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A COMPARATIVE ANALYSIS OF HOLT'S, ARIMA, AND PROPHET METHODS IN FORECASTING KIJANG GOLD PRICES

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Abstract:

This study conducts a detailed comparison of three forecasting methods namely Holt's Method, ARIMA Model, and Prophet Method to evaluate their effectiveness in predicting the fluctuating prices of Kijang Gold. In addition, this paper highlights the importance of accurate forecasts in financial planning and investment, especially emphasizing the role of gold as a stable asset during economic uncertainties. Indeed, five-year periods of data from 2019 to 2023 are used in assessing the methods' accuracy and reliability. This research measures the forecast models obtained by using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Results show that Holt's Method is the most effective method, better than ARIMA Model and Prophet Tool.

Keywords:

Gold Prices, Holt's Method, ARIMA, Prophet Method

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Introduction

Gold has been described as a highly liquidated but limited commodity that can be bought as an investment, as well as a luxury item like jewelleries. As a result, gold can provide long-term return (Nur et al., 2021). Moreover, gold is well-known as the main lead in the precious metals market and considered as a very rare element with its unique properties. Therefore, it is appropriate for investors adopting a short-term, strategic approach for quick returns in gold. In contrast, it is highly valuable to investors with a long-term orientation and a passive strategy of holding their assets for long periods of time (Michis, 2014). Table 1 demonstrates Kijang's gold selling price increasement of about 40.08% in one year from May 2019 to 2020 and 18.55% increase from May 2020 until May 2023. The 67.65% total increase in gold price over the last 5 years has made Kijang gold a safe haven for long-term investments. Gold has shown consistency in providing returns for investors. The significant surge in gold prices in later years attracted many speculators and investors apart from staging intellectual attention with the metal gaining prominence as an investment-grade asset (Pattnaik et al., 2023). In addition, investors prefer investing in gold over other assets mainly due to reduced volatility and consistent returns over the years (Qureshi et al., 2018). Besides that, with the occurrence of cases such as the Silicon Valley Bank collapse. Investors are now on edge about whether its demise could spark a broader banking meltdown (Hanna, 2023), which can lead to a lack of confidence in banks and a preference for gold as a stable investment.

Table 1: Prices Per Ounce of Kijang's Gold Bullion for 5 Years

Date	Selling Price	Buying Price
2 May 2019	RM5,599	RM5,384
4 May 2020	RM7,843	RM7,530
3 May 2021	RM7692	RM7,390
5 May 2022	RM8,728	RM8,388
2 May 2023	RM9,387	RM9,922

Source: (Bank Negara Malaysia)

Despite the significant increase in the price of Kijang gold, it is necessary to take additional measures to provide robust support for the most recent gold price data. This requires the development of a reliable gold price forecasting model tailored to the Kijang market. Currently, Malaysia lacks official research on forecasting the price of Kijang gold bullion. Consequently, the selection of a suitable forecasting method is of the utmost importance, as it ensures that researchers and public investors can comprehend the method's advantages and instils confidence when investing in gold. Many banks such as Maybank, CIMB Bank, and Public Bank rely on Kijang's gold price in doing forecasting and execute simple model to give accurate forecasting results. In relation to this, exponential smoothing and ARIMA methods in forecasting Kijang gold prices are simple and easy approaches without complex or difficult processes (Khamis, 2020). Indeed, Malaysian economists and financial planners can benefit greatly from the development of these two methods of selling gold to customers. The predicted

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price of Kijang gold makes it simpler for them to estimate future profits and losses. In short, good gold price forecasting requires using the right methods to produce reliable results. Therefore, the ability to accurately forecast gold prices is not only crucial for limiting losses but also for maximizing gains from investments. For this reason, this paper's main objective is to determine the best model for forecasting Kijang gold prices between Holt's Method, ARIMA Model, and Prophet Model.

Literature Review

Khamis (2020) concentrated on predicting the price of gold using various models and techniques. In the article, the price of the Kijang gold, a Malaysian gold bullion coin, is predicted using the Holt's Method and ARIMA models. Six years' worth of daily pricing data are gathered by the researchers, who then use error measurements to assess the model's precision. In their opinion, the Holt-Trend exponential smoothing model is the best choice for precise price predictions.

Bandyopadhyay (2016) conducted a study to forecast the gold price in India. The researcher emphasises the growing significance of gold as an investment vehicle in India and seeks to advise clients on the best times to buy and sell gold. He gathered monthly prices of gold and analysed it using SPSS. The paper addresses the method of choosing model parameters and focuses on ARIMA modelling. The findings are presented, and fit statistics are discussed to gauge forecast performance. Another study by Nur et al. (2021) discussed the modelling and forecasting of gold prices in Malaysia. This study aims to predict the average monthly Kijang gold prices from January 2010 to July 2021. Gold's importance as an investment and its performance during economic crises and the COVID-19 pandemic are highlighted in the introduction. It also discusses the factors that affect gold prices, such as crude oil prices, inflation rates, interest rates, and fluctuations in the US dollar. The methodology section describes the dataset used, which consists of 139 monthlies average Kijang gold prices obtained from Bank Negara Malaysia. Using the ITSM2000 software, the time series modelling procedure consists of applying the BoxCox transformation, differentiating the data, and fitting the ARIMA models. The accuracy of the forecast is measured using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percent Error (MAPE). The results of the ARIMA model forecasts for January to July 2021 are presented in the findings and discussion section and show that Arima is suitable for price forecasting. In conclusion, the study demonstrates that time series models, specifically the ARIMA model, can be utilised to forecast Malaysian gold prices with accuracy. In addition, the article offers suggestions for future research in this field.

In addition, Shukor et al (2021) focuses on forecasting the stock market prices of gold, silver, crude oil, and platinum using three methods: Double Exponential Smoothing, Holt's Method, and Random Walk. The study uses data from January 2000 to December 2016 with a total of 204 monthly observations. The results show that Holt's Method is generally the most accurate method for forecasting, especially for crude oil and platinum, based on accuracy measures like Sum Square Error, Mean Square Error, and Root Mean Square Error. They conclude that accurate forecasting is crucial for strategic decision-making in companies and encourages future research to explore other forecasting methods.

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Summary of ARIMA, Holt's, and Prophet Tools

ARIMA (Auto Regressive Integrated Moving Average) is a classic time series forecasting technique that models the relationship between the current observation and a number of lagged observations and error terms. It's a powerful method for modelling and forecasting time series data with trends and seasonal components. The use of ARIMA (AutoRegressive Integrated Moving Average) Model is prevalent in time series modelling (Azzutti, 2016). This method combines autoregressive (AR), differencing (I), and moving average (MA) components to identify and represent data's underlying patterns.

Holt's Method also known as Holt's linear trend method, is used for forecasting time series data with a linear trend. Holt (2004) expanded the concept to linear exponential smoothing, which enables the forecasting of data that exhibits a trend. This method utilizes two smoothing constants, α and β, both ranging from 0 to 1, and involves three equations to calculate forecasts (Cordeiro & Neves, 2010). This method has gained widespread popularity due to its simplicity and consistent performance.

Next, Prophet is a time series forecasting model that has been develop by Facebook in 2017. Prophet is designed to handle daily observation, decompose data in trend, seasonality and holiday. In addition, this tool is an opensource tool for strong seasonal time series figures (Taylor & Letham 2017). Hence, Prophet can make a precise prediction. Additionally, it manages outliers and missing data, which improves performance over alternative methods and nearly automates the matching process (Aditya et al., 2021). It also offers the flexibility to model intricate time series characteristics by incorporating trends and multiple seasonality, including yearly, monthly, weekly, and daily patterns, while also accommodating holiday effects (Chaturvedi et al., 2022). Table 2 displays summary of the three methods used in this paper.

Table 2: Summary of ARIMA, Holt's, and Prophet Tools

Method	Summary
ARIMA	ARIMA (Auto Regressive Integrated Moving Average) is a classic time series forecasting technique that models the relationship between the current observation and a number of lagged observations and error terms. It's a powerful method for modelling and forecasting time series data with trends and seasonal components.
Holt	Holt's Method also known as Holt's linear trend method, is used for forecasting time series data with a linear trend. It extends simple exponential smoothing to allow for forecasting data with trends.
Prophet	Prophet is a forecasting tool developed by Facebook that is designed for analyzing time series data that display patterns on different time scales (such as trends, seasonality, and holiday effects). It is particularly good at handling missing data and outliers in the data.

Methodology

Kijang gold prices retrieved from Bank Negara Malaysia website for the five-year period from January 1, 2019 to December 31, 2023. The data included three sizes: 1 ounce, 12 ounces, and 14 ounces and covered five working days per week. 1 ounce of gold was equated to 31.1 grammes. Figure 1 provides an overview of the analytical approach employed, utilizing three distinct methods for forecasting. To ensure the accuracy of the forecasts, a data splitting technique is applied, allocating 75% of the data for training and reserving the remaining 25%

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for testing purposes. The forecasting results are then compared against the actual prices, specifically the 25% of data designated for testing. This comparison facilitates the calculation of various error metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), offering a comprehensive assessment of forecasting performance.

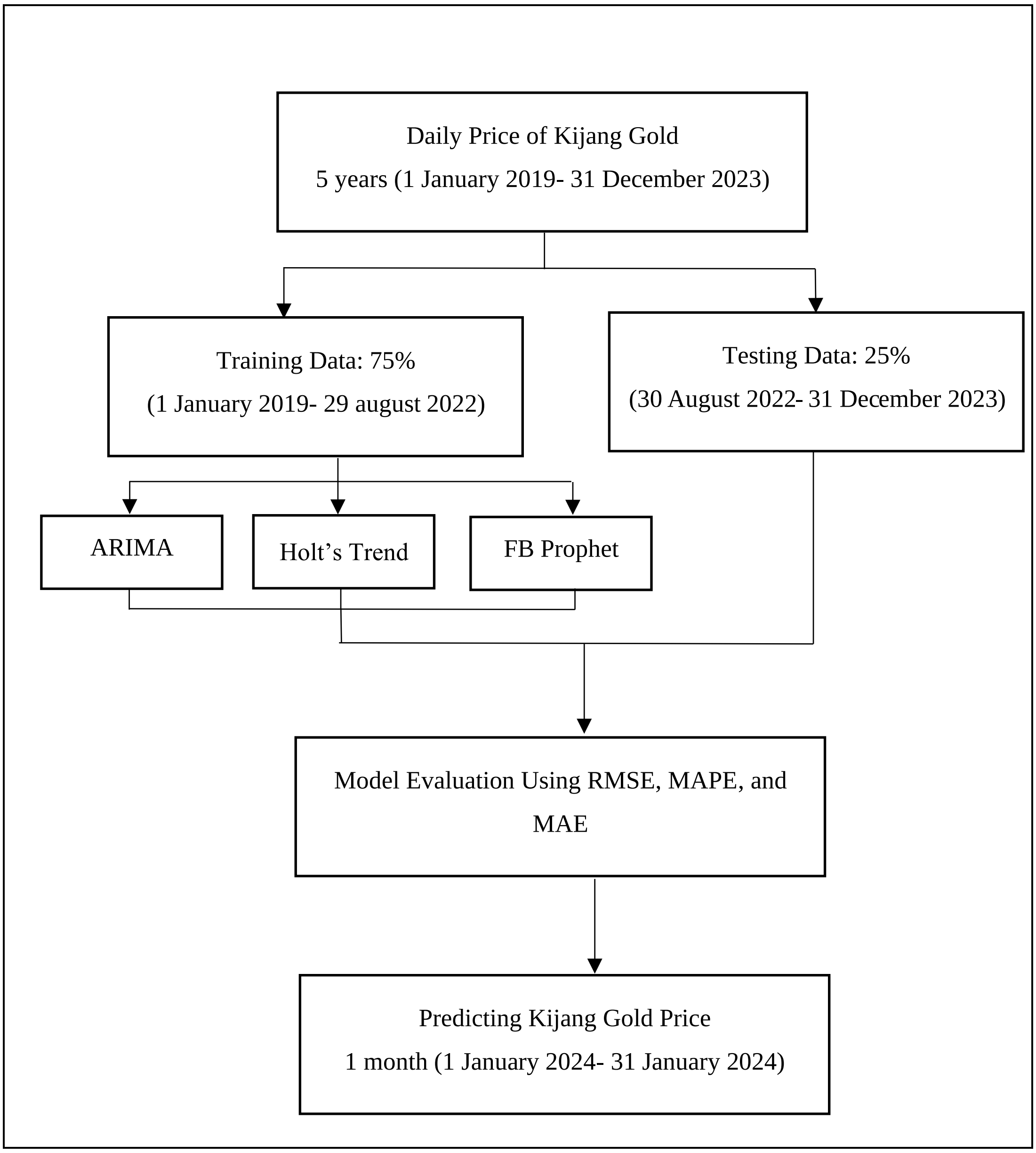

Figure 1: Flowchart Analysis Planning

Autoregressive Integrated Moving Average (ARIMA)
According to the Taneja et al (2016), the ARIMA Model is a popular stochastic time series modelling technique used for forecasting variables. A stationary time series property such as mean, variance, and autocorrelation are all constant over time. If the series is found to be stationary at the outset, the integration order, denoted as "d," is set to zero. This indicates that the ARIMA model does not require any differencing orders to achieve stationarity.

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In cases where the original series is non-stationary, transformations are necessary. Typically, this involves differencing the data. Which is one of the most common methods of inducing stationarity. The differencing order "d" is determined based on the number of transformations required to stabilize the mean of the series. For instance, a first order differencing (d=1) implies that the series has been made stationary by subtracting the current and previous data points' values.

Once the series is transformed to a stationary state, it is essential to ascertain that it is not white noise. White noise is characterized by a random sequence in which all frequencies are present with equal intensity and exhibit no predictable pattern or regularity. Analogous to the consistent hiss of a fan or the indiscriminate static of a radio, a white noise series is inherently unpredictable.

After the series is confirmed not to be white noise, the next phase involves the specification of the remaining two hyperparameters: the autoregressive term "p" and the moving average term "q". The autoregressive component "p" represents the idea that current values within the series can be forecasted from its past values (Ning et al., 2022). The selection of "p" and "q" is informed by examining the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) plots, which provide insights into the correlation of the time series with its own lagged values. These plots aid in the identification of the appropriate lag values for the AR and MA components of the ARIMA model.

The ARIMA Model's robustness is further validated by testing the residuals by the deviations between the observed values and the model's predictions. This test serves as a confirmation that the model has adequately captured the underlying data patterns. If the residuals do not exhibit a white noise pattern, the model requires refinement. Conversely, if the residuals are random, akin to white noise, the model is deemed appropriate for forecasting future values in the time series. This rigorous process ensures that the ARIMA Model is suitably tailored to the data's characteristics, ultimately enhancing the model's predictive accuracy.

To forecast Kijang gold prices, we'll use the ARIMA modelling technique. ARIMA combines autoregressive (AR), differencing (I), and moving average (MA) components to capture data trends and dependencies effectively. It's a proven method for time series analysis and prediction.

In an ARIMA Model (p, d, q):

- p is the number of autoregressive terms, showing how the current observation depends on past ones.
- d is the differencing order, used to make the data stationary by removing trends.
- q is the number of moving average terms, capturing the relationship with past forecast errors.

Holt's Method

In Holt's method, there is only one smoothing constant, so the estimated linear trend values are susceptible to random influences. To solve this issue, Holt's method, which is frequently used to handle data with a linear trend, was developed. This technique not only smooths the trend and slope directions by employing different smoothing constants, but also provides greater flexibility in determining the tracking rates for the trend and slopes.

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Prophet Model

Prophet Model is a time series forecasting model that has been develop by Facebook in 2017. This tool is designed to handle daily observation, decompose data in trend, seasonality, and holiday. Hence, Prophet can make a precise prediction. Additionally, it manages outliers and missing data, which improves performance over alternative methods and nearly automates the matching process (Aditya Satrio et al., 2021).

Forecasting Accuracy Measurement

Typically, the precision of a forecast is evaluated by measuring the error of each model. Mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean squared error (RMSE) are the error measurements that most frequently and favoured by previous researchers in forecast accuracy. The lowest results on MAPE, MAE, and RMSE from the three models determine the best model.

Result And Analysis

Figure 2 shows the actual 5-year kijang gold prices from January 2019 until December 2023. It can be clearly seen that the Kijang gold price is increasing from 2 January 2019 to 31 December 2023. The highest peak is on 13 November which is the value is RM 10,120 per ounce, while the lowest value is on 2 January 2019 is RM 5,620. This figure also contains a trend component indicating an increase in value over the period, but no notable fluctuations that may hint at potential seasonal, irregular and cyclical component exist. The latter part of the series, particularly post-2020, reveals increased volatility, suggesting greater market uncertainty impacting gold prices.

Figure 2: Kijang Gold Prices (2019 – 2023)

Source: Bank Negara Malaysia's

Autoregressive Integrated Moving Average

The procedure for making the ARIMA model for forecasting time series data has three steps: stationarize the data, find optimal parameter (p,d,q), and evaluate the model.

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Time Series Data

Previously, Figure 2 shows a trend component exist in Kijang gold price. The upward trend and fluctuations suggest the data series are nonstationary. The ACF plot (Figure 3) shows a slow decaying pattern of the autocorrelation values as the lags increase suggests a non-stationary time series, which could imply the need for differencing to achieve stationarity. Partial Autocorrelation Function (PACF) plot show the sharp significant spike at lag one followed by insignificant spikes suggests that there is no partial autocorrelation in the data at lags greater than zero, indicating an AR(0) process might be suitable for this series.

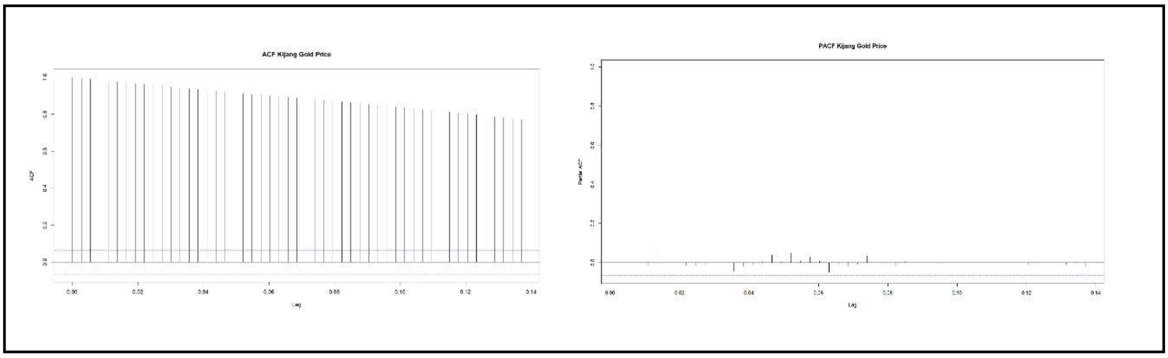

Figure 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of Original Data

Additionally, according to ADF Test result (Table 3), the p-value of 0.7054 is greater than 0.05, indicating that the time series is not stationary. In order to detect the data series is white noise, the Box-Pierce test is applied. The p-value of Box-Pierce test (Table 3) is less than 0.05 significant level indicate that the data series is not white noise confirm that Kijang gold prices can be modelled and predicted.

Table 3: ADF Test

	Augmented Dickey-Fuller Test	Box-Pierce Test
P-value	0.7054	0.00000000000000022

Stationaries Time Series Data

Figure 4 depicts the time series plot of first differencing of Kijang gold price does not show the presence of trend component, while ACF indicate significant spike at certain lag. ADF Test result (Table 4) shows that the p-value of 0.01 is less than 0.05, confirmed that the time series now is stationary.

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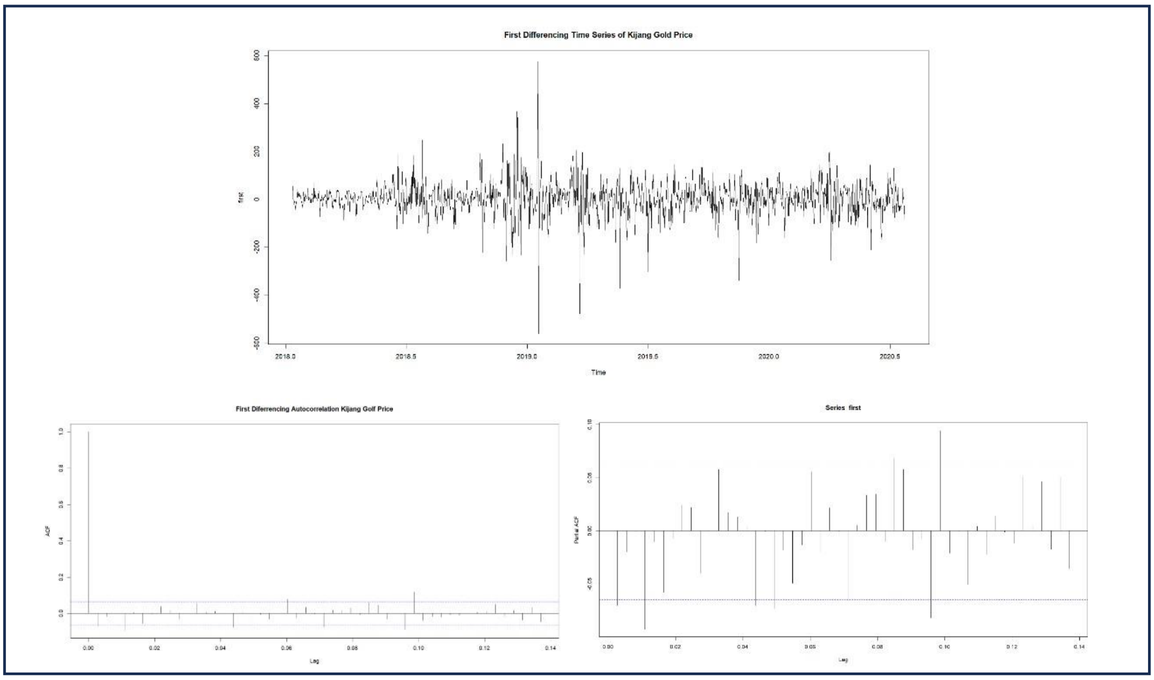

Figure 4: Time Series, ACF and PACF Plot after First Order Differencing

ADF Test result (Table 4) shows that the p-value of 0.01 is less than 0.05, confirmed that the time series now is stationary.

Table 4: ADF Test

Test statistic	-10.402
P-value	0.01

Parameter and Model

ARIMA Model involves the specification of three fundamental parameters: p, d, and q. In the process of making the time series stationary, by employ first-order differencing, which corresponds to setting the parameter d to 1. The determination of parameters p and q is initially guided by the examination of PACF and ACF plot (Figure 4).

Specifically, the choice of "p" was based on identifying significant spikes in the PACF plot at lags 1, and 2, while the selection of "q" was determined by significant spikes in the ACF plot at lag 1 and 3. Consequently, a total of six distinct ARIMA Models were created to explore different combinations of these parameters. These models are designated as ARIMA (0,1,1), ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,0), ARIMA (2,1,1), and ARIMA (2,1,2). This rigorous approach to parameter selection ensures a comprehensive exploration of potential model structures and allows for the identification of the most suitable ARIMA Model for the time series under investigation, enhancing the robustness and reliability of the analysis.

ARIMA Model Evaluation

The model selection process will be based on a thorough comparison of several key metrics, including Root Mean Square Error (RMSE), evaluation for white noise test of residual, and the

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Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The chosen model will be the one that yields the lowest values across these metrics, indicating superior performance. The detailed results of this model evaluation process will be presented comprehensively in Table 5, providing a clear and systematic overview of the model comparisons and their respective performance measures. This rigorous approach ensures the selection of the most appropriate ARIMA model for the time series analysis, enhancing the reliability and robustness of the findings.

Table 5: Comparison of ARIMA Models

	Model					
ARIMA	(0,1,1)	(1,1,1)	(1,1,2)	(2,1,0)	(2,1,1)	(2,1,2)
White Noise	Yes	Yes	Yes	Yes	Yes	Yes
AIC	10524	10699	10527	10525	10527	10525
BIC	10533	10533	10547	10540	10547	10550
RMSE (training set)	78.8139	78.7011	78.80415	78.80723	78.80706	78.63856
RMSE (testing set)	1158	1176	1159	1159	1159	1176

Table 5 shows significant interest due to its ARIMA (0,1,1) model, which demonstrated the lowest AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values among all the models under consideration. Specifically, it recorded AIC and BIC values of 10524 and 10533.62, respectively, which were the most favourable outcomes in terms of model fit and performance. Nevertheless, it's worth noting that when considering the RMSE for the training set, the ARIMA (0,1,1) model did not achieve the lowest value. Instead, the model with the lowest RMSE was ARIMA (2,1,2), with an impressive RMSE value of 78.6385. However, when transitioning to real-world applications and assessing the ability to make precise short-term forecasts by comparing forecast accuracy with actual data, the RMSE for ARIMA (0,1,1) emerged as the standout performer. It achieved the lowest RMSE value among all tested models, with a remarkable score of 1158. This underscores its excellence in delivering accurate forecasts in practical scenarios. Considering these insights, ARIMA (0,1,1) clearly stands out as the top choice.

Table 6: Measurement Error of Testing Set on ARIMA (0,1,1)

		Model		
(0,1,1)	(1,1,1)	(1,1,2)	(2,1,0)	(2,1,1)
Yes	Yes	Yes	Yes	Yes
10524	10699	10527	10525	10527
10533	10533	10547	10540	10547
78.8139	78.7011	78.80415	78.80723	78.80706
1158	1176	1159	1159	1159

Therefore, by accumulating 304 prediction errors and computing their mean, the Root Mean Square Error (RMSE) was calculated to be 1158. Additionally, as indicated in Table 6 and will be compared with other method which is Holt's Method and prophet, the MAPE (Mean Absolute Percentage Error) and MAE (Mean Absolute Error) values were found to be 10.6656 and 1013, respectively. This measurement error analysis suggests that among the tested models, ARIMA (0,1,1) outperforms the others and emerges as the most favourable choice.

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Holt's Method

In pursuit of this research objectives to evaluate forecasting accuracy, Holt's Exponential Smoothing emerges as a streamlined and straightforward approach. This method offers a simpler means to assess predictive performance through the computation of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). By applying Holt's Method to the time series data and efficiently generate forecasts, which are subsequently compared with actual data over the forecast horizon. The result is a comprehensive and accessible assessment of forecast accuracy, providing valuable insights for decision-making and model evaluation.

Table 7: Holt's Trend Model Summary

Error Measure	RMSE	MAE	MAPE
Training Set	78.76182	53.38395	0.7004
Testing Set	667.8285	574.7120	6.0451

The RMSE training in Table 7 is 78.76182 and RMSE testing is 667.8285. Meanwhile, the value of MAPE training data is 0.7005 and 6.0451 for training data value, conveyed the average percentage difference between forecasts and actual observations. Three key error measures were computed to evaluate the precision of the forecasts. served as a gauge of the average forecasting error magnitude. The Mean Absolute Error (MAE) reflected an average absolute deviation of about 574.7120 between predicted and actual values. Hence, the value obtained from measurement error for testing data will be compared with the other method which is ARIMA and Prophet.

Prophet Model

The Prophet Model which developed by Facebook, is a straightforward and robust forecasting method known for its strong predictive capabilities. Table 7 provides an overview of the error metrics associated with the Prophet model's forecasting accuracy. These metrics serve as valuable indicators of the model's performance and include the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The Prophet model's ability to deliver accurate forecasts is highlighted through these metrics, demonstrating its effectiveness in capturing underlying patterns and trends in the data.

Table 8: Error Measure of Prophet Model

Error Measure	RMSE	MAE	MAPE
Training Set	286.8718	236.3447	299.00
Testing Set	1001.35	937.63	1028.00

Table 8 displays error metrics for the Prophet Model applied to the training data. These metrics serve as indicators of the model's forecasting accuracy and are crucial for evaluating its performance. The Root Mean Squared Error (RMSE) measures the average magnitude of forecasting errors which is 286.8718 for training data. The Mean Absolute Error (MAE) quantifies the average absolute difference between predicted and forecasted values which is 236.3447 for training data. Additionally, the Absolute Percentage Error (MAPE) expresses the average percentage difference between forecasts and actual values is 299 error of training data, providing a comprehensive view of the model's predictive capabilities. Prophet forecasting model is succinctly summarized in Table 8, showcasing its performance through three key error metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute

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Percentage Error (MAPE). The RMSE value of 920.1829 indicates the model's average prediction error in testing data. This metric is particularly useful as it gives a sense of the magnitude of errors, though it can be sensitive to outliers. The MAE, recorded at 937.63, provides a straightforward interpretation of the average error in predictions. Lastly, the MAPE of 1028 represents the average error as a percentage of the actual values, offering a relative measure of the model's accuracy. This percentage-based metric is invaluable for understanding the model's performance in a more intuitive and contextually relevant manner, especially when dealing with varying scales of data. Together, these metrics offer a comprehensive evaluation of the Prophet model, highlighting its strengths and limitations in forecasting accuracy within the specific domain of this study.

Forecasting Accuracy

During this research, a comprehensive analysis of three distinct forecasting methods was carried out. The primary objective of this analysis was to assess the accuracy and reliability of these methods in predicting price trends by comparing their forecasted values with the actual market prices. The culmination of this evaluation is presented in Table 8, which reveals the forecasted values for the Kijang gold Prices dataset obtained through each of the three methods. Furthermore, this table serves as a vital reference point for identifying the best-performing forecasting method among the three under consideration. To gauge the effectiveness of these methods, error metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were utilized. The results of this comparative analysis not only shed light on the accuracy of each method but also provide valuable insights into their practical applicability in the context of price forecasting.

Table 9: Error Metric Measurements Between Three Models

Error Measurement	RMSE	MAE	MAPE
ARIMA (0,1,1)	1158	1013	10.6656
Holt’s Method	**667.8285**	**574.71**	**6.0451**
Prophet Model	1001.35	937.63	10.28

In Table 9, the forecasting accuracy of three distinct methods: ARIMA (0,1,1), Holt’s Method, and Prophet were compared, using three fundamental error metrics: RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). These metrics serve as essential benchmarks for assessing the quality of the forecasts generated by each method. Starting with RMSE, which measures the average magnitude of errors in the same units as the data, we observe that Holt’s Method achieved the lowest RMSE value of 667.8285. This signifies that, on average, the predictions generated by Holt’s Method were closer to the actual values, in terms of the underlying data, compared to the other methods. Lower RMSE values suggest superior accuracy, making Holt’s Method the top-performing method in this regard.

Moving on to MAE, which quantifies the average absolute errors, this paper find that Holt’s Method again excels with the lowest MAE of 574.71. This implies that, on average, the absolute discrepancies between the forecasts and actual observations are minimal when using Holt’s Method. This further reinforces the notion that Holt’s Method provides the most accurate predictions, as lower MAE values indicate better accuracy.

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Lastly, MAPE which measures the average percentage error in predictions. Once more, Holt's Method emerges as the superior method with the lowest MAPE of 6.0451. This percentage-based metric indicates that, on average, Holt's Method exhibits the smallest relative error in forecasts. A lower MAPE reflects a more accurate forecasting method, emphasizing the superiority of Holt's Method.

Conclusion

Kijang Gold Bullion appears to be a profitable investment, but only if it is timed strategically according to daily price changes. Consequently, forecasting becomes a valuable skill when figuring out when to invest, all things considered. This study investigated three different approaches to address this problem: the Prophet Method, Holt's Exponential Smoothing Method, and the ARIMA Model. The main thing of this study is wanted to do was figure out which forecasting method worked best.

It is important to consider the price behaviour of Kijang Gold before starting the prediction process. This preliminary evaluation guarantees the dataset's applicability and relevance for forecasting. Upon closer inspection, we found that the data was trending upward, indicating that it could be used for predictive modelling.

Table 10: Measurement Error of Testing Set on ARIMA (0,1,1)

Root Mean Squared Error (RMSE)	Mean Absolute Percentage Error (MAPE)	Mean Absolute Error (MAE)
1158	10.6656	1013

Therefore, by accumulating 304 prediction errors and computing their mean, the Root Mean Square Error (RMSE) was calculated to be 1158. Additionally, as indicated in Table 10 and will be compared with other method which is Holt's Method and Prophet Model, the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) values were found to be 10.6656 and 1013, respectively. This measurement error analysis suggests that among the tested models, ARIMA (0,1,1) outperforms the others and emerges as the most favourable choice. Overall, the forecasting process can have a significant impact on the investment decisions made by investors and companies. The ability to predict and plan with greater precision may increase confidence and ultimately result in improved investment decisions and economic conditions.

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