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Gold Price Forecasting Using Disaggregation of Time Series Data

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Abstract

The price of gold plays a crucial role in shaping investment strategies and influencing financial markets. Financial institutions, policymakers, and investors rely heavily on accurate gold price forecasts, given the unique position of gold as a safe-haven asset for hedging and diversification. Recognizing the increasing importance of gold in the eyes of investors, it becomes imperative to employ the most suitable forecasting technique. This study employs the Naïve method, ARIMA, Double Exponential Smoothing and K-Nearest Neighbours algorithm to predict future gold prices. The primary objectives include constructing forecast models for gold prices using these methods, determining the best-performing model among them, and comparing their forecasting performances using metrics such as mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), and mean forecast error (MFE). The findings reveal that the ARIMA (1,1,1) model outperforms the Naïve method, Double Exponential Smoothing and KNN boasting the lowest values for MAPE, MAE, RMSE, and MFE—122.242, 7.90%, 154.136, and 133.350, respectively. In summary, the ARIMA (1,1,1) model demonstrates superior performance, making it the most accurate model for forecasting future gold prices

1. Introduction

Gold, renowned as the most secure investment globally, has persisted as an asset throughout history. Universally recognized as a treasury of wealth, gold's enduring significance is evident in its multifaceted role within the global economy [1]. With applications ranging from long-term investment to its inclusion in central bank foreign reserves, gold possesses a strong connection with financial and macroeconomic factors [2]. Gold captivates the attention of investors, economists, and policymakers due to its diverse applications in jewellery, technology, and as a reserve currency [3]. Given its pivotal role, accurately forecasting gold prices becomes imperative for stakeholders, including financial organizations, politicians, and investors.

In addition, forecasting gold prices is a complex yet pivotal task influenced by multifaceted factors such as macroeconomic indicators, investor sentiment, political events, and market trends. Accurate predictions are crucial for making informed investment decisions and managing risks, given the significant role gold plays in the global financial landscape [4]. Researchers have extensively utilized ARIMA models to forecast gold prices, unveiling insights into their relationship with other financial assets. Baur and Lucey (2010) explored the negative correlation between gold prices and stock returns, indicating gold's potential as a hedge during stock market downturns. Different studies proposed varying ARIMA models, such as (3, 1, 2), (0, 1, 1), and (1, 1, 1), each claiming superior forecasting performance by [5], [6], [7] and [8]. Studies incorporating the Naïve approach as a benchmark for gold price forecasting have compared its performance with advanced predictive models. [9] found that Multiple Linear Regression (MLR) outperformed Naïve [9], while [10] compared Naïve Bayes with other models, emphasizing the need for considering multiple methodologies. Artificial Neural Network (ANN) models, such as Multi-Layer Neural Network (MLNN) and variations like (2-6-1), have demonstrated high accuracy in forecasting gold prices by [1], [11], [12], [13], [14] and [15]. Exponential Smoothing methods, encompassing Single, Double, and Triple Exponential Smoothing, have been employed in forecasting gold prices. Studies highlight the superiority of certain models, such as DES (Double Exponential Smoothing) and Triple Exponential Smoothing, based on accuracy metrics like RMSE, MAE, and MAPE by [1], [16], [17], [18], and [19]. The exploration of KNN's capabilities extends into exchange market liquidity prediction, as evidenced by [20], who found KNN to outperform traditional ARMA and GARCH models in predicting liquidity dynamics across 19 currencies [20]. This paper contributes to the ongoing discourse on predictive modelling in finance, establishing KNN as a valuable tool for enhancing the accuracy of exchange rate and stock price predictions through diverse financial datasets and performance metrics [21].

Gold prices play a pivotal role in financial markets and investment strategies, making accurate forecasting crucial for investors, policymakers, and financial institutions [22]. However, the reliability of traditional forecasting methods has come under scrutiny, particularly in capturing the volatility and non-linear patterns exhibited by gold prices [23]. The complexity of sudden price changes poses challenges for traditional methods, creating a need for more accurate statistical models that can adapt to the dynamic nature of the gold market [24]. The literature presents conflicting findings on the effectiveness of forecasting methods for gold prices, leading to uncertainty among stakeholders [22].

This study aims to address the need for accurate gold price forecasts through the following objectives, which are to build forecast models for gold prices using the Naïve method, ARIMA model, Double Exponential Smoothing method and KNN algorithm; to determine the best-performing model among these methods; and to compare the forecasting performance using metrics such as MAPE, MAE, RMSE, and MFE.

2. Methodology

The gold price data used in this study was obtained from Bank Negara Malaysia's official website. This dataset was published by the Central Bank of Malaysia, which consists of gold price data in daily trading price (in ringgit) of Malaysia's gold bullion coin, the Kijang Emas. The data collected covered the period from 1 January 2010 to 31 December 2019, which had 2458 data observations. The daily gold price data was converted to monthly data by dividing the number of days in the following months, which becomes 120 data observations (10 years). The first 108 data points (90.00%) were designated as the training set while the rest of the 10 data points (10.00%) were designated as the testing set.

2.1 Naïve Method

The Naïve Method is a straightforward technique employed in this study as a benchmark for comparison with other models [23]. It serves as a simple baseline for predicting future values, assuming they will remain constant from recently observed values or the average or historical data. The expression of the Naïve method is shown in Equation (1).

$$\hat{y}_t = Y_{t-1} \tag{1}$$

where $\hat{y}_t$ is the observed value at time t, Y_{t-1} is the previous observation data and t is time.

2.2 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is developed by Box & Jenkin and the model includes *AR* and *MA* models as well as differencing in the model formulation. The ARIMA model forms in ARIMA (*p,d,q*), where p is the order of the *AR* part, *d* is the degree of first differencing involved and *q* is the order of the *MA* part. A full model of the non-seasonal ARIMA model can be expressed in Equation (2), Equation (3), Equation (4) and Equation (5) by [25].

$$\phi_p(B)\nabla^d y_t = \theta_q(B)e_t \tag{2}$$

$$\nabla^d y_t = (1-B)^d \tag{3}$$

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p \tag{4}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \tag{5}$$

where $\nabla^d y_t$ is the degree of differencing, $\phi_p(B)$ is the non-seasonal autoregressive operator of order p, $\theta_q(B)$ is the non-seasonal moving average operator of order q. By substituting Equation (3), Equation (4) and Equation (5) into Equation (2), the ARIMA model can derived as in Equation (6).

$$(1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p)(1-B)^d y_t=(1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q)e_t \tag{6}$$

where y_t is the differenced series, ϕ is a parameter of the differencing AR model, θ is a parameter of the differencing MA model, p is the order of the autoregressive part, d is the degree of first differencing involved, q order of the moving average part, e_t is white noise and B backshift operator.

Besides, model identification is a critical step in developing an effective ARIMA forecasting model. It involves deciphering the underlying structure of the time series data by examining the AutoCorrelation Function (ACF) plot and Partial AutoCorrelation Function (PACF) plot [25].

Table 1 : Model identification from ACF and PACF plots

ACFs	PACFs	Model
Decay to zero with exponential pattern	Cuts off lag p	AR (p)
Cuts off after lag q	Decay to zero with exponential pattern	MA (q)
Decay to zero with exponential pattern	Decay to zero with exponential pattern	ARMA (p, q)
Cuts off after q	Cuts off after lag p	AR (p) or MA (q)

The ACF plot illustrates the correlation between the current observation and its lagged values. In the context of ARIMA, it helps identify the AutoRegressive (AR) component. When examining the ACF plot, significant lags represent points in time where past observations are correlated with the current observation. The decay of correlations as the lag increases provides insights into the order of the AR component. The PACF plot complements the ACF plot by depicting the correlation between the current observation and its lags, excluding the intermediate lags. PACF aids in identifying the AR component, providing insights into the direct relationship between the current observation and past observations at specific lags.

2.3 Double Exponential Smoothing Method (Holt's Linear Trend)

The Double Exponential Smoothing method also as known as the Holts Linear Trend method, is a forecasting method that incorporates the average value and trend component of the data. It exponentially applies decreasing weights to both components, enabling it to capture and predict changes in data over time. Double Exponential Smoothing is one of the exponential smoothing methods used to forecast time series which contain trend components but not seasonality [23]. Double Exponential Smoothing be can derived as Equation (7), Equation (8) and Equation (9).

$$S_t=\alpha y_t+(1-\alpha)(S_{t-1}+b_{t-1}),\ 0\leq\alpha\leq 1 \tag{7}$$

$$b_t=\gamma(S_t-S_{t-1})+(1-\gamma)b_{t-1},\ 0\leq y\leq 1 \tag{8}$$

$$\hat{y}_{t+p}=S_t+pb_t,\ p=1,2,3,\ldots \tag{9}$$

where α is the smoothing constant for the level, γ is the smoothing constant for the trend, S_t is the level at time t, b_t is the trend at time t, y_t is the data value at time t and $\hat{y}_{t+p}$ is the fitted value at time, $t + p$.

2.4 K-Nearest Neighbours Algorithm (KNN)

One frequently used method in forecasting study is KNN especially in predicting financial products. The regression model of KNN differs from the classification model of KNN, as it maps patterns to continuous labels, to predict computed the mean of function values. The value of parameter k is influenced by the characteristics of the data. A higher level of noise in the data will result in larger values for k. KNN can derived as Equation (10) by [5].

$$Q_i=\sum_{k=1}^{K}(W_k\times t_k) \tag{10}$$

where Q_i is the forecast value, w_k is the weight of the observed value, t_k is the observed value and k is the number of nearest neighbours.

2.5 Forecast Accuracy Measure

The forecasting performance of Naïve method, ARIMA model and Double Exponential Smoothing method can be evaluated by using accuracy measurement in this study. The forecast accuracy measurements such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Forecast Error (MFE) will be applied to compare the accuracy of the methods. The smaller the value of MAPE, MAE, RMSE and MFE, the higher the accuracy of the forecasting methods [23]. The formula for the MAPE, MAE, RMSE and MFE are shown in Equation (10), Equation (11), Equation (12), and Equation (13) respectively [25].

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{y_t - \widehat{y_t}}{y_t} \right|}{n} \times 100 \tag{11}$$

$$MAE = \frac{\sum_{t=1}^{n} |y_t - \widehat{y_t}|}{n} \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \widehat{y_t})}{n}} \tag{13}$$

$$MFE = \frac{\sum_{t=1}^{n} (y_t - \widehat{y_t})}{n} \tag{14}$$

where y_t is the actual value at period t, $\widehat{y_t}$ is the predicted value at period t, and n is the number of periods used in the calculation.

Table 2 : Interpretation of MAPE forecast measurement.

MAPE (%)	Level of Forecast Accuracy
< 10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate and weak forecasting

3. Results and Discussion

This section included a thorough examination and clarification of the study's findings.

3.1 Time Series Plot

The time series plot for the Kijang Emas Price – Bank Negara Malaysia starting from January 2010 to December 2019 which for a total of 10 years (120 months). The plot has been plotted as shown in Fig. 1.

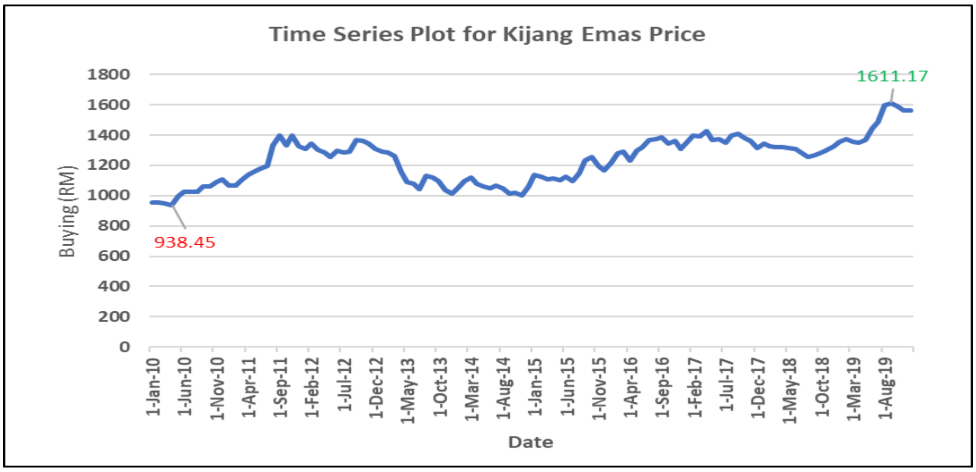

Fig. 1 Time series plot for overall monthly gold price in Malaysia

Fig. 1 indicates the monthly gold prices in (RM) from January 2010 to December 2019. The pricing trend of Kijang Emas witnessed an upward trajectory from mid-2018 to mid-2019, reaching its zenith at RM 1611.17 in September 2019, potentially influenced by economic uncertainties or geopolitical events. Conversely, the lowest recorded gold price in the given dataset occurred in August 2010, registering at RM 938.45. This time series provides valuable insights into the fluid dynamics of the gold market, shedding light on the significant impact of external factors on the pricing dynamics of precious metals.

3.2 Naïve method

The Naive method for forecasting gold prices takes a simple approach by predicting that future prices will be the same as the most recent observed value. Table 3 displays the forecasts of gold prices in Malaysia by using Naïve. The table includes the actual value and forecast values of gold prices in Malaysia from January 2019 to December 2019. Table 4 displayed the forecast accuracy measurement of the Naïve method with a training set and testing set. Fig. 2 displays the time series plot of gold price in Malaysia by using Naïve. The plot displays the actual value and forecasted value of gold prices in Malaysia. As the Naïve method relies on predicting future values based on the last observed data point, it is evident that in the forecast period, the forecasted values form a consistent, straight orange line. This observation indicates that all the forecasts during that period are identical, reflecting the simplicity of the Naïve approach where each prediction corresponds to the most recent data point.

Table 3 : Forecasts of Gold Price in Malaysia by using Naïve.

Time	Actual Value (RM)	Forecast Value (RM)
January-2019	1354.67	1328.85
February-2019	1371.53	1328.85
March-2019	1353.33	1328.85
April-2019	1348.23	1328.85
May-2019	1365.00	1328.85
June-2019	1443.56	1328.85
July-2019	1487.23	1328.85
August-2019	1600.76	1328.85
September-2019	1611.17	1328.85
October-2019	1593.45	1328.85
November-2019	1560.67	1328.85
December-2019	1564.15	1328.85

Table 4 : Forecasts Accuracy Measurement of Naïve.

Forecast Accuracy Measurement	Naïve method	
	Training Set	Testing Set
MAE	31.195	142.295
MAPE (%)	2.57	10.05
RMSE	39.636	176.958
MFE	3.510	155.231

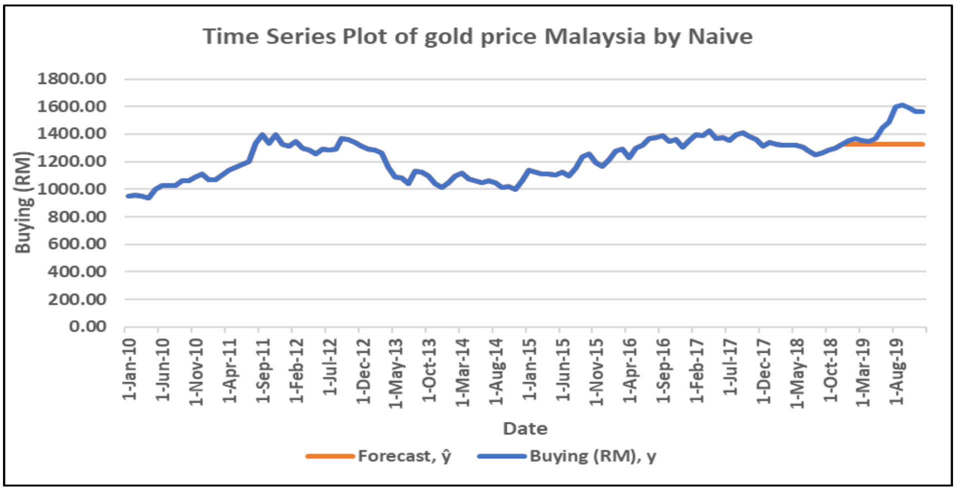

Fig. 2 Time series plot of gold price Malaysia by using Naïve

3.3 Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) model was employed to forecast gold prices, leveraging historical data to make future price predictions. The analysis involved selecting an appropriate order for the ARIMA model through the examination of autocorrelation and partial autocorrelation functions and assessing the stationarity of the time series. ARIMA involves several iterative steps processes which are model identification and parameter estimation of the ARIMA model. Table 5 shows the summary of tentative models' parameter estimation and Ljung-Box statistics. The most suitable model of ARIMA will be chosen to forecast Kijang Emas Price data after comparing the parameters estimation and p-value of Ljung-Box statistics.

Table 5 : Summary of tentative model's parameter estimation and Ljung-Box statistics

No	ARIMA models	Parameters Estimation		*p*-value of Ljung-Box Statistics
		Coefficient	*p*-value	
1	ARIMA (2,1,0)	AR1: 0.1344	0.170	0.311
		AR2: -0.0922	0.346	
2	ARIMA (2,1,1)	AR1: -0.8029	0.000	0.348
		AR2: 0.0389	0.695	
		AR3: -0.9960	0.000	
3	ARIMA (2,1,2)	AR1: 0.4020	0.092	0.345
		AR2: -0.7857	0.000	
		MA1: 0.2623	0.317	
		MA2: -0.7069	0.002	
4	ARIMA (1,1,0)	AR1: 0.1232	0.205	0.296
5	**ARIMA (1,1,1)**	**AR1: -0.8257**	**0.000**	**0.416**
		MA1: -0.9819	**0.000**	
6	ARIMA (1,1,2)	AR1: 0.3393	0.766	0.240
		MA1: 0.2133	0.851	
		MA2: 0.1172	0.450	
7	ARIMA (0,1,1)	MA1: -0.1421	0.143	0.317
8	ARIMA (0,1,2)	MA1: -0.1259	0.200	0.281
		MA2: 0.0744	0.447	

From Table 5, all the ARIMA models show a *p*-value of Ljung-Box Statistics greater than 0.05. For parameters estimation, the ARIMA (1,1,1) model is the only model which gives all values lower than 0.05. Thus, the ARIMA (1,1,1) model will be selected to forecast the Kijang Emas Price data. Besides, table 6 displays the forecasts of gold prices in Malaysia by ARIMA (1,1,1). Table 7 displayed the forecast accuracy measurement of ARIMA (1,1,1) with a testing set. Figure 3 displays the time series plot of gold prices in Malaysia by using the ARIMA (1,1,1) model.

Table 6 : Forecasts of gold price in Malaysia by ARIMA (1,1,1).

Time	Actual Value (RM)	Forecast Value (RM)
January-2019	1354.67	1325.82
February-2019	1371.53	1335.12
March-2019	1353.33	1334.04
April-2019	1348.23	1341.69
May-2019	1365.00	1341.99
June-2019	1443.56	1348.49
July-2019	1487.23	1349.77
August-2019	1600.76	1355.44
September-2019	1611.17	1357.41
October-2019	1593.45	1362.50
November-2019	1560.67	1364.96
December-2019	1564.15	1369.63

Table 7 : Forecasts accuracy measurement of ARIMA (1,1,1)

Forecast Accuracy Measurement	ARIMA (1,1,1)
	Training Set
MAE	31.195
MAPE (%)	2.57
RMSE	39.636
MFE	3.510

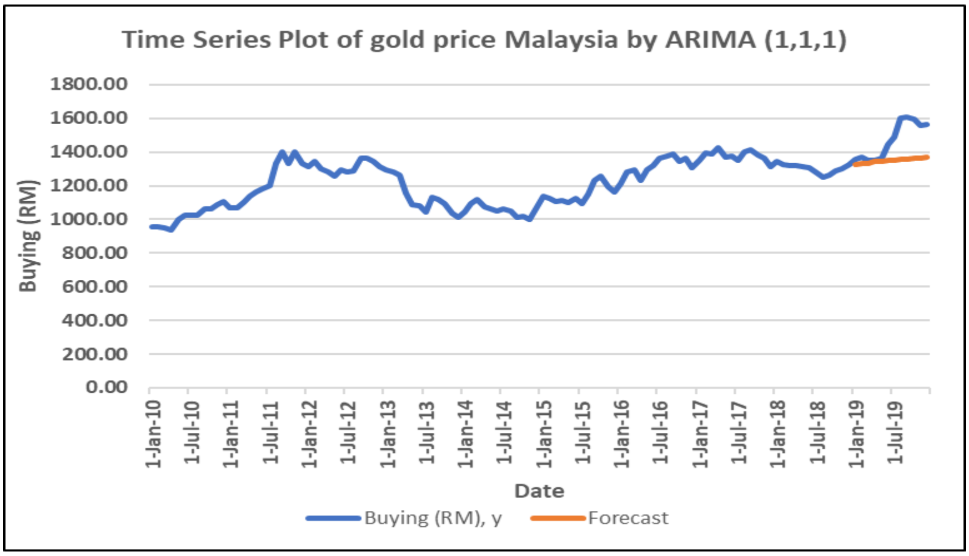

Fig. 3 Time series plot of gold price Malaysia by using ARIMA (1,1,1)

3.4 Double Exponential Smoothing Method (Holt's Linear Trend)

The Double Exponential Smoothing method, commonly known as Holt's method, is employed in forecasting gold prices by capturing both the trend and level of the time series data. Table 8 shows the forecasts of gold prices in Malaysia by using Holt's Linear Trend. The smoothing parameters of level and trend were both set up as 0.2 initially. After by solver in Excel, the best combination of smoothing parameters is alpha equal to 1.0 and gamma equal to 0.0 which minimizes the error of SSE. Table 9 shows the forecast accuracy measurement of Holt's Linear Trend with a training set and testing set. Fig. 4 shows the time series plot of gold prices in Malaysia by Holt's Linear Trend. The forecast value of gold price data from January 2019 to December 2019 by using Holt's Linear Trend. It shows an increasing trend from RM1,330.50 in January 2019 to RM 1,348.70 in December 2019.

Table 8 : Forecasts of Gold Price in Malaysia by using Holt's Linear Trend.

Time	Actual Value (RM)	Forecast Value (RM)
January-2019	1354.67	1330.50
February-2019	1371.53	1332.16
March-2019	1353.33	1333.81
April-2019	1348.23	1335.47
May-2019	1365.00	1337.12
June-2019	1443.56	1338.78
July-2019	1487.23	1340.43
August-2019	1600.76	1342.09
September-2019	1611.17	1343.74
October-2019	1593.45	1345.39
November-2019	1560.67	1347.05
December-2019	1564.15	1348.70

Table 9 : Forecasts the accuracy measurement of Holt's Linear Trend.

Forecast Accuracy Measurement	Holt's Linear Trend	
	Training Set	Testing Set
MAE	32.451	131.54
MAPE (%)	2.71	8.50
RMSE	42.378	165.327
MFE	0.325	143.499

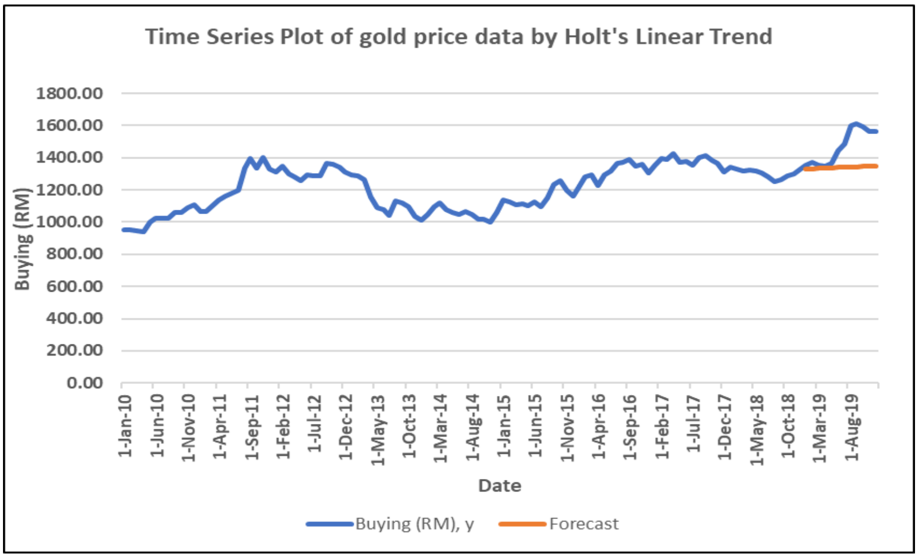

Fig. 4 Time series plot of gold price Malaysia by Holt's Linear Trend

3.5 K-Nearest Neighbours algorithm (KNN)

K-nearest neighbours (KNN) is a supervised machine learning algorithm used for classification and regression tasks. Table 10 displays the forecasts of gold prices in Malaysia by KNN. Fig. 5 shows the time series plot of gold prices in Malaysia by KNN from January 2019 to December 2019. It shows a slightly increasing trend from RM1,297.69 in January 2019 to RM1,301.25 in December 2019.

Table 10 : Forecasts of Gold Price in Malaysia by using KNN.

Time	Actual Value (RM)	Forecast Value (RM)
January-2019	1354.67	1297.69
February-2019	1371.53	1298.18
March-2019	1353.33	1298.65
April-2019	1348.23	1299.13
May-2019	1365.00	1299.53
June-2019	1443.56	1299.88
July-2019	1487.23	1300.19
August-2019	1600.76	1300.46
September-2019	1611.17	1300.70
October-2019	1593.45	1300.90
November-2019	1560.67	1301.09
December-2019	1564.15	1301.25

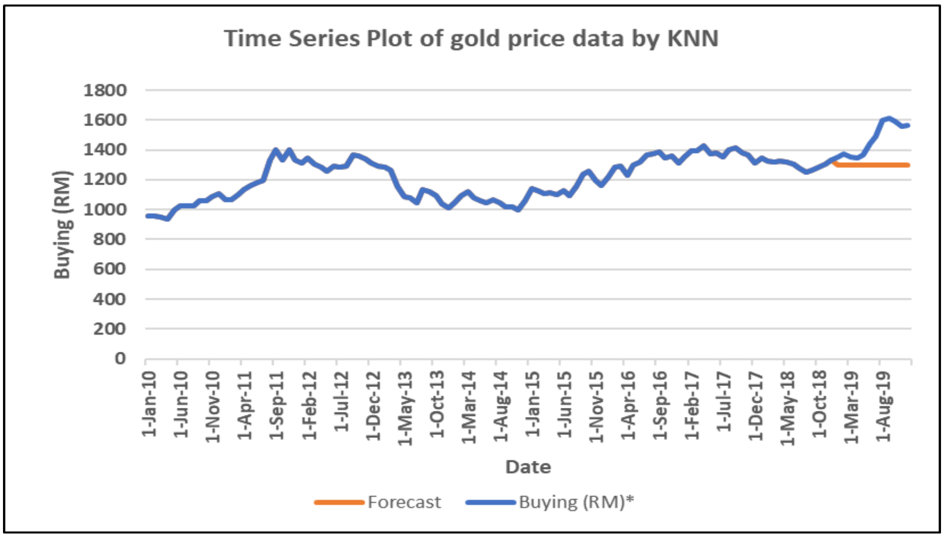

Fig. 5 Time series plot of gold price Malaysia by KNN

3.6 Forecasting Performance Comparison

The Kijang Emas Price data has been forecasted from January 2019 to December 2019 by using 108 data which is from January 2010 to December 2018. The most accurate method can be obtained by observing the forecast values and time series plots of the forecast patterns. Table 11 shows the comparison of the actual value and forecast value of Kijang Emas Price data by using the Naïve method, ARIMA (1,1,1) model, Holt's Linear Trend and KNN. Figure 6 displayed the time series plot of the actual and forecast value of Kijang Emas Price data from January 2019 to December 2019 by using the Naïve method, ARIMA (1,1,1) model, Holt's Linear Trend and KNN. Table 12 displayed the comparison of forecast accuracy measurements for the Naïve method, ARIMA model, Holt's Linear Trend and KNN with the testing set. The forecast accuracy measurements (MAE, MAPE, RMSE and MFE) have been used to obtain the best method with the lowest values.

Table 11 : Comparison of actual value and forecast value of Kijang Emas Price data by using the Naïve method, ARIMA (1,1,1), Holt's Linear Trend and KNN

Date	Actual Values (RM)	Forecast Values (RM)			
		Naïve	ARIMA (1,1,1)	Holt's Linear Trend	KNN
January-2019	1354.67	1328.85	1325.82	1330.50	1297.69
February-2019	1371.53	1328.85	1335.12	1332.16	1298.18
March-2019	1353.33	1328.85	1334.04	1333.81	1298.65
April-2019	1348.23	1328.85	1341.69	1335.47	1299.13
May-2019	1365.00	1328.85	1341.99	1337.12	1299.53
June-2019	1443.56	1328.85	1348.49	1338.78	1299.88
July-2019	1487.23	1328.85	1349.77	1340.43	1300.19
August-2019	1600.76	1328.85	1355.44	1342.09	1300.46
September-2019	1611.17	1328.85	1357.41	1343.74	1300.70
October-2019	1593.45	1328.85	1362.50	1345.39	1300.90
November-2019	1560.67	1328.85	1364.96	1347.05	1301.09
December-2019	1564.15	1328.85	1369.63	1348.70	1301.25

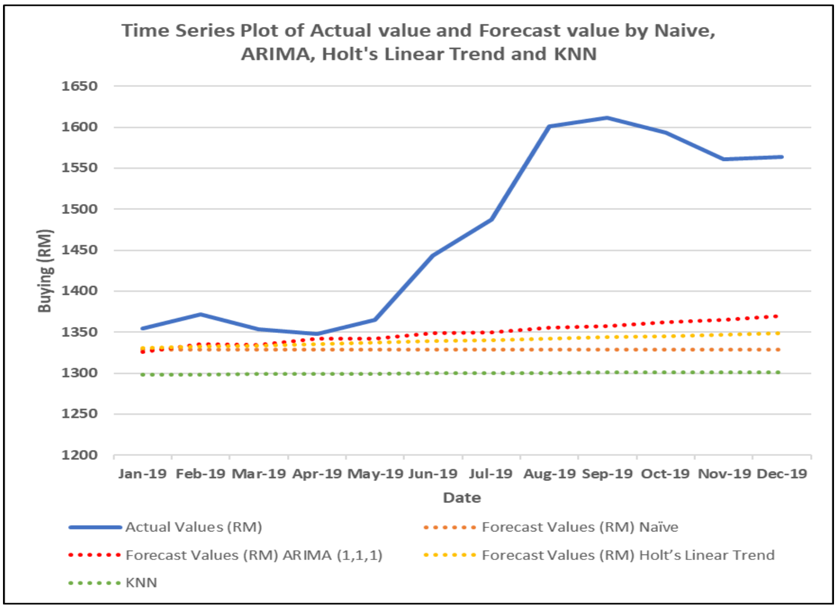

Fig. 6 Time series plot of actual value and forecast value by Naïve method, ARIMA (1,1,1), Holt's Linear Trend and KNN

Fig. 6 shows the actual data of gold prices in Malaysia exhibiting an abnormal upward trend in May 2019, suggesting that there were external factors contributing to this phenomenon during this period. The abnormal surge in gold prices in Malaysia from May 2019 may be attributed to external factors, notably the occurrence of a general election during that period. Elections typically introduce a level of uncertainty into financial markets, prompting investors to seek refuge in safe-haven assets such as gold. This precious metal is widely recognized as a store of value, and investors often gravitate towards it during times of heightened uncertainty, valuing its reputation for stability [26]. Furthermore, general elections have the potential to induce geopolitical tensions or alter international relations due to the gold serving as a safe-haven asset, which tends to be in high demand during such periods of geopolitical uncertainty. The perceived stability and reliability of gold make it an appealing choice for investors navigating the uncertainties associated with election-related events and potential geopolitical shifts [26].

Table 12 : *Accuracy Measurement of Naïve method, ARIMA (1,1,1), Holt's Linear Trend and KNN*

Forecast Accuracy Measurement	Forecast Method			
	Naive	ARIMA (1,1,1)	Holt's Linear Trend	KNN
MAE	142.295	**122.242**	131.541	171.3417
MAPE (%)	10.05	**7.90**	8.50	11.20%
RMSE	176.958	**154.136**	165.327	200.5412
MFE	155.231	**133.35**	143.499	186.9182

4. Conclusion

This study provides a detailed exploration of gold price forecasting using Naïve, ARIMA, Double Exponential Smoothing methods and KNN, achieving its three primary objectives. The forecasting models showed different trends. The Naïve method had a steady trend, while ARIMA, Double Exponential Smoothing and KNN suggested a small increase in gold prices from January 2019 to December 2019. The second objective involved model selection, with ARIMA (1,1,1) emerging as the optimal fit based on parameter estimation and statistical tests, outperforming other tentative models. Subsequently, a comprehensive performance evaluation utilizing metrics such as MAPE, MAE, RMSE, and MFE confirmed the superior accuracy of ARIMA (1,1,1) compared to Naïve, Double Exponential Smoothing methods and KNN. These findings establish ARIMA as the most effective method for forecasting Kijang Emas Price, providing crucial insights for investors and financial institutions in managing their gold assets.

The study makes significant contributions by thoroughly comparing three forecasting methods, employing a robust model selection process, and conducting a comprehensive performance evaluation. These aspects enhance the understanding of how gold prices behave. The identification of ARIMA (1,1,1) as the most suitable model strengthens the methodological approach to gold price forecasting which had 122.242 of MAE, 7.90% of MAPE, 176.958 of RMSE and 133.35 of MFE. Despite these valuable contributions, the study acknowledges limitations, including data constraints, assumptions of stationarity, external factors, and a restricted forecast horizon. Suggestions for future research involve extending the forecast period, incorporating additional influencing factors, and implementing data validation protocols to improve model reliability. Furthermore, this study found that there are external factors that would affect the actual gold prices which are general election and pandemic covid-19. The study suggests that the external factors must be excluded in forecast the gold prices in Malaysia to make the results accurate and precise. This study lays the groundwork for further advancements in gold price forecasting, providing practical insights for informed investment decisions and portfolio management.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Kek Kim Bing, Maria Elena Nor* ***data collection:*** *Kek Kim Bing;* ***analysis and interpretation of results:*** *Kek Kim Bing, Maria Elena Nor* ***draft manuscript preparation:*** *Kek Kim Bing. All authors reviewed the results and approved the final version of the manuscript.*

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