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01

Research Background

Research Background

(Dahal & Raju, 2022)

The currency exchange rate facilitates the international trade of goods and services as well as the transfer of capital. It indicates the external competitiveness of a country's economy.

(Boyoukliev et al., 2022)

Currency strength is directly dependent on the changes in key macroeconomic indicators such as gross domestic product, main interest rate, inflation, foreign exchange rate, unemployment, etc.

(Thevakumar & Jayathilaka, 2022)

Gauging the sensitivity of currency exchange rates reacting to changes assists policymakers to predict their future direction and further understand the potential impacts brought to the country's economy. Understanding the exchange rate movements guides them in formulating appropriate monetary and fiscal policies.

02

Literature Review

Literature Review

Research gap - Include more variables for currency exchange pair prediction, specifically macroeconomic factors of both countries which has been overlooked in the existing studies.

References	Datasets	Approaches	Techniques	Evaluations	Limitations
Influence Of Macroeconomic Variables On Exchange Rate: A Study On Bangladesh **(Hasan & Islam, 2023)**	**Annual** time series data from 2002 to 2021 for US dollar (USD), interest rates, current account balance, remittances, foreign exchange reserve, foreign direct investment (FDI). and GDP growth rates.	Two regression models were developed with slight variations in the included independent features to comprehensively examine their influence on the exchange rates.	Pearson's correlation analysis and multiple linear regression analysis	**Model 1** Adjusted R^2: 0.933 F-statistics: 45.06 **Model 2** Adjusted R^2: 0.940 F-statistics: 76.06	• Annual data was used which maybe not that comprehensive • Only linear model was used in the study
The Impact of Macroeconomic Factors on Nigerian-Naira Exchange Rate Fluctuations (1981-2021) **(Ohaegbulem & Iheaka, 2024)**	**Annual** time series data from 1981 to 2021 for Nigerian-Naira exchange rate external reserve, inflation rates, Gross Domestic Product Growth (GDPGR), public debt, unemployment rates and export.	Two regression models were developed with slight variations in the included independent features to comprehensively examine their influence on the exchange rates.	Pearson's correlation analysis and multiple linear regression analysis	**Model 1** Adjusted R^2: 0.969 F-statistics: 207.211 **Model 2** Adjusted R^2: 0.9688 F-statistics: 415.066	• Annual data was used which maybe not that comprehensive • Only linear model was used in the study
The Macroeconomic Fundamentals of the Real Exchange Rate in Malaysia: Some Empirical Evidence **(Shukri et al., 2021)**	**Annual** time series data from 1970 to 2019 on exchange rates, inflation rates, real interest rates and national income growth rates.	ARDL model was used to estimate the long-run and short-run relationships. A forecasting model was then developed to generate in-sample and out-of-sample dynamic predictions.	Autoregressive Distributed Lag (ARDL) model	**ARDL Model** RMSE: 0.13421,	• Annual data was used which maybe not that comprehensive

Literature Review (Cont.)

Research gap - Include more variables for currency exchange pair prediction, specifically macroeconomic factors of both countries which has been overlooked in the existing studies.

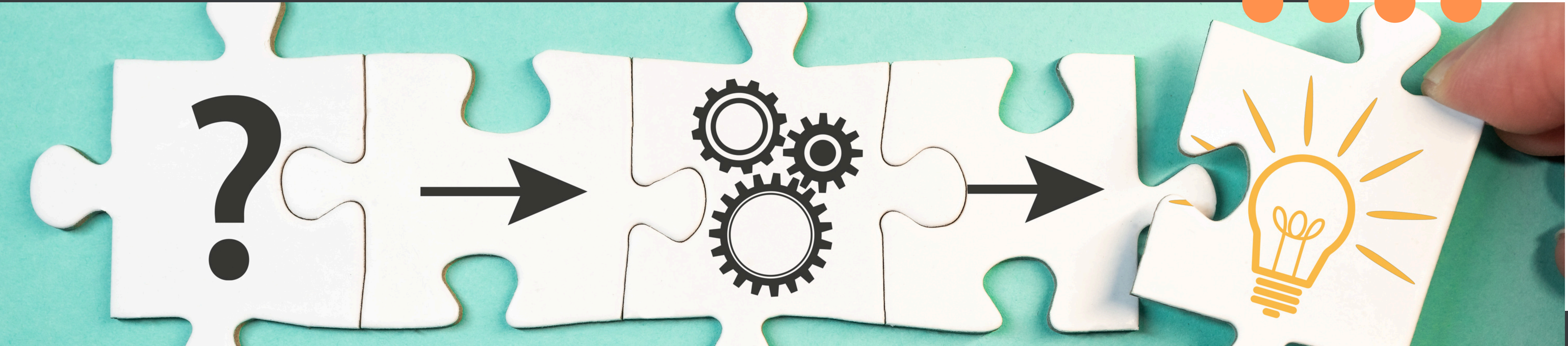
References	Datasets	Approaches	Techniques	Evaluations	Limitations
Impact of Economic Factors towards Exchange Rate in Malaysia **(Mohamed et al., 2021)**	**Annual** time series dataset spanning from 1989 to 2018 for foreign exchange rates, GDP, unemployment and inflation rates.	**Multiple regression analysis with general-to-specific approach** was used to examine the impact of independent variables (GDP, unemployment, and inflation) on the foreign exchange rate.	Pearson's correlation analysis and multiple linear regression analysis	**MLR Model** R^2: 0.8015 Adjusted R^2: 0.7785	• Annual data was used which may not concise • Only linear model was used in the study
Macroeconomic determinants of the real exchange rate in Pakistan **(Munir & Iftikhar, 2023)**	**Quarterly** time series dataset spanning from the Q1 of 1980 to the Q4 of 2020 for money supply, trade openness, government consumption expenditure, FDI, productivity, terms of trade and remittances	**ARDL models with general-to-specific approach** was conducted to examine both short-run and long-run relationships. Breusch Godfrey LM test, Breusch-Pagan-Godfrey test, and the Ramsay RESET test and ECT were done to assess the models.	Autoregressive Distributed Lag (ARDL) model	**Model IV passes diagnostic tests** for serial correlation, heteroscedasticity, and model misspecification	• Quarter data was used which may not concise • Only consider factors of own country instead of the economic condition of the paired country
Exchange rate sensitivity influencing the economy: The case of Sri Lanka **(Thevakumar & Jayathilaka, 2022)**	**Monthly** data spanning from Jan 2009 to May 2021 on monthly USD/LKR rates, inflation rates, policy interest rates, remittance, reserve, trade balance and broad money growth.	**Combinations of ARIMA, ARCH and GARCH models** were built. Godfrey autocorrelation, Breusch-Pagan heteroskedasticity tests and Jarque-Bera normality were done to assess the models.	ARIMA, ARDL, ARCH, GARCH family models	**ARIMA (1,0,0)-ARCH (1)** Log-likelihood: -249.1334 $\alpha 1$: 0.833	• Only consider factors of own country instead of the economic condition of the paired country

Literature Review (Cont.)

Research gap - Include more variables for currency exchange pair prediction, specifically macroeconomic factors of both countries which has been overlooked in the existing studies.

References	Datasets	Approaches	Techniques	Evaluations	Limitations
The effect of macroeconomic variables on exchange rate: Evidence from Ghana **(Antwi et al., 2020)**	**Quarterly** time series dataset spanning from 2000 to 2019 for foreign exchange rates, GDP, broad money supply, inflation rates and inflation rates.	**Granger causality/block exogeneity test** to find out if certain variables could predict real output and inflation, **impulse response analysis** to look at the overall effect the variables had on exchange rate and **forecast error variance decomposition** to determine the degree to which a variable's fluctuations were caused by shocks from other variables.	**Vector Autoregression (VAR)** model	**VAR Model** Log Likelihood: −4369.056 Akaike information criterion (AIC): 37.65154	• Quarter data was used which maybe not that comprehensive • Only consider factors of own country and exclude the economic conditions of the paired country
Forecasting the United State Dollar(USD)/Bangladeshi Taka (BDT) exchange rate with deep learning models: Inclusion of macroeconomic factors influencing the currency exchange rates **(Biswas et al., 2023)**	**Quarterly** time series dataset spanning from 2000 to 2019 of both USA and Bangladesh which include GDP, inflation rates, foreign reserves, exports, imports, money supply (M0 and M1), interest rates, government revenue, and balance of trade.	**A range of deep learning and machine learning models** to forecast the USD/BDT exchange rate based on macroeconomic factors. A proposed pipeline further refines the predictions by considering the exchange rate fluctuations derived from a Random Forest regressor trained on the feature fluctuations.	LSTM, Bi-LSTM, Stacked LSTM, GRU, ANN, CNN, CNN-LSTM, Encoder-Decoder, Time Distributed MLP, SVM, XGBoost.models	**Time Distributed MLP** RMSE: 0.1984 MAPE: 0.205 R^2**:** 0.9563	• Quarter data was used which maybe not that comprehensive

03 Problem Statement



Problem Statement

Lack of Malaysia Studies

Even though many of the researchers come up with different approaches such as VAR model (Antwi et al., 2020), ARDL model (Munir & Iftikhar, 2023; Thevakumar & Jayathilaka, 2022) and deep learning models (Biswas et al., 2023) to examine the effect of macroeconomic factors on the currency exchange rates., they are focusing the studies on their own countries.

Annual Data Ignores Short-Term Fluctuations

Several studies had been conducted in Malaysia (Shukri et al., 2021; Mohamed et al., 2021) to investigate the impact of economic factors on Malaysia's exchange rate volatility. However, these studies utilised annual data which may not effectively capture the fast-paced fluctuations in currency exchange rates.

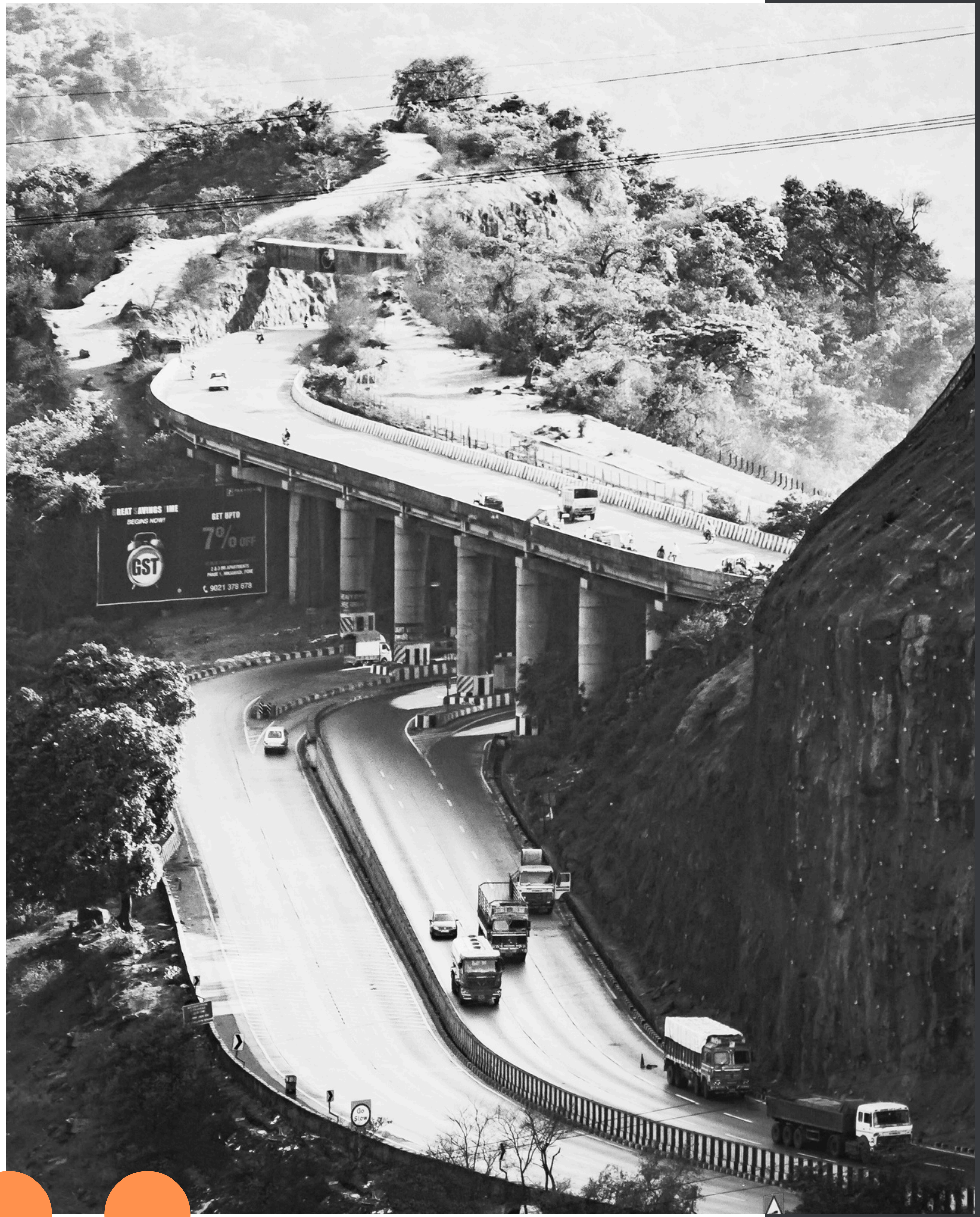
Problem Statement (Cont.)

Not Up-to-Date Data

Many of the recent research undertook a variety of new methods and models to draw relationships between macroeconomic features and the currency pairs. Nevertheless, the data they used is mostly not up-to-date. For instance, (Biswas et al., 2023) used data until 2019 and (Ohaegbulem & Iheaka, 2024) used data until 2021 only in their studies. This limits the relevance of their findings in the context of current economic conditions.

Miss Out Bilateral Macroeconomic Influences

Most studies focus solely on the macroeconomic factors of only one country. Since currency pairs represent the relative value between two countries' currencies, we may overlook the potential mutual influence from the other country on the strength of currency pairs.



Concluding the problem,

This study aims to address the research gap by applying an extensive set of features from both the U.S. and Malaysia with up-to-date monthly data through the second quarter of 2024 to explore the relationship between the macroeconomic factors and USD/MYR exchange rates movements throughout the time.

04

Research Questions & Objectives

Reseach Questions

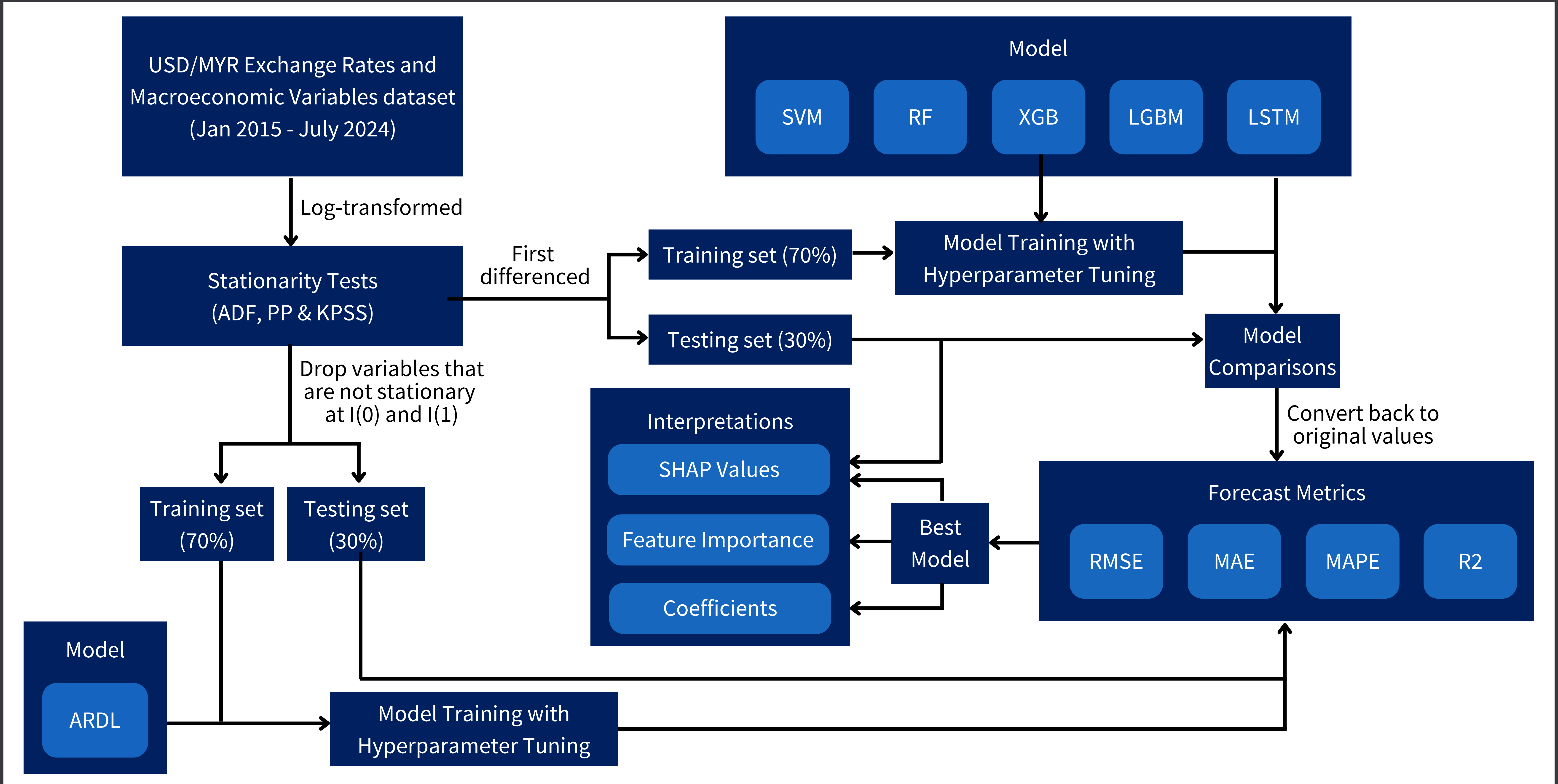
Reseach Objectives

How do macroeconomic factors in the United States and Malaysia exhibit influence on their paired exchange rates?	1	To investigate the influence that each identified macroeconomic factor has on the paired exchange rates between United States and Malaysia.
Can we map macroeconomic factors and currency exchange rates of US Dollars against Malaysian Ringgits to forecast future rates?	2	To develop an econometric model that can predict the USD/MYR exchange rates using multiple macroeconomic indicators.
How do the predictive performances of different econometric models differ in forecasting the USD/MYR exchange rates?	3	To evaluate the performance of different econometric models in forecasting the USD/MYR exchange rates.

05

Research Methodology

Research Flow Diagram



Research Methodology

SEMMA

SAMPLE

Data Collection

- USD/MYR Exchange Rates
- Macroeconomic Factors

EXPLORE

Data Exploration

- Descriptive Statistics
- Time-Series Analysis
- Correlation Analysis
- Unit Root Tests

MODIFY

Data Preprocessing

- Log Transform
- Differencing
- Lagged Features
- Train-Test Split

MODEL

Model Training

- Autoregressive Distributed Lag (ARDL)
- Support Vector Machine (SVM)
- Random Forest (RF)
- Light Gradient Boosting Machine (LightGBM)
- eXtreme Gradient Boosting (XGBoost)
- Long Short Term Memory (LSTM)

ASSESS

Model Evaluation

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- R-Squared (R^2)

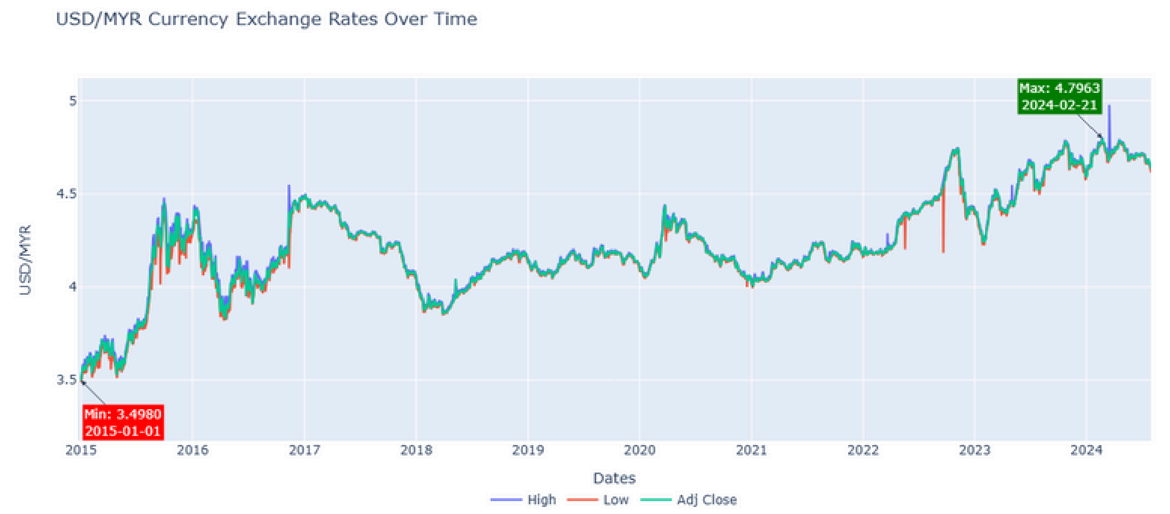
1 Data Collection

No.	Variables	Abbreviations	Unit	Sources
1	USD/MYR Currency Exchange Rates	ER	USD/RM	Yahoo Finance
2	Crude Oil Prices	CRUDE	USD/barrel	Yahoo Finance
3	Dow Jones Industrial Average	DJ	USD	Yahoo Finance
4	Kuala Lumpur Composite Index	KLCI	RM	Yahoo Finance
5	Malaysia Exports	EXPMY	RM (million)	Malaysia Open Data
6	Malaysia Imports	IMPMY	RM (million)	Malaysia Open Data
7	Malaysia Industrial Production Index	IPIMY	Index	Malaysia Open Data
8	Malaysia Consumer Price Index	CPIMY	Index	Malaysia Open Data
9	Malaysia Money Supply M1	M1MY	RM (billion)	Malaysia Open Data
10	Malaysia Money Supply M2	M2MY	RM (billion)	Malaysia Open Data
11	Malaysia Overnight Policy Rates	OPR	Percentages	BNM
12	U.S. Exports	EXPUS	USD (million)	U.S. Census Bureau
13	U.S. Imports	IMPUS	USD (million)	U.S. Census Bureau
14	U.S. Industrial Production Index	IPIUS	Index	FRED
15	U.S. Consumer Price Index	CPIUS	Index	FRED
16	U.S. Money Supply M1	M1US	USD (billion)	FRED
17	U.S. Money Supply M2	M2US	USD (billion)	FRED
18	U.S. Federal Fund Effective Rates	FFER	Percentages	FRED

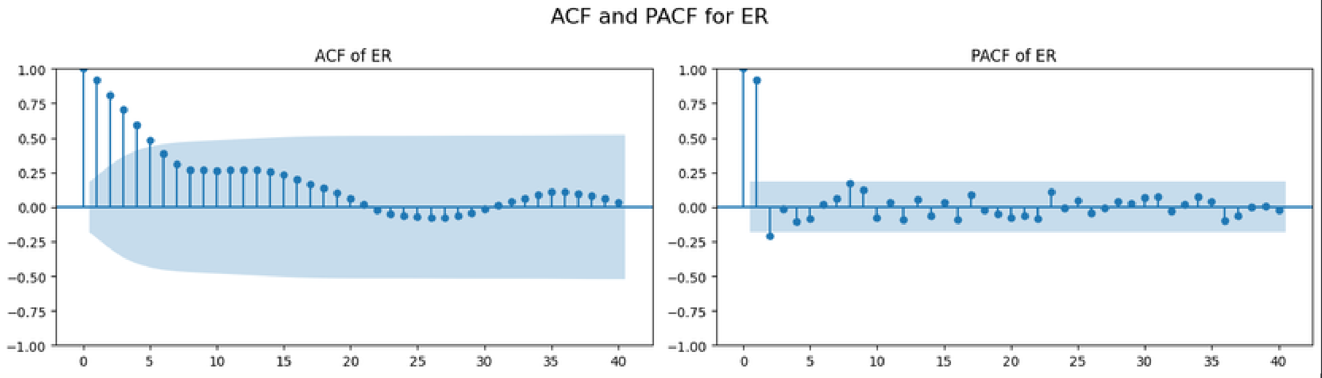
- There are a total of 18 variables utilised in this study to map the relationship between the macroeconomic factors and USD/MYR currency exchange rates.
- The data obtained is of monthly time series data which spans the period from January 2015 until July 2024.

2 Data Exploration

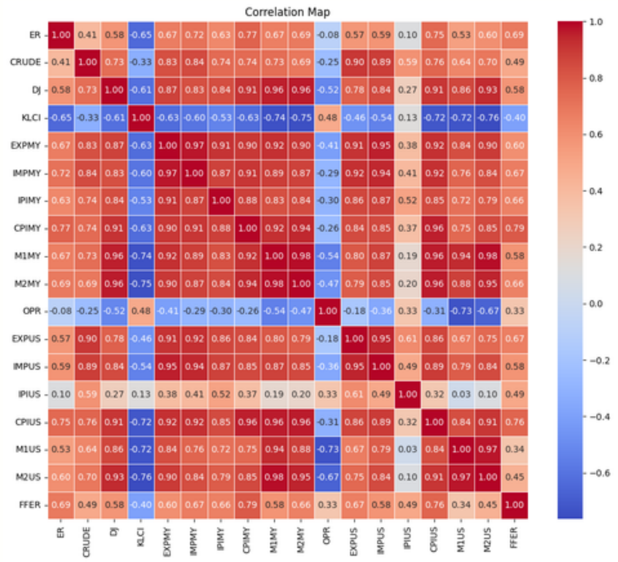
Time-Series Analysis



ACF & PACF Plots



Correlation Analysis

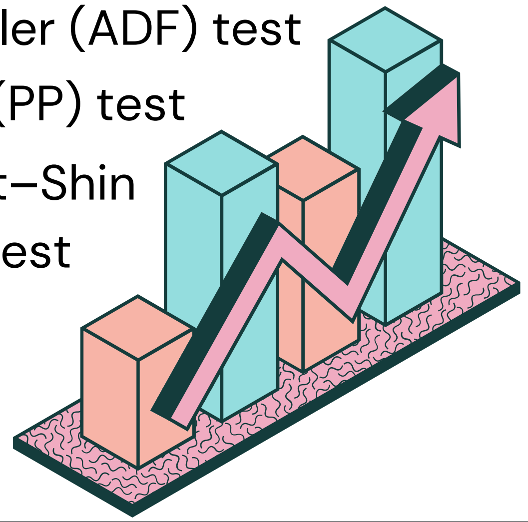


Unit Root Test

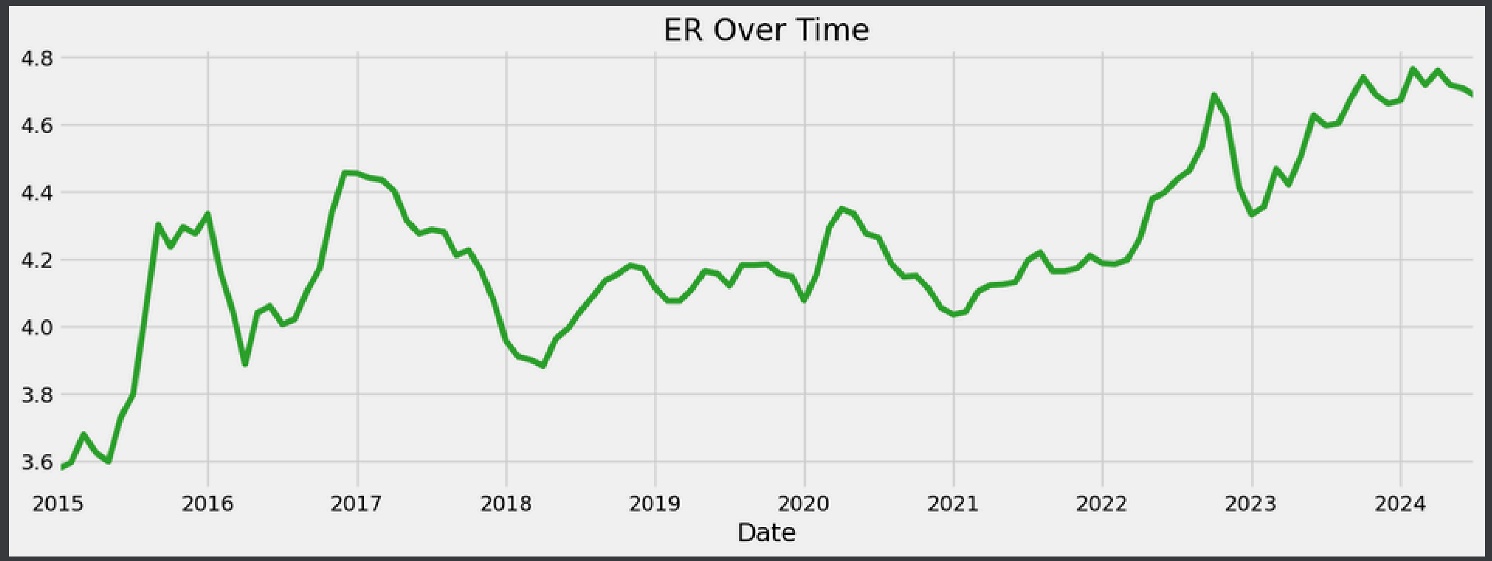
Augmented Dickey-Fuller (ADF) test

Phillips-Perron (PP) test

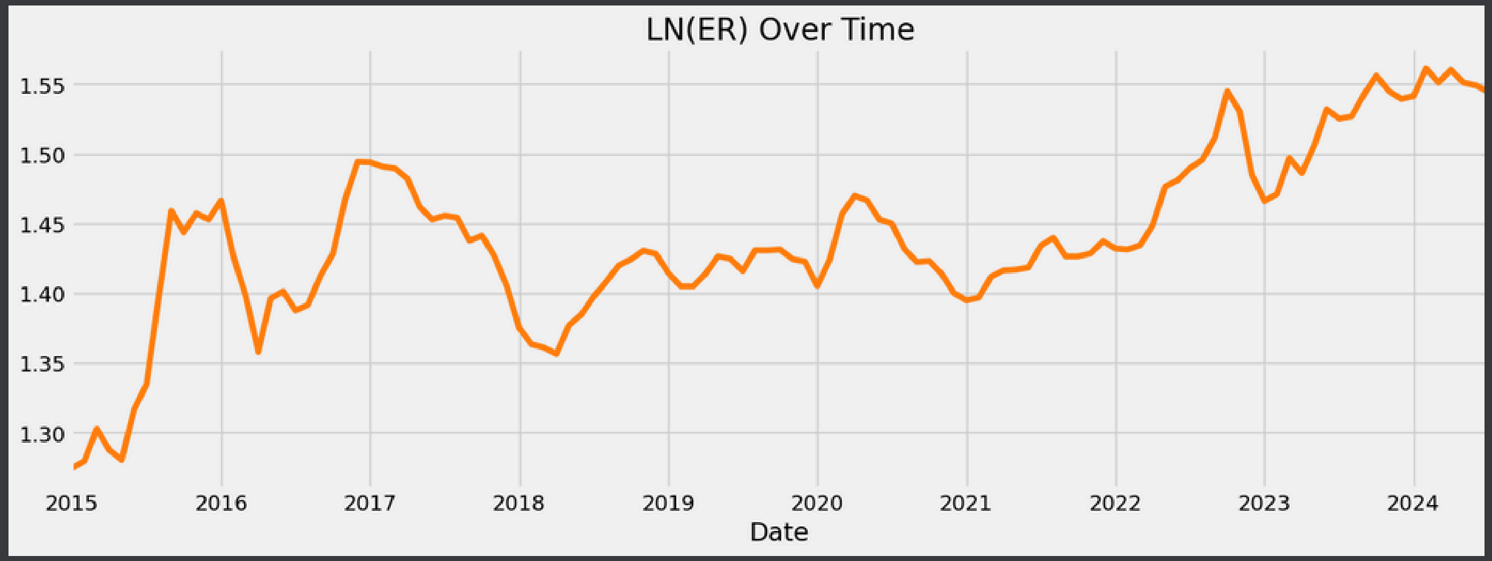
Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test



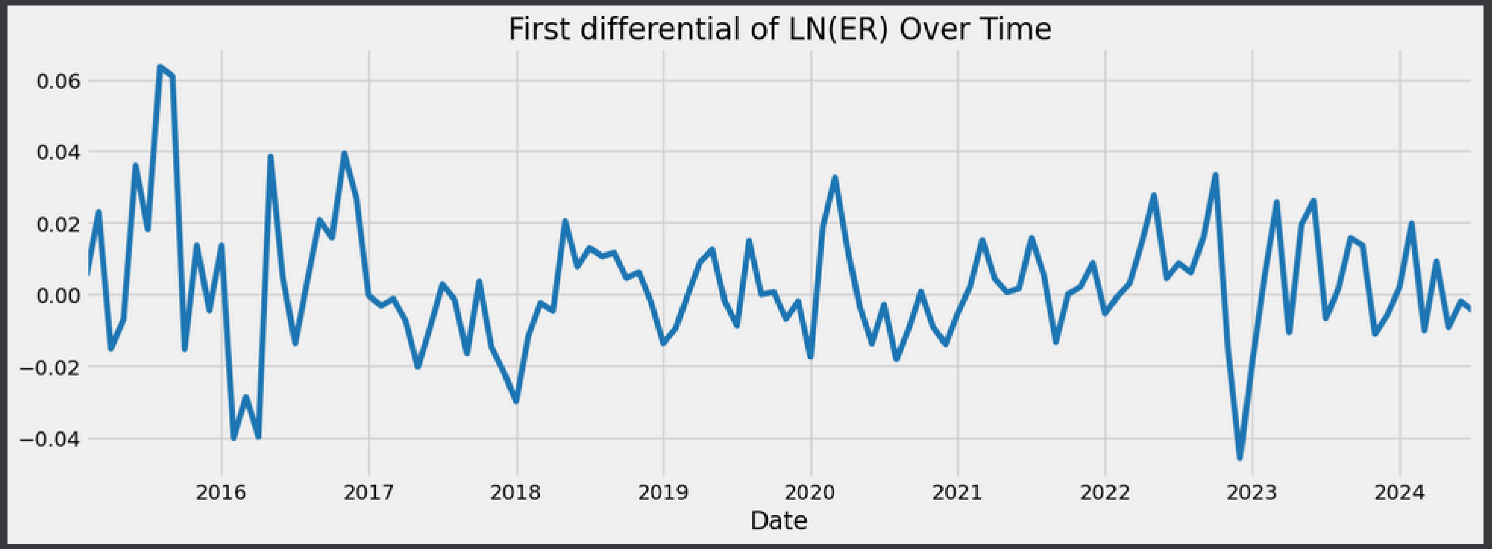
3 Data Preprocessing



Original Data



Log Transformation



First Differencing

- Several studies use log transformation to address heteroscedasticity and skewness issues in their data (Dahal & Raju, 2022; Ohaegbulem & Iheaka, 2024).
- Log differencing, which involves taking the first difference of the log-transformed data, is often used to approximate percentage change. It had been used in the study by (Thevakumar & Jayathilaka, 2022).
- We also perform lagging to capture delayed responses to shocks in the data, such as policy changes or global events.
- Data is further split into 7:3 for training and testing.

4 Model Training

The specifications of the models used in this study are as follows.

	ARDL	SVM	RF	XGB	LGBM	LSTM
Full Term	Auto Regressive Distributed Lag	Support Vector Machine	Random Forest	eXtreme Gradient Boosting	Light Gradient-Boosting Machine	Long Short-Term Memory
Type	Econometric Model	Machine Learning Model	Ensemble Learning (Tree-Based)	Ensemble Learning (Boosting)	Ensemble Learning (Boosting)	Deep Learning (RNN Variant)
Methodology	• Combines lagged dependent and independent variables. • Cointegration testing with bounds testing.	• Finds hyperplanes in a high-dimensional space to separate data. • Uses kernels for non-linear mapping.	• Constructs multiple decision trees. • Aggregates outputs via averaging for regression.	• Sequentially builds trees to minimise error. • Uses regularisation to prevent overfitting.	• Focuses on leaf-wise tree growth for speed and efficiency.	• Utilises memory cells to capture long-term dependencies in sequential data.
Purpose	• Captures short- and long-term dynamics.	• Predicts based on support vectors.	• Captures non-linear relationships.	• Optimises predictive performance.	• Faster gradient boosting for large data.	• Captures temporal patterns in data.
Pros	• Provides clear interpretability of coefficients and relationships.	• Sensitive to hyperparameter tuning and feature scaling.	• Robust to overfitting. • Handles multicollinearity well.	• Efficient for large datasets. • Includes regularisation to reduce overfit.	• Efficient memory usage. • Can be trained very fast.	• Can model complex non-linear relationships.

5 Evaluation Metrics

- Root Mean Squared Error (RMSE) measures the average magnitude of error in USD/MYR exchange rate predictions.
- This metric is sensitive to outliers and best in capturing extreme fluctuations in the exchange rate.

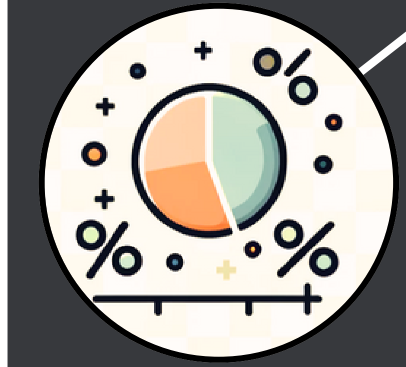
RMSE

MAE

- Mean Absolute Error (MAE) quantifies the average absolute error in USD/MYR exchange rate predictions,
- It treats all errors equally, less sensitive to large deviations and more reflective of overall performance.

Evaluation Metrics

- Mean Absolute Percentage Error (MAPE) indicates the percentage difference between predicted and actual USD/MYR exchange rates.
- A lower MAPE value reflects better predictive performance.



MAPE

R^2

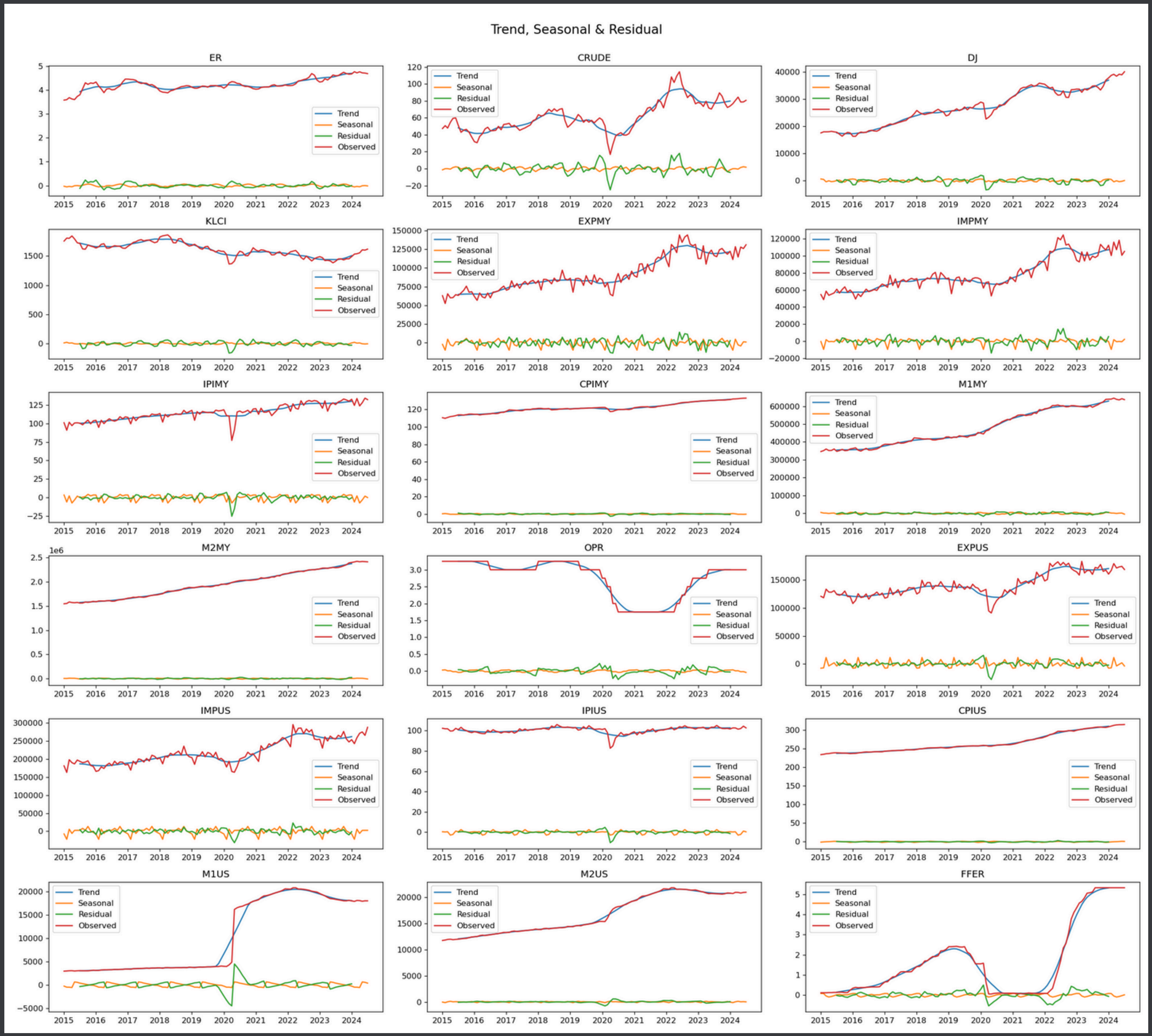
- R-squared (R^2) describes how well the model explains the variance in actual USD/MYR exchange rates.
- It provides a holistic measure of the model’s predictive capability.
- A value closer to 1 shows a better fit.

06 Results & Discussions

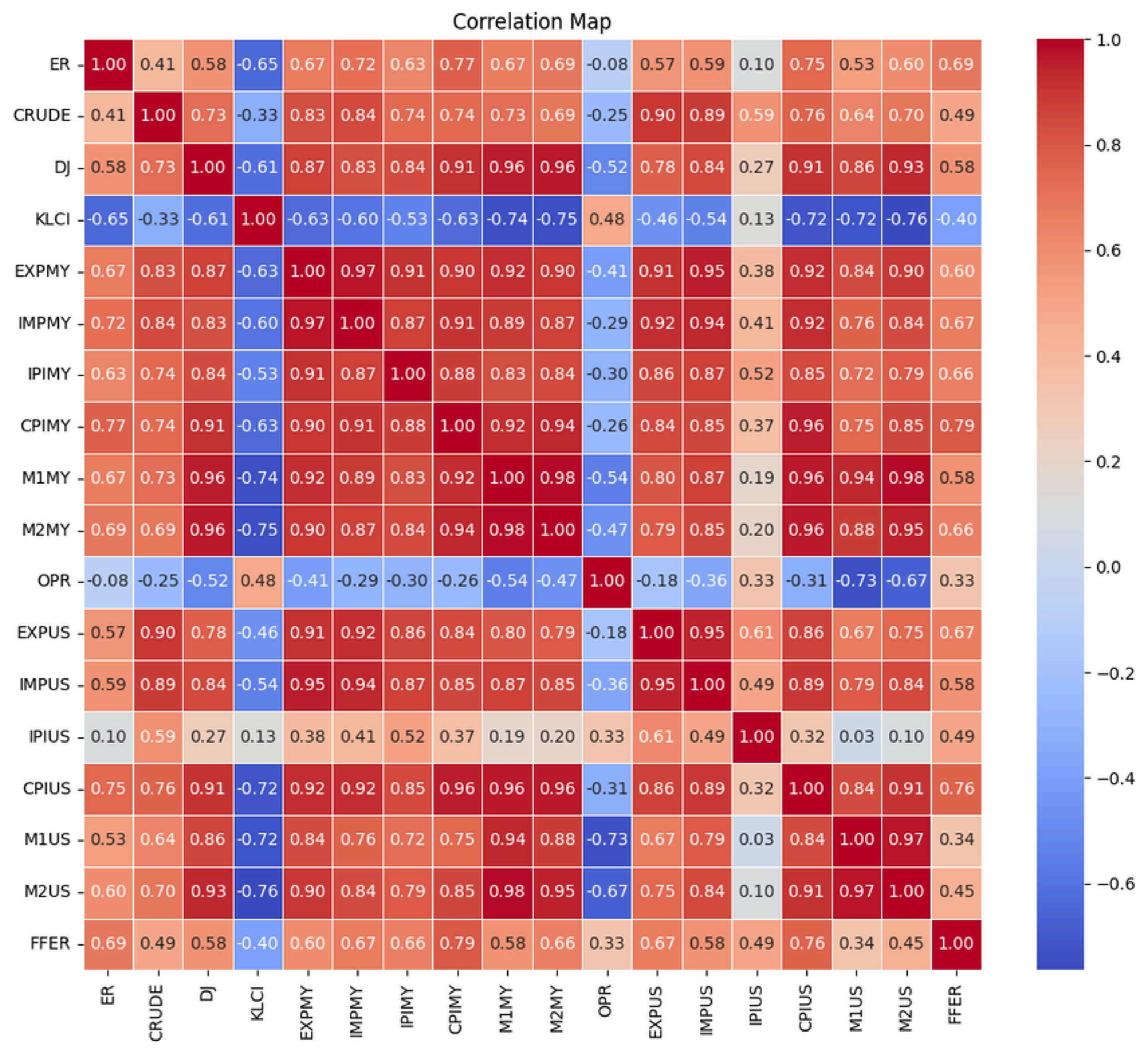
Exploratory Data Analysis

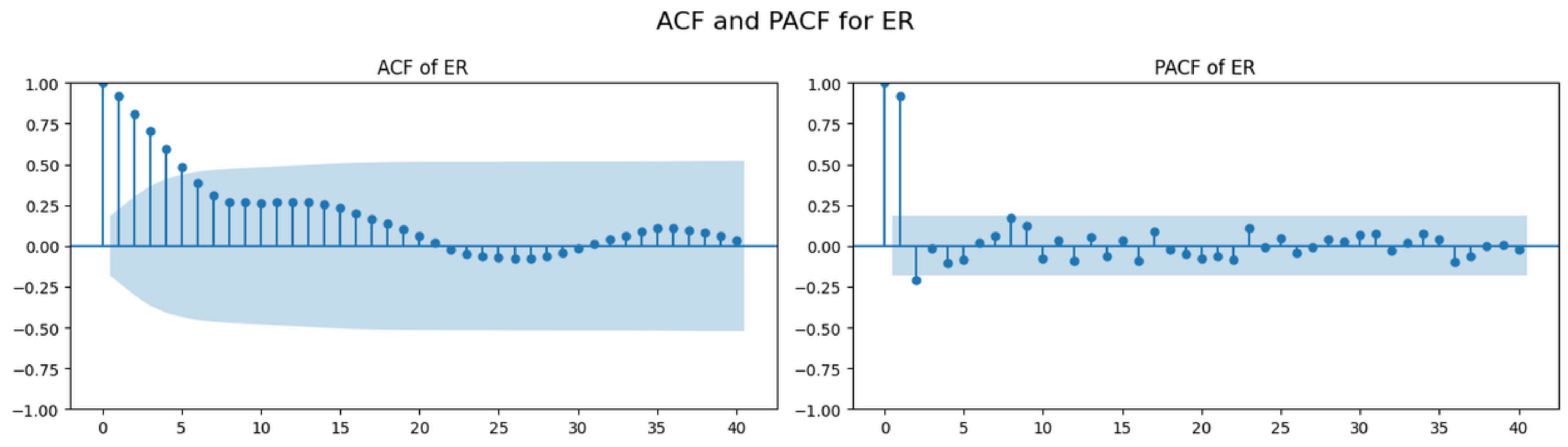
	count	mean	std	min	25%	50%	75%	max	Skewness	Kurtosis
ER	115	4.23	0.26	3.58	4.10	4.18	4.39	4.76	-0.01	0.18
CRUDE	115	61.58	18.23	16.70	48.30	58.17	73.62	114.34	0.47	0.11
DJ	115	27058.12	6776.11	16299.90	21127.30	26232.67	33565.26	40050.00	0.05	-1.19
KLCI	115	1615.24	122.59	1363.54	1524.24	1607.52	1702.33	1863.15	0.00	-0.77
EXPMY	115	91836.43	23562.21	52473.78	73607.23	84721.27	112668.00	144275.50	0.51	-0.88
IMPMY	115	78274.77	19052.11	48643.97	63746.67	73156.94	93166.07	124231.30	0.67	-0.62
IPIMY	115	114.56	10.90	77.05	108.03	114.77	122.19	134.30	-0.28	0.13
CPIMY	115	121.85	5.76	109.90	118.85	121.10	125.40	133.10	0.20	-0.64
M1MY	115	478185.4	100236.1	346300.4	392007.3	435747.0	589935.5	645343.9	0.25	-1.48
M2MY	115	1944426.0	271682.7	1545766.0	1682104.0	1922423.0	2193223.0	2423484.0	0.14	-1.25
OPR	115	2.75	0.56	1.75	2.50	3.00	3.25	3.25	-0.96	-0.71
EXPUS	115	141575.40	21127.75	91026.76	126070.70	135977.00	159680.80	183432.80	0.33	-0.68
IMPUS	115	218598.00	34006.91	162949.70	192717.40	207985.50	248725.30	295671.00	0.47	-0.89
IPIUS	115	100.70	3.29	82.68	98.92	101.53	102.74	106.09	-2.51	10.40
CPIUS	115	264.87	24.92	233.71	244.76	256.57	285.61	314.54	0.70	-0.92
M1US	115	10321.28	7707.93	2941.10	3522.40	3924.90	18288.55	20826.80	0.26	-1.88
M2US	115	16714.31	3632.22	11759.00	13543.55	15112.20	20750.05	21859.70	0.17	-1.69
FFER	115	1.65	1.79	0.05	0.12	1.15	2.38	5.33	1.05	-0.23

Exploratory Data Analysis (Cont.)



Exploratory Data Analysis (Cont.)



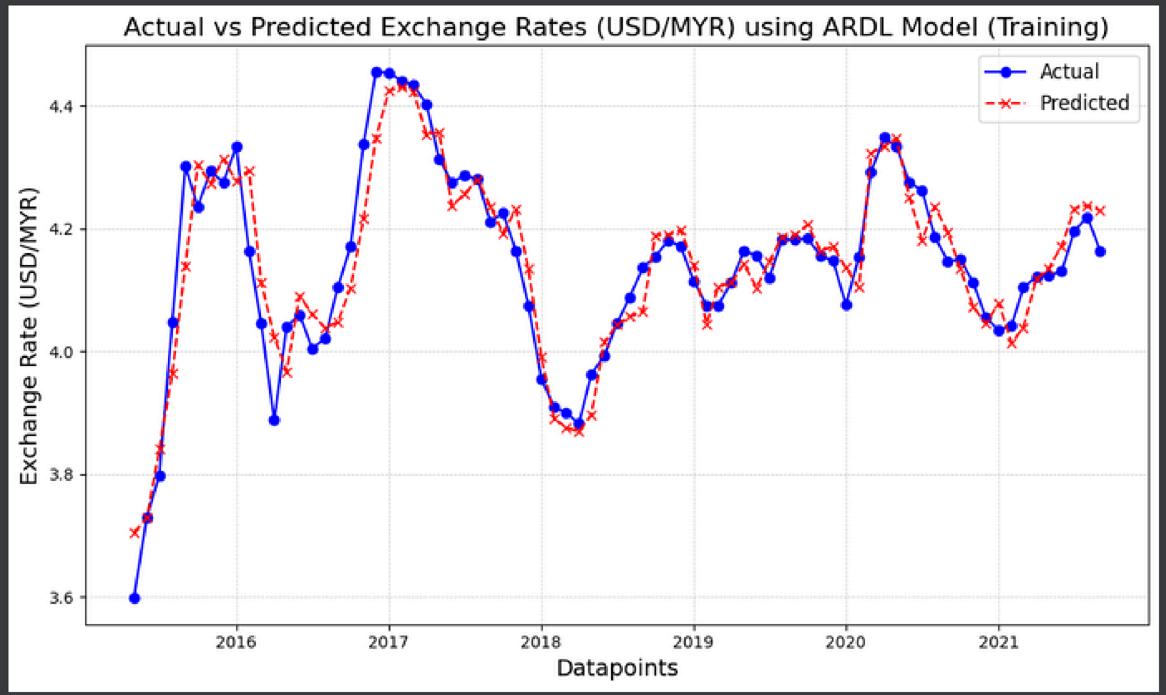


- The ACF plot shows significant positive autocorrelation at the first few lags which then gradually decreases.
- The PACF plot has a strong spike at lag 1, followed by values close to zero at subsequent lags.
- This pattern implies that the current value of ER is mainly dependent on its immediate past value.

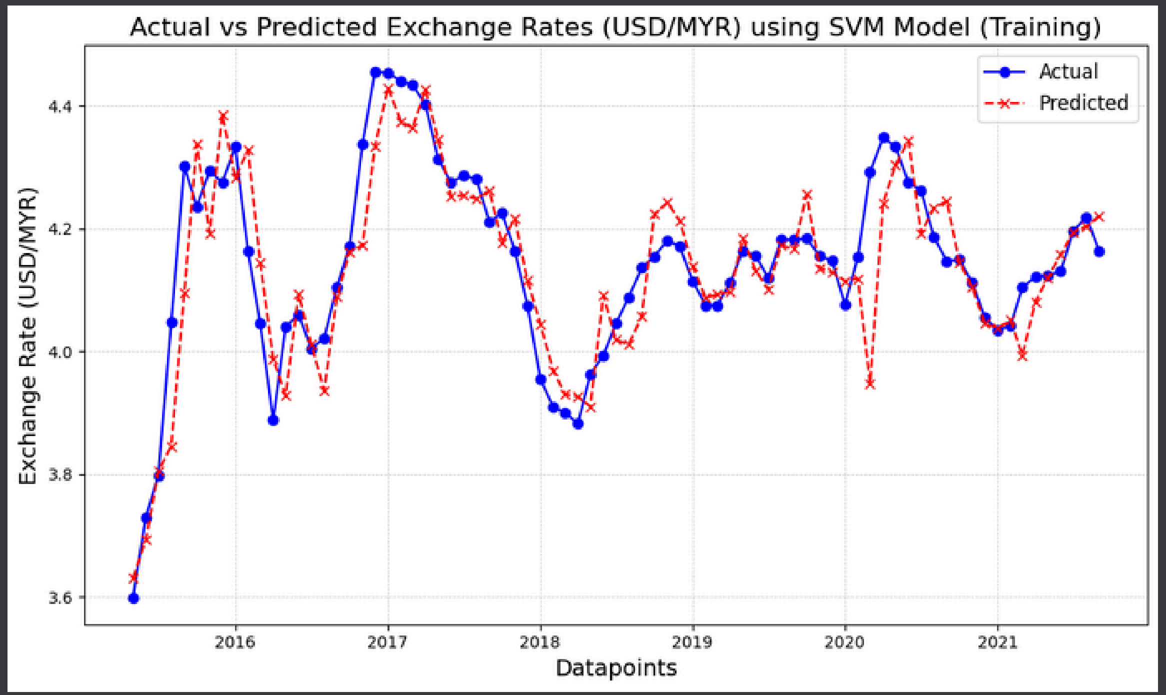
Exploratory Data Analysis (Cont.)

Variable	ADF Level	ADF 1st Diff	PP Level	PP 1st Diff	KPSS Level	KPSS 1st Diff	Order ADF	Order PP	Order KPSS
ER	-2.6196*	-	-2.147	-7.1948***	0.9866	0.0713***	I(0)	I(1)	I(1)
CRUDE	-2.0822	-7.7400***	-1.7146	-8.1041***	0.9621	0.0505***	I(1)	I(1)	I(1)
DJ	-0.202	-9.8518***	-0.0587	-9.8575***	1.6626	0.0649***	I(1)	I(1)	I(1)
KLCI	-1.954	-9.2435***	-1.9437	-8.1795***	1.2123	0.0966***	I(1)	I(1)	I(1)
EXPMY	-0.61	-3.2946**	-1.5746	-23.2177***	1.5333	0.1020***	I(1)	I(1)	I(1)
IMPMY	-0.7734	-3.8305***	-1.68	-21.5964***	1.4229	0.0477***	I(1)	I(1)	I(1)
IPIMY	-0.2698	-3.9792***	-3.3342**	-	1.76	0.0711***	I(1)	I(0)	I(1)
CPIMY	-0.5209	-7.6479***	-0.5438	-7.8745***	1.5721	0.0967***	I(1)	I(1)	I(1)
M1MY	0.2538	-2.037	0.171	-11.1549***	1.7007	0.1898***	Not Stationary	I(1)	I(1)
M2MY	0.8213	-10.2125***	1.1374	-10.2699***	1.7376	0.1718***	I(1)	I(1)	I(1)
OPR	-1.6533	-4.0755***	-1.5633	-12.0824***	0.6646	0.2332***	I(1)	I(1)	I(1)
EXPUS	-0.9158	-3.3616**	-2.2262	-17.6903***	1.2178	0.0763***	I(1)	I(1)	I(1)
IMPUS	-0.8656	-2.6257*	-1.5698	-20.0113***	1.4123	0.0639***	I(1)	I(1)	I(1)
IPIUS	-2.0401	-2.6743*	-3.9888***	-	0.2100***	-	I(1)	I(0)	I(0)
CPIUS	-0.1506	-1.7177	1.5908	-6.0002***	1.6134	0.5974	Not Stationary	I(1)	Not Stationary
M1US	-0.7074	-9.7408***	-0.8492	-9.8346***	1.4584	0.1347***	I(1)	I(1)	I(1)
M2US	-0.947	-1.7511	-0.7548	-6.0674***	1.6417	0.2474***	Not Stationary	I(1)	I(1)
FFER	-1.8173	-2.9061**	-0.5488	-5.5451***	0.7736	0.2413***	I(1)	I(1)	I(1)

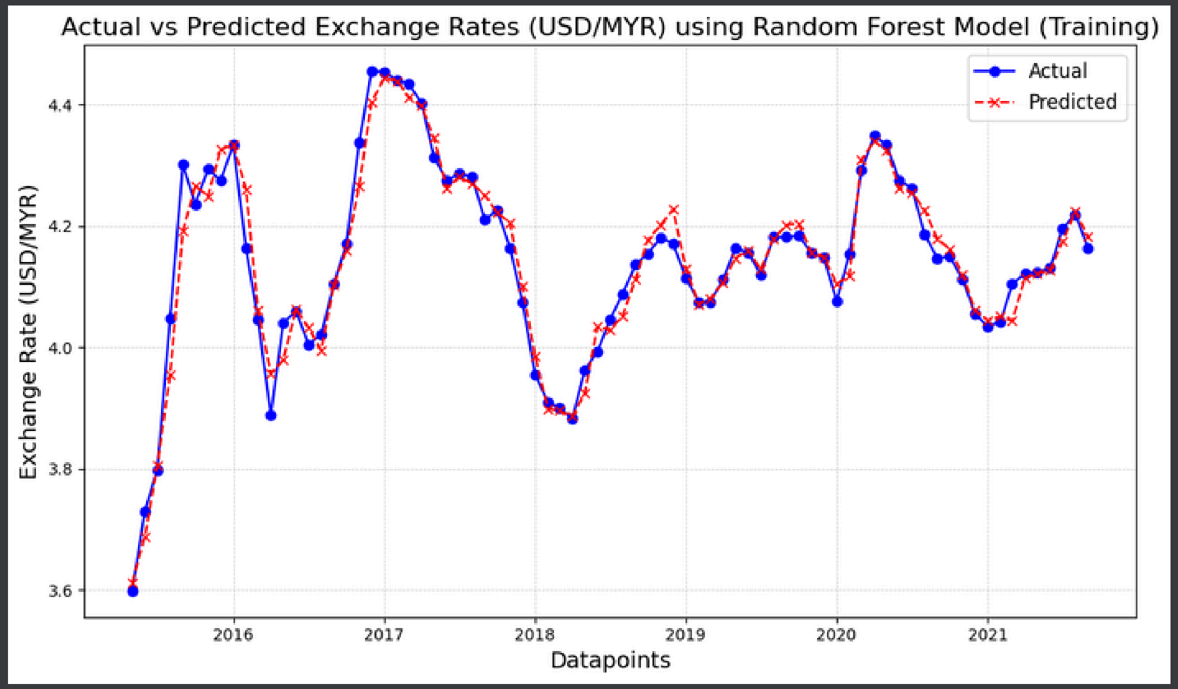
Actual vs Predicted (Training)



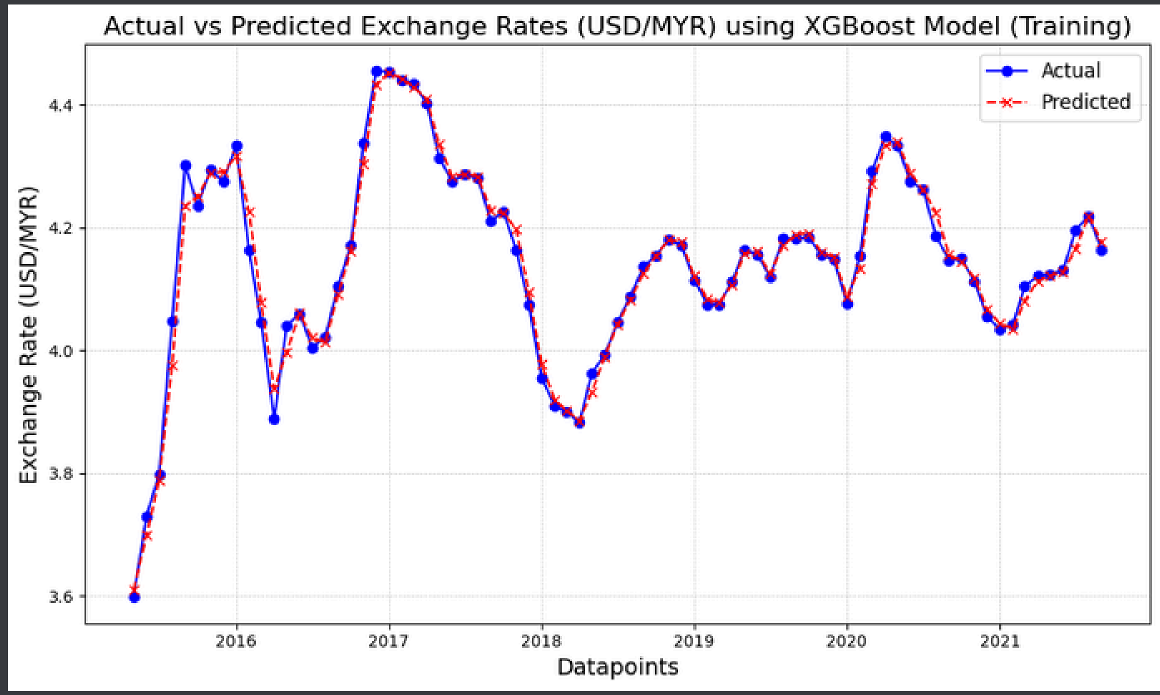
ARDL



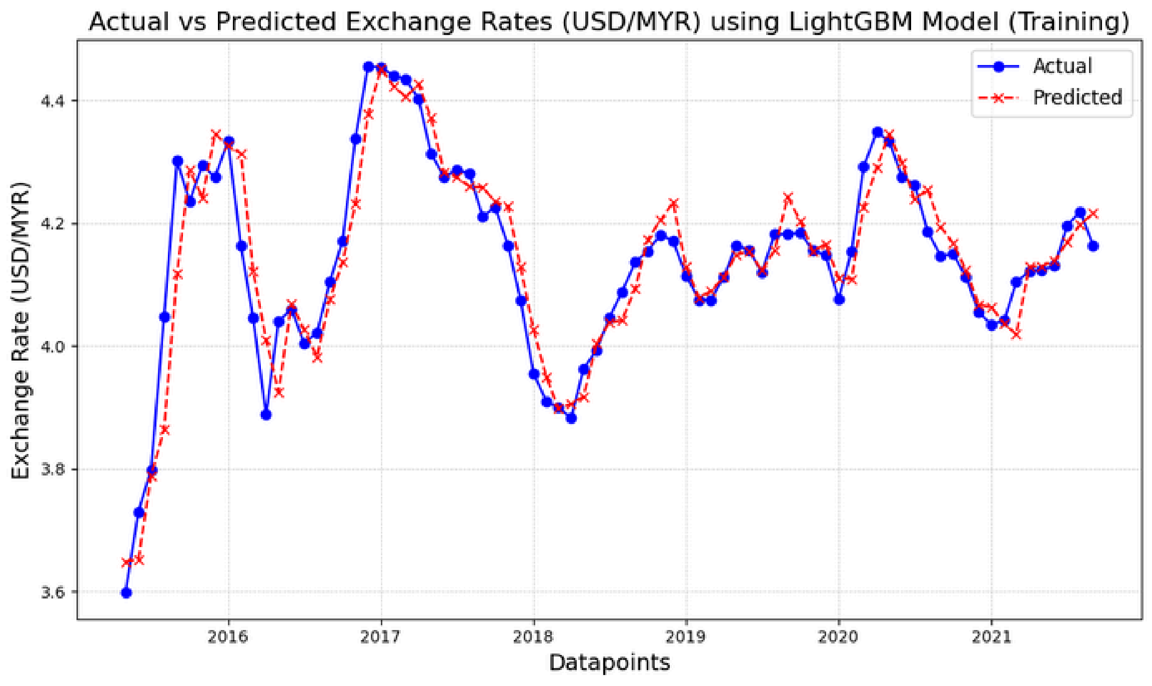
SVM



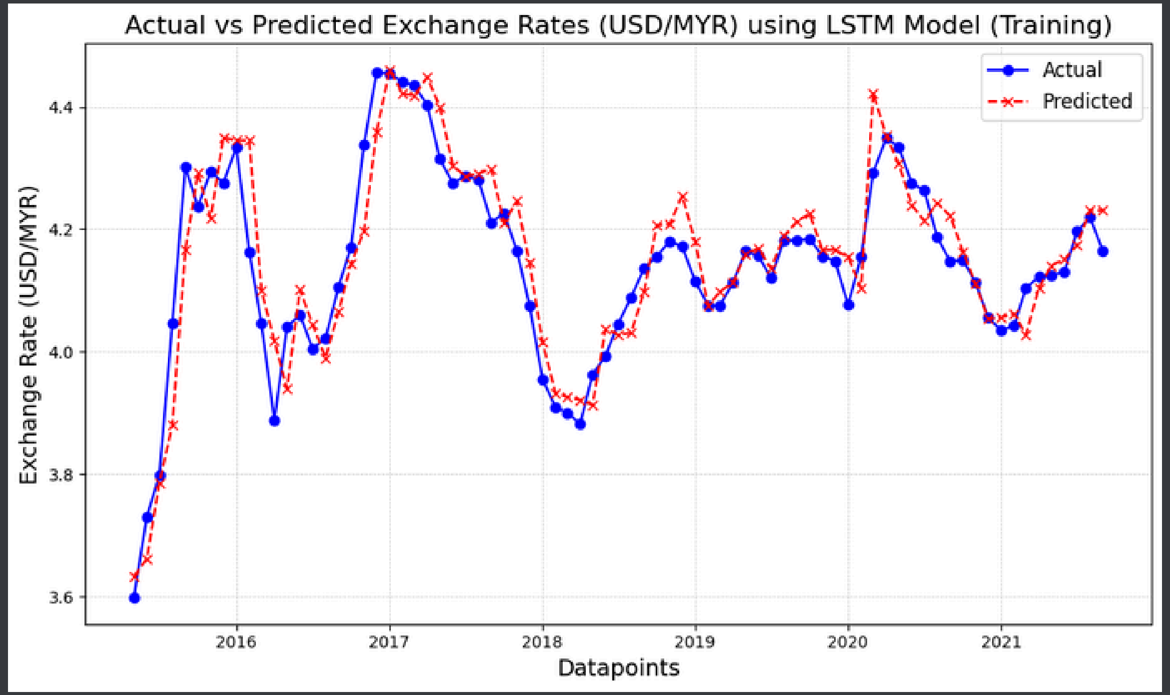
Random Forest



XGBoost

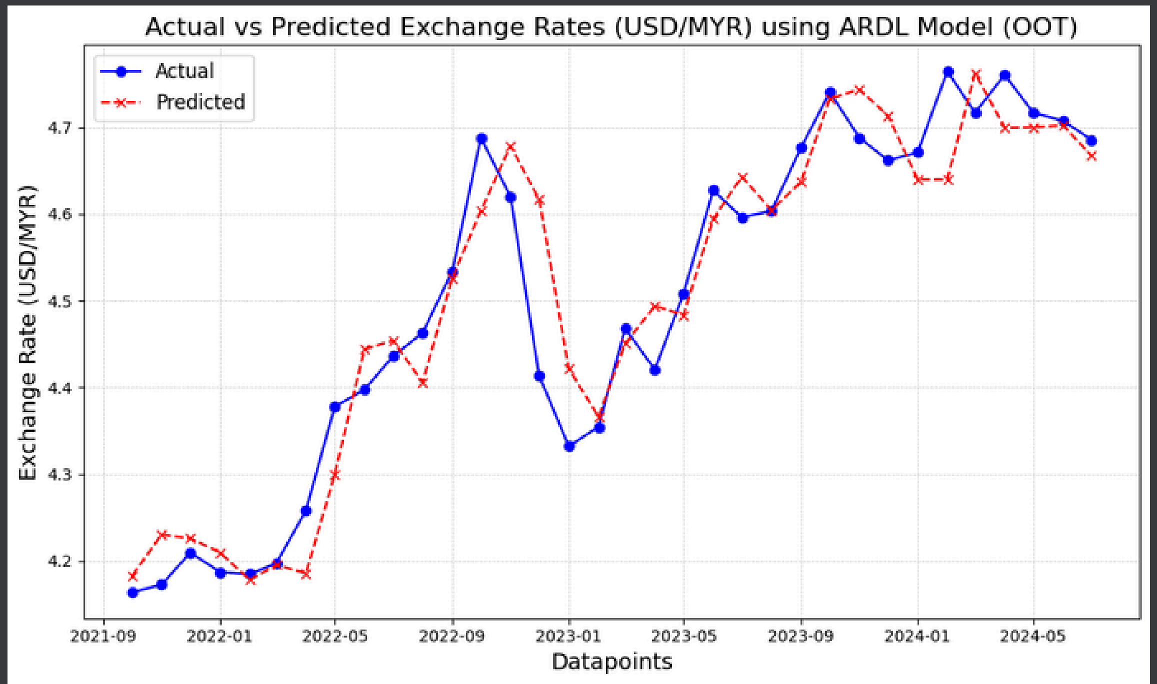


LightGBM

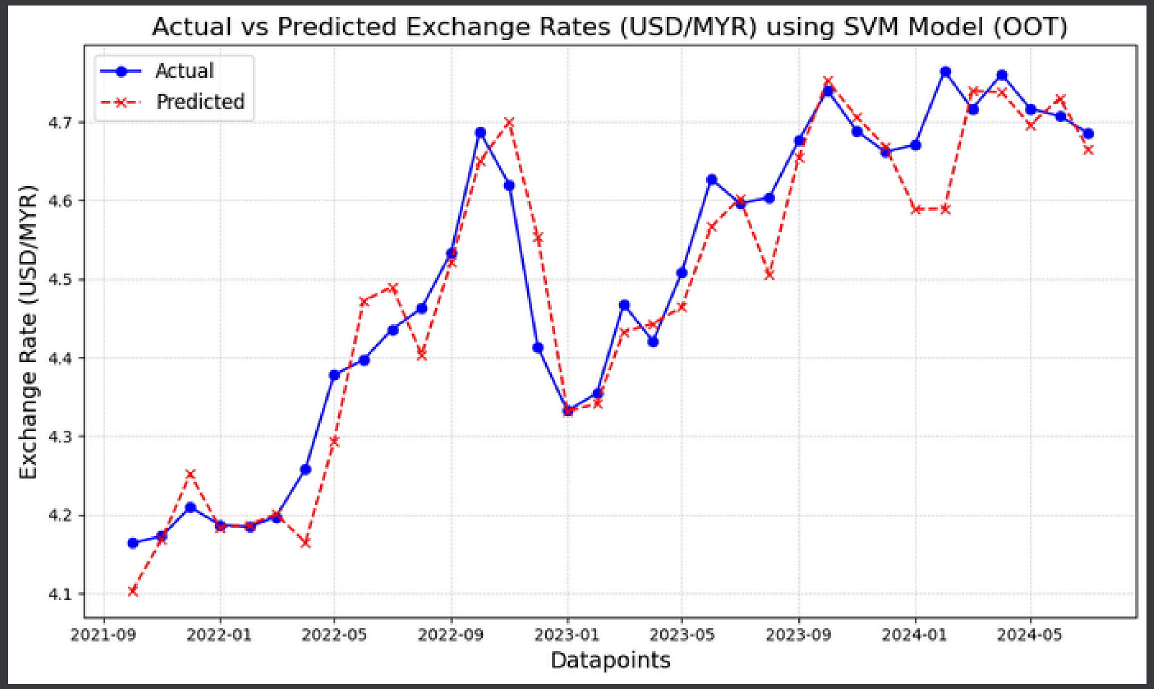


LSTM

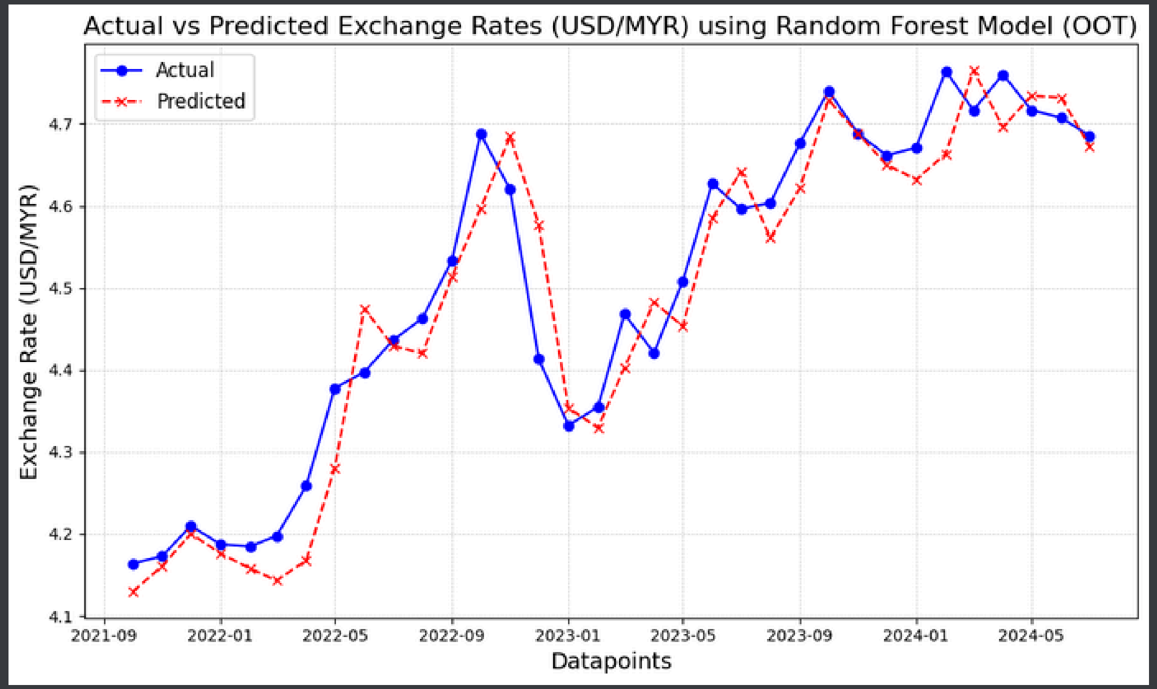
Actual vs Predicted (OOT)



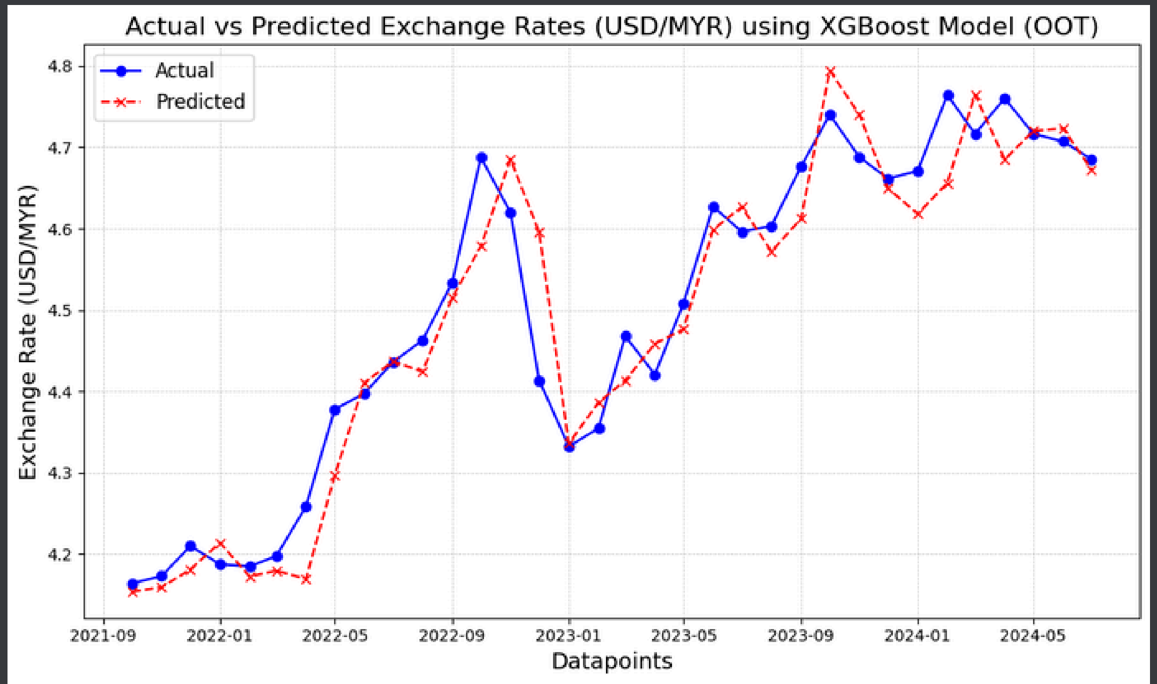
ARDL



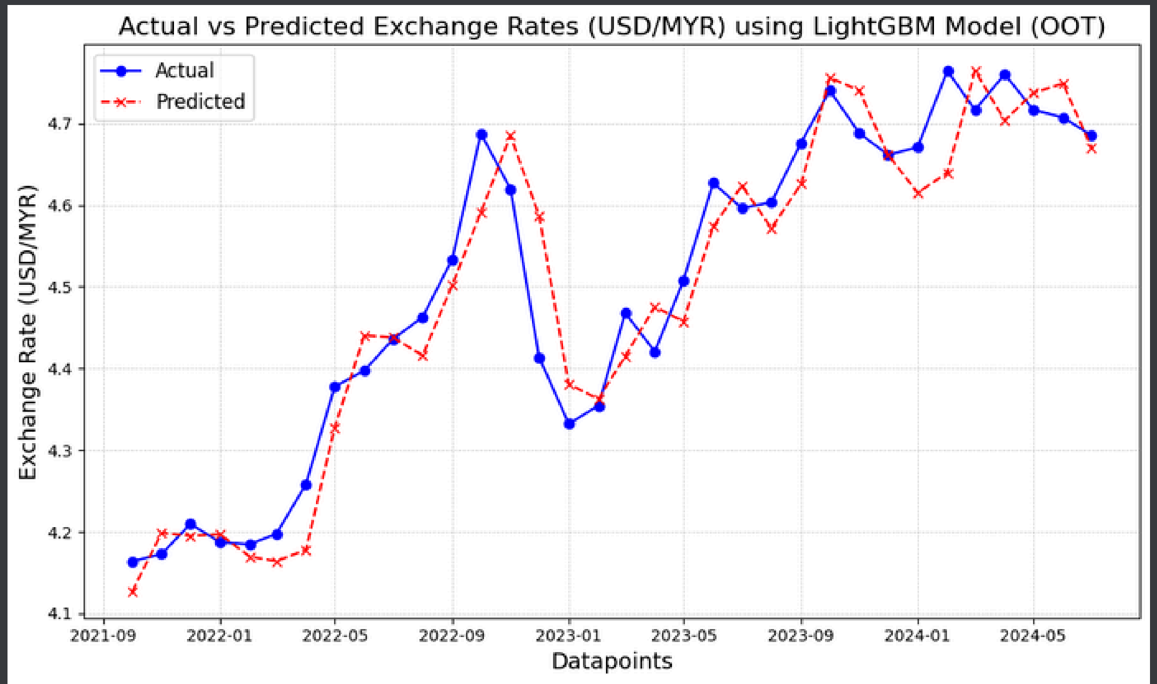
SVM



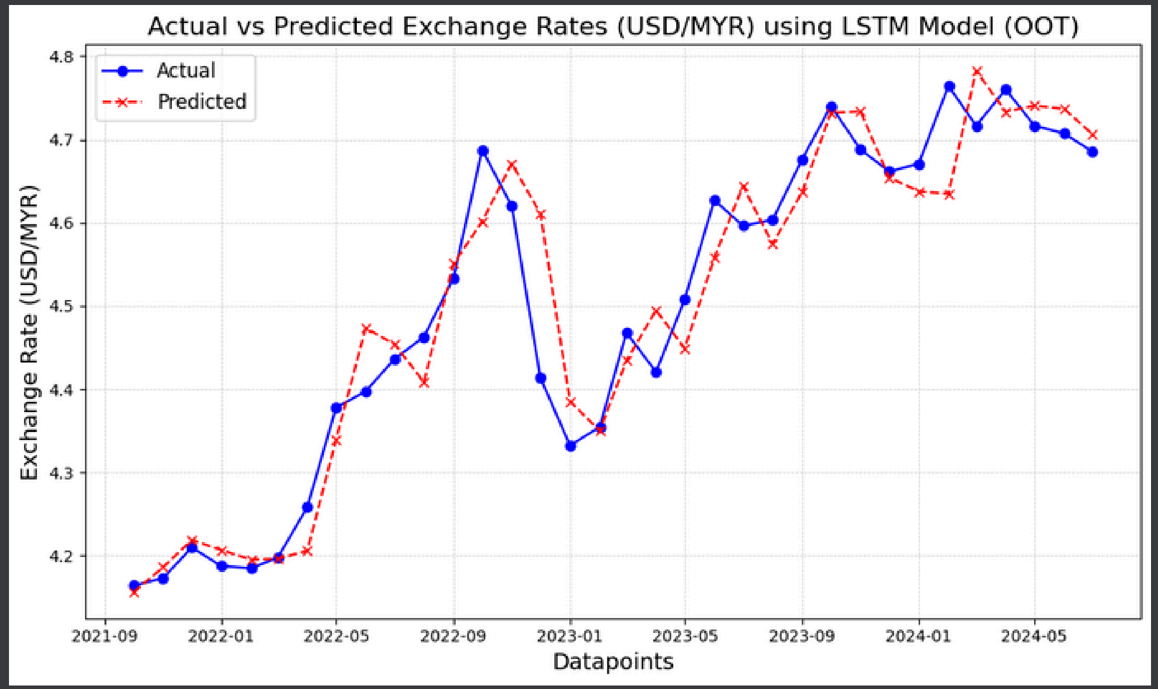
Random Forest



XGBoost



LightGBM



LSTM

Model Performance Evaluation

In our analysis, we evaluated five different predictive models using testing data (OOT) based on several performance metrics.

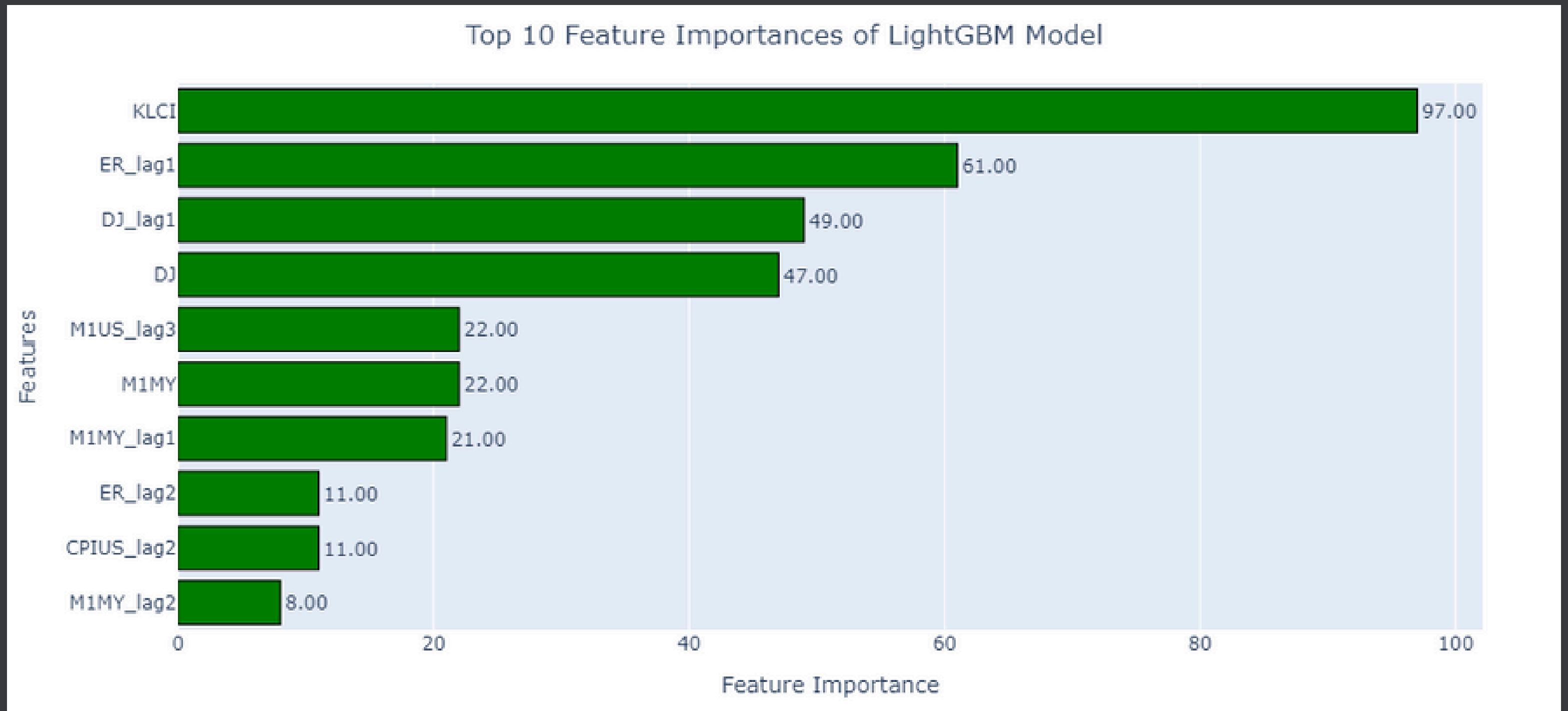
	Models	RMSE	NRMSE	MAE	MAPE (%)	R^2	Training Time (sec)
High computational resources	**ARDL**	0.059774	0.099519	0.044245	0.982527	0.908098	30872.70
Resource efficient	**SVM**	0.059151	0.098482	0.042905	0.950491	0.910002	**1.59**
High computational resources	**RF**	0.057159	0.095165	0.045548	1.012725	0.915962	175.26
Balance of all evaluation metrics	**XGB**	0.056988	0.094880	**0.042901**	**0.946951**	0.916465	49.95
Balance of all evaluation metrics	**LGBM**	**0.056604**	**0.094241**	0.045134	0.998747	**0.917586**	17.95
High computational resources	**LSTM**	0.058234	0.096955	0.043763	0.966392	0.912771	92.97

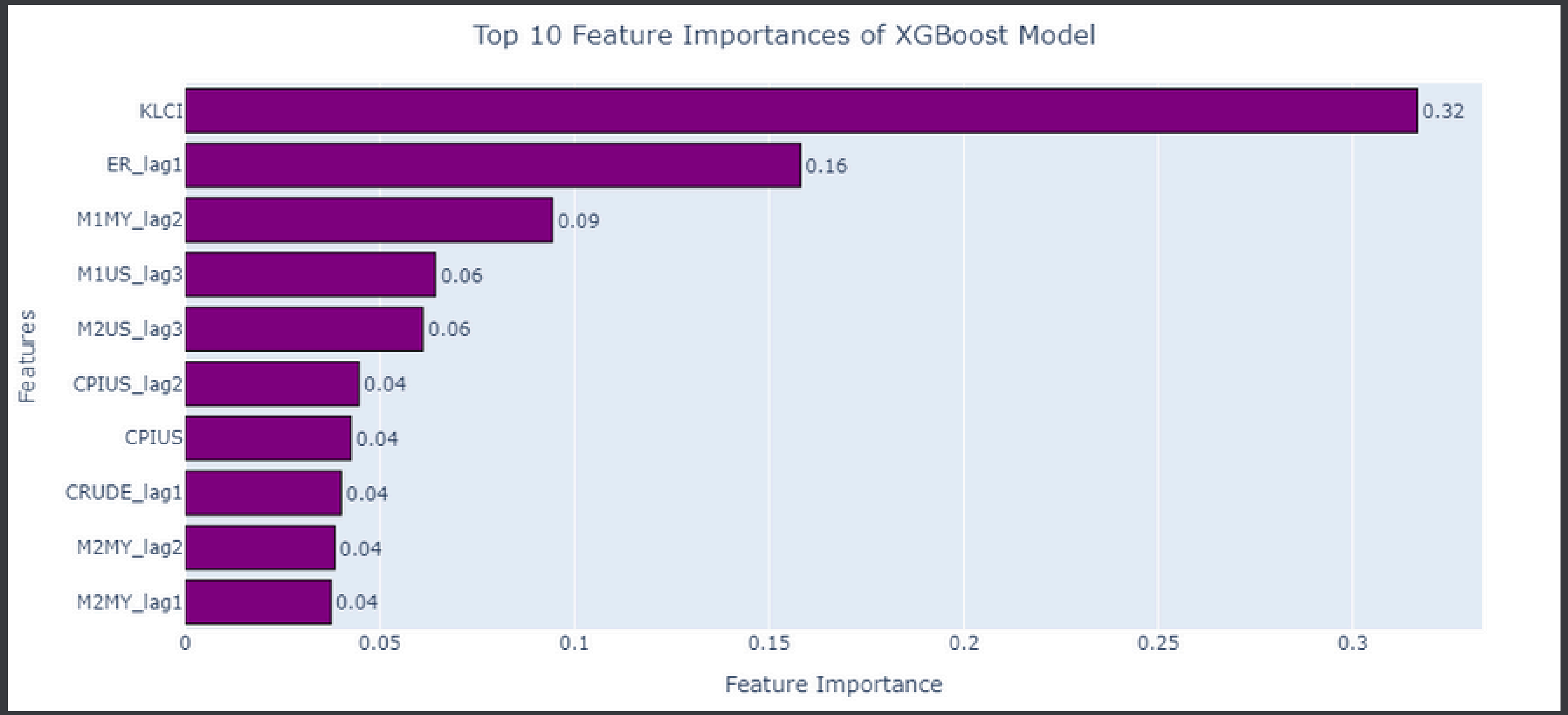
- **Best Performing Model:** The LightGBM (LGBM) model
  - LGBM achieved the lowest RMSE (Root Mean Squared Error) of 0.056604 ⇛ It has the best predictive accuracy.
  - It also has a high R^2 value of 0.917586 ⇛ Roughly 91.76% of the variance in the dependent variable is explained by the model.

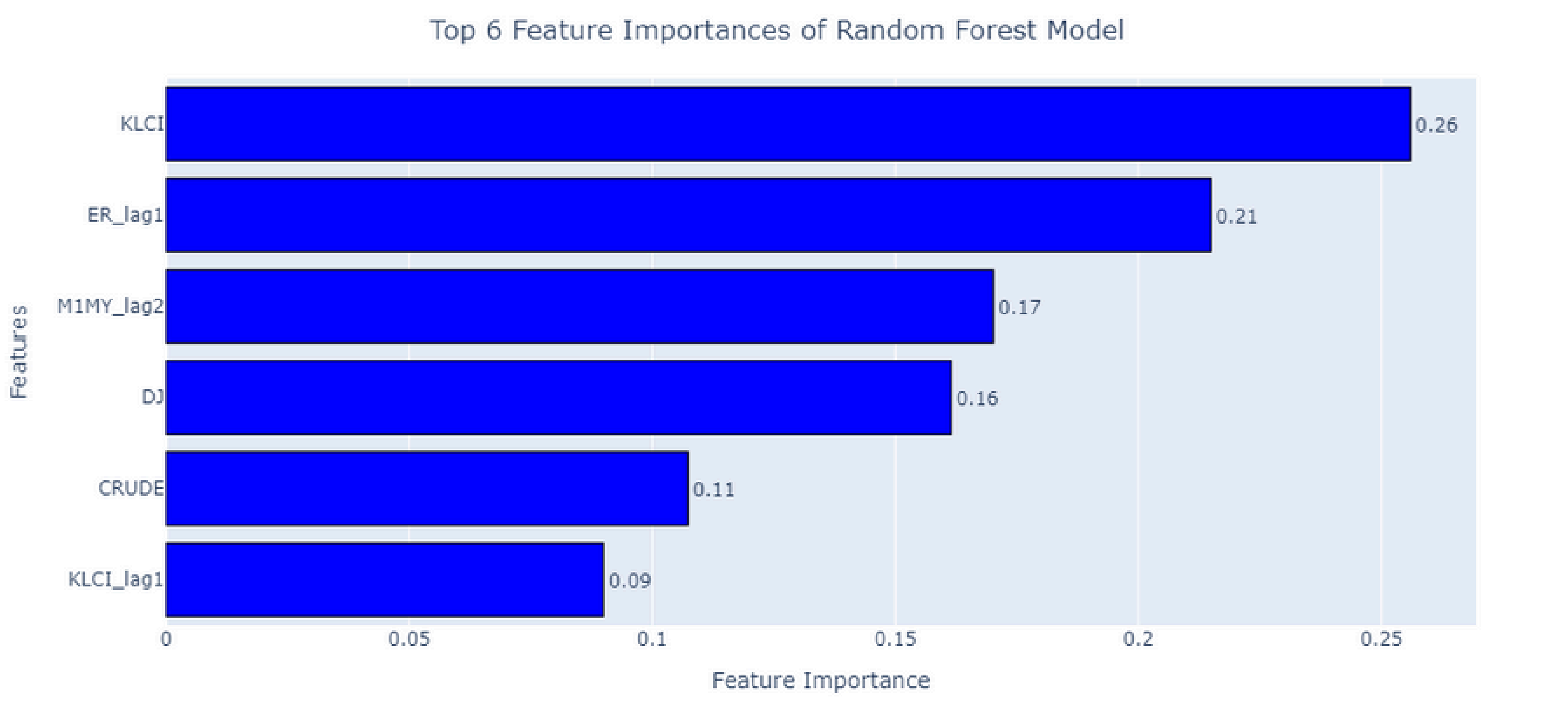
- **Winner of Training Time:** Support Vector Machine (SVM) model
  - SVM completed its training within 1 second and significantly outperformed the other models in terms of training time.

Feature Importance (RF, XGB, LGBM)

Feature importance indicates how much each feature contributes to the model prediction. Basically, it determines the degree of usefulness of a specific variable for a current model and prediction.



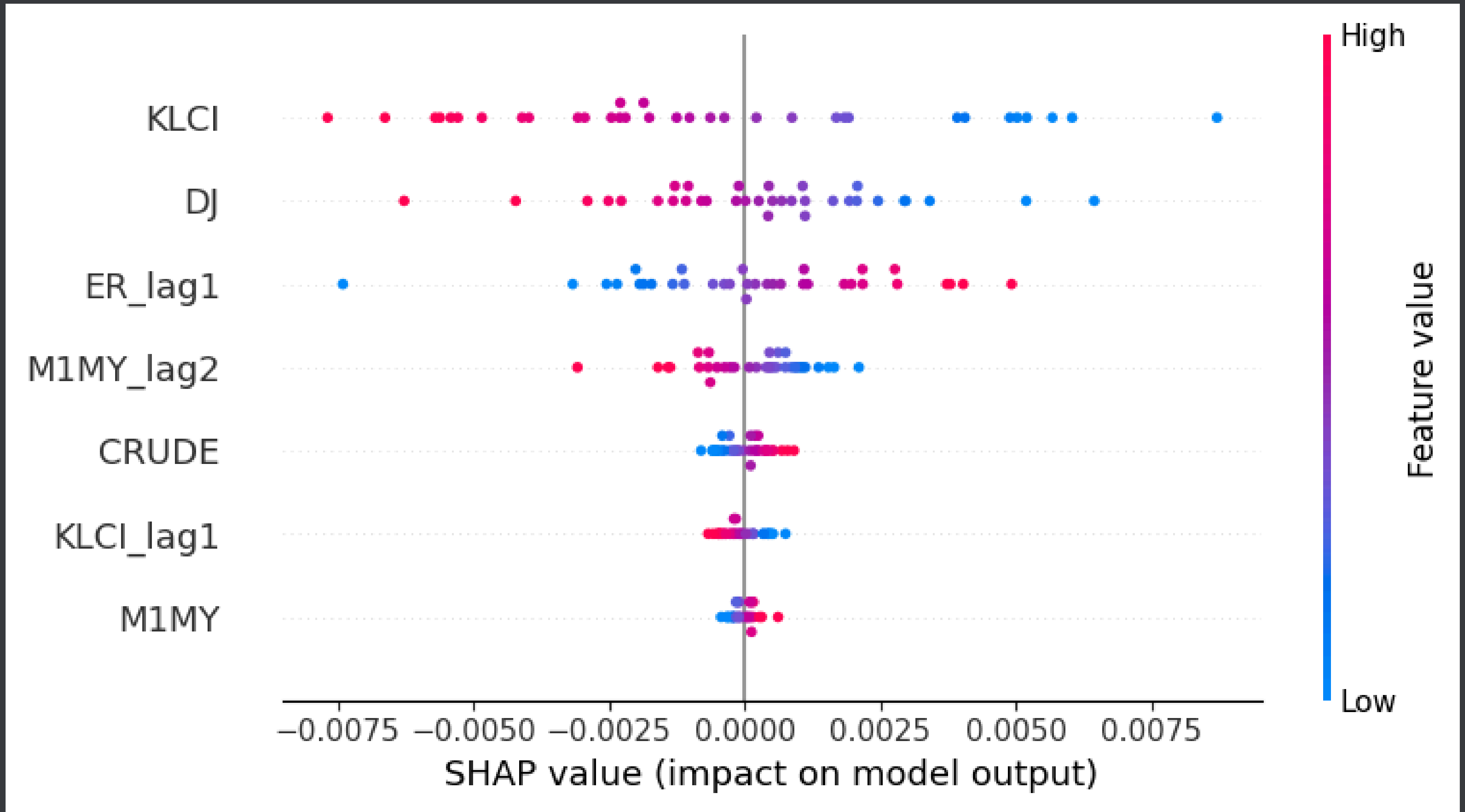




- KLCI shows the strongest influence on USD/MYR rates.
- It is followed by ER_lag1 which suggests recent exchange rate movements are critical for predictions.
- Other features like DJ, M1MY_lag2, and M1US_lag3 are moderately important in all models while features like CPIUS_lag2 and CRUDE have lower contributions.

SHAP (SVM)

SHAP (SHapley Additive exPlanations) values are a tool for interpreting machine learning models and provide insights into the contribution of each feature to a model's predictions. They provide both global and local insights into model behaviour to enhance transparency and trust in machine learning applications.



SHAP values derived from SVM Model

- KLCI is the most influential feature with both strong positive and negative impacts.
- Higher values of ER_lag1 at the right side (red dots) tend to have positive impact on predictions.
- The bottom features (CRUDE, KLCI_lag1, M1MY) have relatively concentrated SHAP values around zero. It suggests they have less overall impact.

Coefficients (ARDL)

Aside from feature importance and SHAP values, we can interpret the model from the coefficients returned by the ARDL model.

```
                              ARDL Model Results
==============================================================================
Dep. Variable:                    LER   No. Observations:                   78
Model:             ARDL(1, 1, 0, 0, 0)   Log Likelihood                 219.278
Method:               Conditional MLE   S.D. of innovations              0.014
Date:                Fri, 03 Jan 2025   AIC                           -422.555
Time:                        11:23:43   BIC                           -403.805
Sample:                    05-01-2015   HQIC                          -415.055
                         - 09-01-2021
=============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------
const          0.3724      0.385      0.967      0.337      -0.395       1.140
LER.L1         0.9217      0.052     17.795      0.000       0.818       1.025
LKLCI.L0      -0.3348      0.068     -4.933      0.000      -0.470      -0.199
LKLCI.L1       0.2302      0.080      2.874      0.005       0.070       0.390
LOPR.L0        0.0418      0.014      2.935      0.005       0.013       0.070
LEXPUS.L0      0.0398      0.026      1.533      0.130      -0.012       0.092
LFFER.L0      -0.0058      0.002     -2.406      0.019      -0.011      -0.001
=============================================================================
```

- The model has an AIC of -422.555 indicating a reasonably good fit.
- The 1-month lag of the USD/MYR exchange rate (LER.L1) is highly significant with a coefficient of 0.9217. This implies that the past exchange rate strongly influences the current rate.
- The contemporaneous KLCI index (LKLCI.L0) has a significant negative impact at coefficient of -0.3348. It means higher KLCI levels strengthen the MYR (lower USD/MYR).
- The overnight policy rate (LOPR.L0) has a small but statistically significant positive effect at coefficient of 0.0418. It indicates higher OPR values may weaken the MYR slightly (increase USD/MYR).
- The Federal Funds Effective Rate (LFFER.L0) has a significant negative impact with coefficient of -0.0058. It means higher US interest rates may strengthen the MYR (lower USD/MYR).

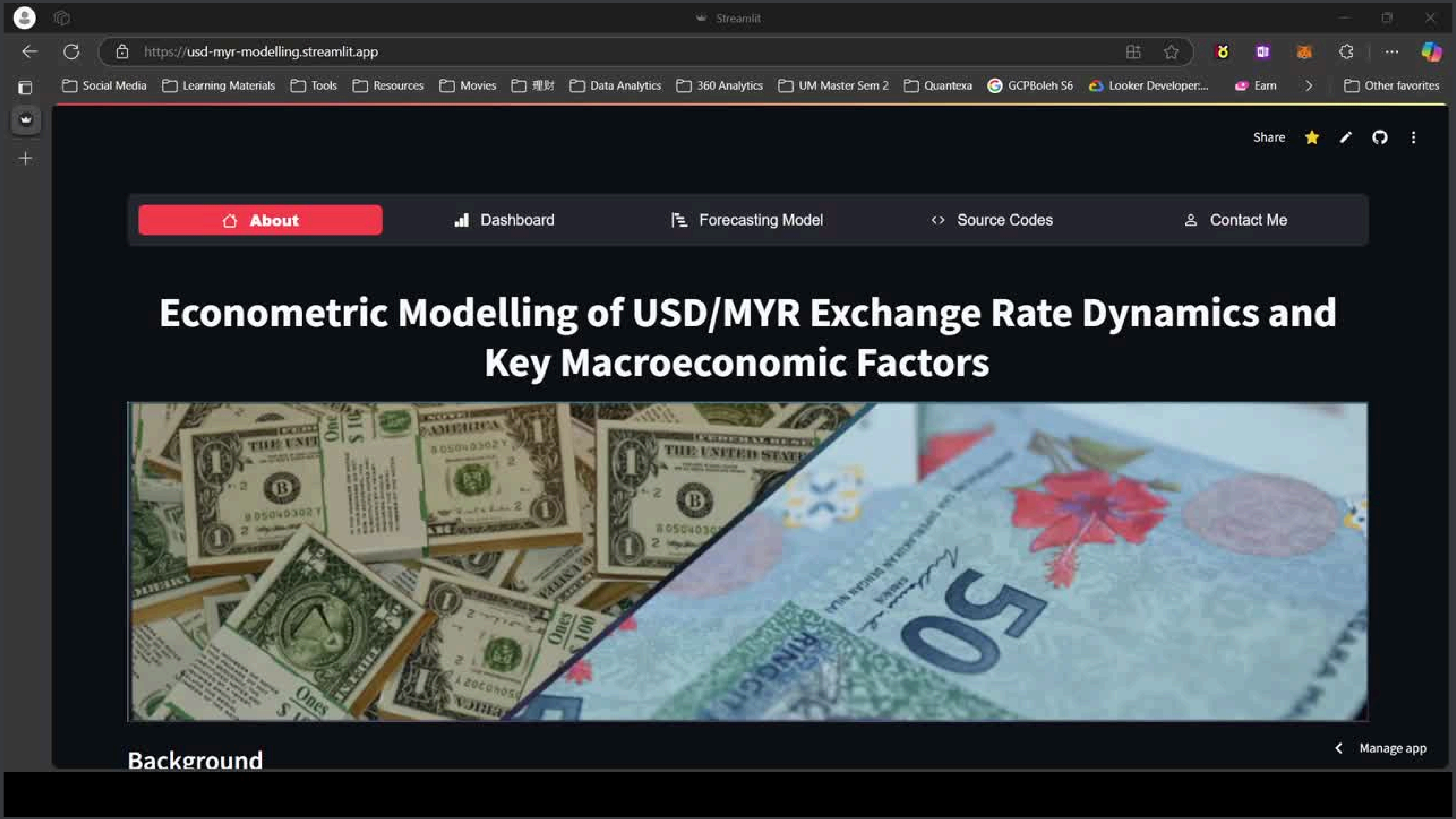
Benchmarking

Generally, the performance of all models in this research consistently outperformed previous studies.

Studies	Models	RMSE	MAE	MAPE (%)	R^2	Observations
(Biswas et al., 2023)	LSTM	0.2526	-	0.244	0.9016	Surpassed the study in terms of RMSE and R^2
(Johari et al., 2021)	ARDL	0.1342	-	-	-	Surpassed the study in term of RMSE
(Erçen et al., 2022)	SVM	0.2252	-	3.906	0.9246	Surpassed the study in terms of RMSE and MAPE
(Joseph et al., 2022)	BPNN	0.3227	0.2897	7.000	0.8460	Surpassed the results of neural network model for all metrics
This Research	**ARDL**	0.059774	0.044245	0.982527	0.908098	
	SVM	0.059563	0.045335	1.000069	0.908745	
	RF	0.057159	0.045548	1.012725	0.915962	
	XGB	0.056988	**0.042901**	**0.946951**	0.916465	
	LGBM	**0.056604**	0.045134	0.998747	**0.917586**	
	LSTM	0.057978	0.043175	0.953237	0.913538	

Streamlit Deployment

https://usd-myr-modelling.streamlit.app



07

Conclusions

Revisiting the Objectives

1st Objective:
To investigate the influence that each identified macroeconomic factor has on the paired exchange rates between United States and Malaysia.

- The KLCI index and previous exchange rates (ER_lag1) are the most influential factors across all models.
- Monetary indicators i.e, OPR and FFER play significant roles in explaining exchange rate movement as shown by clear directional impacts in the ARDL model.
- Commodity prices (CRUDE) and inflation rates (CPIUS & CPIMY) have comparatively smaller influences.
- These findings highlight the dominance of financial market dynamics and monetary policies in shaping the USD/MYR exchange rate.

Revisiting the Objectives (Cont.)

2nd Objective:
To develop an econometric model that can predict the USD/MYR exchange rates using multiple macroeconomic indicators.

- Six different models were trained on the training dataset (up to October 2021) and tested on unseen data (November 2021 to July 2024).
- ARDL for understanding long and short-term relationships between macroeconomic factors and exchange rates.
- SVM, Random Forest, XGBoost, LightGBM and LSTM for prediction and handling complex non-linear relationships.
- Evaluation metrics such as RMSE, MAE, MAPE and R^2 were used to compare model performance.
- Streamlit was used to develop dashboard and app for users to forecast the future USD/MYR exchange rates.

Revisiting the Objectives (Cont.)

3rd Objective:
To evaluate the performance of different econometric models in forecasting the USD/MYR exchange rates.

- LightGBM emerges as the best-performing model, with the lowest RMSE (0.056604), lowest NRMSE (0.094241) and the highest R^2 (0.917586). It also has a very fast training time (17.95 seconds). It is both accurate and efficient.
- XGBoost closely follows LightGBM in performance, with slightly higher RMSE (0.056988) and NRMSE (0.094880).
- Random Forest also performs well but has a higher RMSE and training time compared to LightGBM and XGBoost.
- SVM and LSTM have competitive RMSE values but slightly lower R^2 scores and efficiency.
- ARDL has good predictive accuracy but it is significantly slower to train with a long training time of 30,872.7 seconds. This makes it less practical for large-scale applications.

Limitations

Exclusion of Sentiment Factors

- The study does not account for unexpected geopolitical events, natural disasters or other external shocks that may influence exchange rates.
- Limited inclusion of market sentiment indicators or other qualitative variables.

Limited Generalisability

- Models trained on USD/MYR dynamics may not generalise to other currency pairs or different time periods due to economic regime shifts.

Future Works

Inclusion of Additional Variables

- Extract sentiment data from financial news or social media platforms using natural language processing (NLP).
- Incorporate geopolitical risk indices such as Baker-Bloom-Davis geopolitical uncertainty index.

Scenario-Based Modelling

- Simulate scenarios involving major macroeconomic changes (e.g., policy shifts, trade disruptions) to assess model adaptability.
- It helps improve model flexibility.

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Thank you.