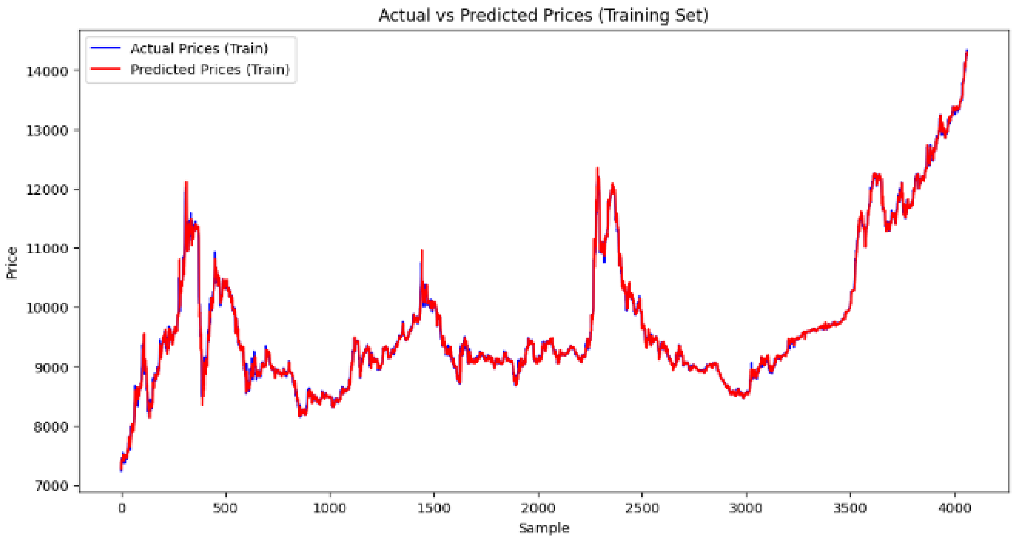

Figure 7 USD/IDR testing predicted using SVR model

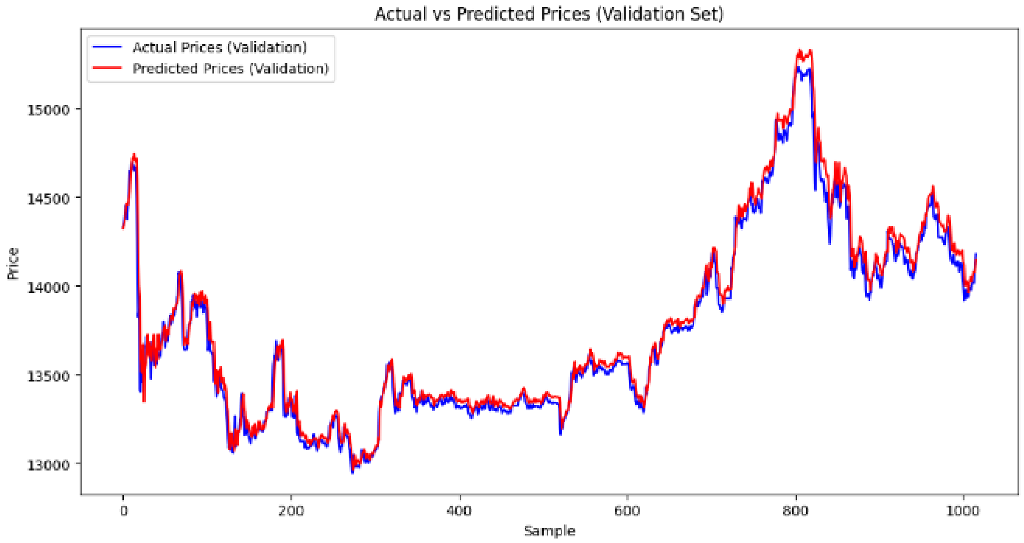

Figure 8 USD/IDR testing predicted using SVR model

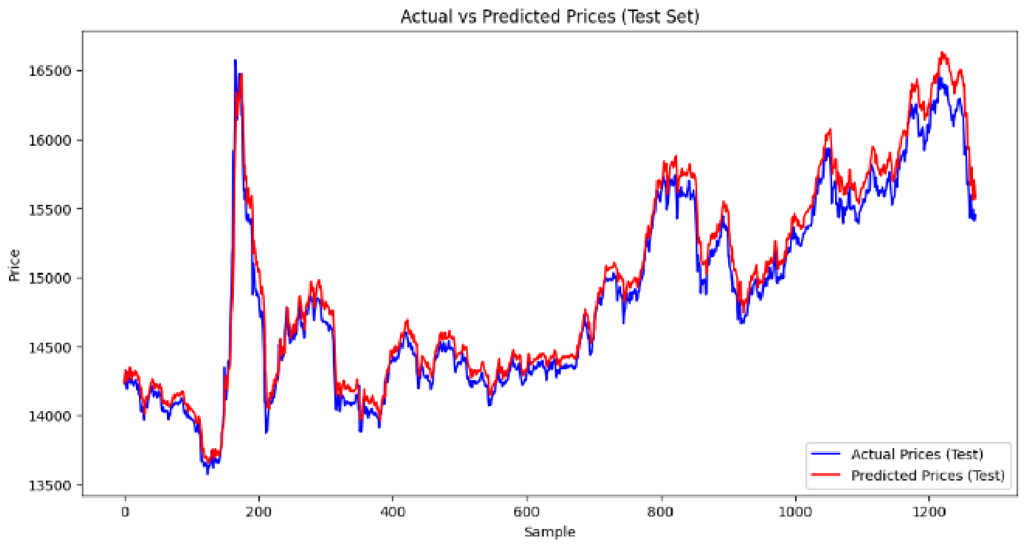

Figure 9 USD/IDR testing predicted using SVR model

Figures 7, 8 and 9 show that SVR model performs best to predicted USD/IDR. Demonstrating that in most instances SVR can be used more successfully than LSTM and MLP and that LSTM can be used more effectively than SVR in relation to certain currency pairs, this study can provide useful advice to researchers and practitioners in choosing the best model to use in the time series forecasting, especially in the financial market.

5 Conclusions

The results of this comparative study indicate that LSTM is better suited to SAR/PKR exchange rate forecasting owing to its ability to better represent time series data as well as the capability to model long-term dependencies. The best and most reliable model in general and in particular with the SAR/IDR and USD/IDR exchange rates was the SVR. It gave the least error rates and the highest R-squared values suggesting that it was able to model the intricacies of these exchange rates with a high level of accuracy. Nevertheless, MLP showed a sustained poor performance in all pairs of currencies with larger errors and less R-squared values, which means that it could not be successfully used without additional optimization. Future research may further investigate more features, may be aimed at improving these models or may investigate ensemble techniques or sophisticated tuning strategies to further enhance the overall performance of these models.

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