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THE COMPARISON OF ARIMA AND RNN FOR FORECASTING GOLD FUTURES CLOSING PRICES

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ABSTRACT

In the financial markets, accurately forecasting the closing prices of gold futures is crucial for investors and analysts. Traditional methods like ARIMA (Autoregressive Integrated Moving Average) have been widely used for this purpose, particularly for their effectiveness in short-term stable data forecasting. However, the inherent complexity and dynamic nature of financial data, coupled with trends and seasonal patterns, present significant challenges for long-term forecasting with ARIMA. Conversely, advanced methods such as Recurrent Neural Networks (RNN) have shown promise in handling these complexities and providing reliable long-term forecasts. This research seeks to evaluate and compare the performance of ARIMA and RNN in forecasting daily gold futures closing prices using forecast accuracy tests namely RMSE and MAPE, aiming to identify the optimal method that balances accuracy, stability, and adaptability to trends and seasonal variations in the financial market. The daily data for this analysis is sourced from Investing.com (https://www.investing.com).

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1. INTRODUCTION

Time series data is a collection of observations gathered at successive time intervals, allowing for the analysis of patterns and trends from historical data to forecast future values. This method is widely applied in various fields that require continuous data collection, such as finance, meteorology, industry, and healthcare. By utilizing time series data, analysts can identify fluctuations, seasonality, and long-term changes that affect the behavior of observed variables, enabling more precise and strategic decision-making based on the predictions generated [1][2].

While time series data is highly useful for forecasting future values, there are some drawbacks to its use. Time series data often exhibits nonlinear or non-stationary properties, posing challenges for forecasting when using statistical techniques such as the ARIMA model. These models are less effective in producing accurate predictions when dealing with time series data that exhibit nonlinear or non-stationary properties. However, ARIMA performs well in handling linear and non-stationary data, providing accurate short-term results [3][4]. Previous research examining the global gold price forecasting using the ARIMA (0,1,1) model reported an AIC value of 1264.731 and a MAPE value of 11.972% [5]. A 2021 study comparing the ARIMA model and the Artificial Neural Network (ANN) method for predicting the number of positive cases of covid-19 in DKI Jakarta found that the ARIMA model was more accurate than the ANN method in forecasting the number of positive cases [6].

Time series data can be forecasted not only using conventional statistical methods but also using deep learning methods such as RNN. RNN is quite effective in handling nonlinear data [7]. While RNN is good at predicting nonlinear data, it has computational drawbacks due to its repetitive nature, leading to longer computational processes. RNN is highly suitable for time series prediction because it can utilize previously recorded information for time series data prediction [8]. However, deep learning is often referred to as a black box because it is difficult to interpret and lacks transparency compared to conventional statistical methods [9][10]. Research by [11] showed that RNN is effective in predicting computer network traffic, which has similar nonlinear properties to financial data. One advantage of time series analysis is its ability to forecast prices within the realm of investment.

In the context of investment and market prices, gold has always been an attractive asset for investors. One popular form of gold investment is futures gold, where parties agree to buy or sell a certain amount of gold on a specific future date at a price set today. Futures gold investment is often used by traders or investors to speculate on future gold price movements. With the potential for significant gains from relatively small price changes, but also high risk of loss due to high leverage levels, the ability to accurately forecast futures gold prices is crucial in making trading and investment decisions. Therefore, accurately forecasting futures gold closing prices is crucial for investors or traders and market participants, as accurate futures gold price forecasting can help market participants make better trading and investment decisions [12].

Previous research on predicting gold futures closing prices during the COVID-19 using the deterministic trend model found that model showed an 80.11% fit between predicted and observed values. Thus, the quadratic trend method used in this research can be applied to forecast data for the next 30 periods, i.e., in February 2021 [13]. Additionally, there is research comparing the LSTM method as an ANN model and the ARIMA method, which found that the LSTM method had the smallest RMSE compared to ARIMA [5].

Further research comparing the RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory) methods in forecasting rice prices concluded that the RNN (Recurrent Neural Network) method has the smallest RMSE compared to the LSTM (Long Short-Term Memory) method [14]. Research comparing LSTM, ARIMA, and Holt Winters Exponential methods on motorcycle sales data from 2015 to 2021 concluded that the ARIMA method was the best method because it had the smallest RMSE [15].

This research is expected to make a significant contribution in understanding the advantages and disadvantages of each method in forecasting gold futures prices, as well as help in making better investment decisions. Thus, the comparison of the two models, namely ARIMA and RNN, is expected to produce accurate forecasts for gold futures closing price data.

2. RESEARCH METHODS

This research was carried out with several stages of research, starting from data collection sourced from the website https://www.investing.com with a daily time period (01 January 2021 to 29 February 2024) which amounted to 1155 data. Gold futures closing price data (US Dollar) has a trend data pattern and there is no seasonal element in the data. The research will perform forecasting or prediction of data by comparing two methods, namely traditional (classic) statistical methods and machine learning methods. In this research, we use ARIMA for traditional method and RNN for machine learning method.

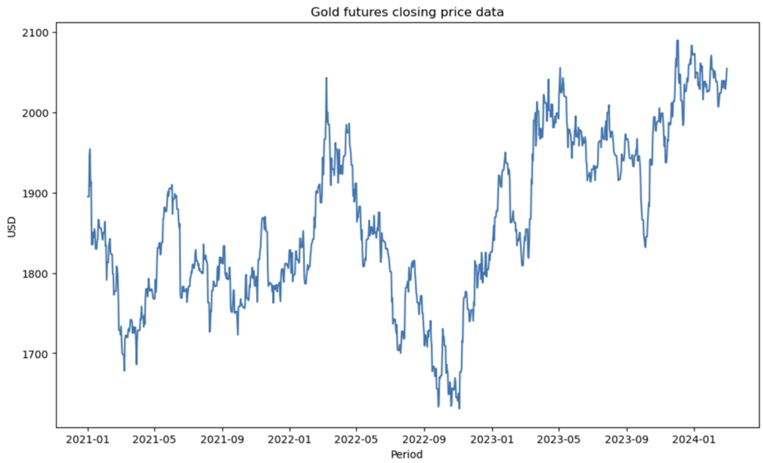

Figure 1. Gold Futures Closing Price Data (January 2021 - February 2024

The time series plot in **Figure 1** shows the dynamic nature of gold futures prices over the past three years, characterized by significant fluctuations. The overall trend indicates periods of both decline and recovery, with the most recent data points showing a stable high price around $2000 USD. This information can be useful for traders and analysts.

2.1 ARIMA (Autoregressive Integrated Moving Average)

Forecasting plays a significant role in the decision-making process by projecting events that may occur in the future based on historical data analysis. Forecasting methods, such as time series, are used to interpret and project trends or patterns based on historical data. In this context, past information about a particular variable represented in a periodic series or time series, becomes the basis for estimating possible future events **[16]**. The following is the general formula of the ARIMA model

$$\Delta Y_t = \varphi_1 \Delta Y_{t-1} + \varphi_2 \Delta Y_{t-2} + \varphi_p \Delta y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_p e_{t-p} \tag{1}$$

Where

t	: Time coefficient
Y_t	: Series value at time t
Y_{t-1}, Y_{t-2}	: Past series values
e_{t-1}, e_{t-2}	: Past residual values
$\theta_1, \theta_p, \varphi_1, \varphi_p$	: Model Coefficients

2.2 RNN (Recurrent Neural Network)

Recurrent Neural Networks (RNNs) are adept at uncovering hidden patterns within data. RNNs excel in domains like natural language processing, speech recognition, and time series forecasting due to their ability to effectively handle sequential data. Their recursive connections enable them to merge new information with what has been previously processed, allowing for a dynamic and contextually aware modeling of data sequences **[13]**. A Recurrent Neural Network (RNN) is made up of input units, output units, and hidden units. Information moves in one direction: from the input unit to the hidden unit, and from the previous hidden unit to the current hidden unit. The hidden units function as the network's memory, storing and recalling data across different states **[20]**.

The advantages of RNNs are seen when inputs and outputs are directly connected. This allows the integration of data from the previous node to the next. Recurrent Neural Networks (RNNs) are capable of managing long-term dependencies, but they struggle with retaining information over extended periods due to the vanishing gradient problem in 1997, Hochreiter and Schmidhuber introduced Long Short-Term Memory (LSTM) to tackle this issue. This variant of RNN architecture enhances performance by effectively overcoming the vanishing gradient issue [21].

$$s_t = f((U \times x_t) + (W \times s_{t-1}) \tag{2}$$

Where:

s_t : Represents the memory (or state) of the network at time t
U : A weight matrix applied to the input x_t
W : A weight matrix applied to the previous state s_{t-1}
F () : Represents a non-linear activation function applied to the sum of the weighted input and previous state.

$$o_t = g(V \times S_t) \tag{3}$$

Where:

o_t : Represents the output of the network at time t.
U : A weight matrix applied to the current state s_t
W : A weight matrix applied to the previous state S_{t-1}
g () : Represents another non-linear activation function applied to the weighted state to produce the output.

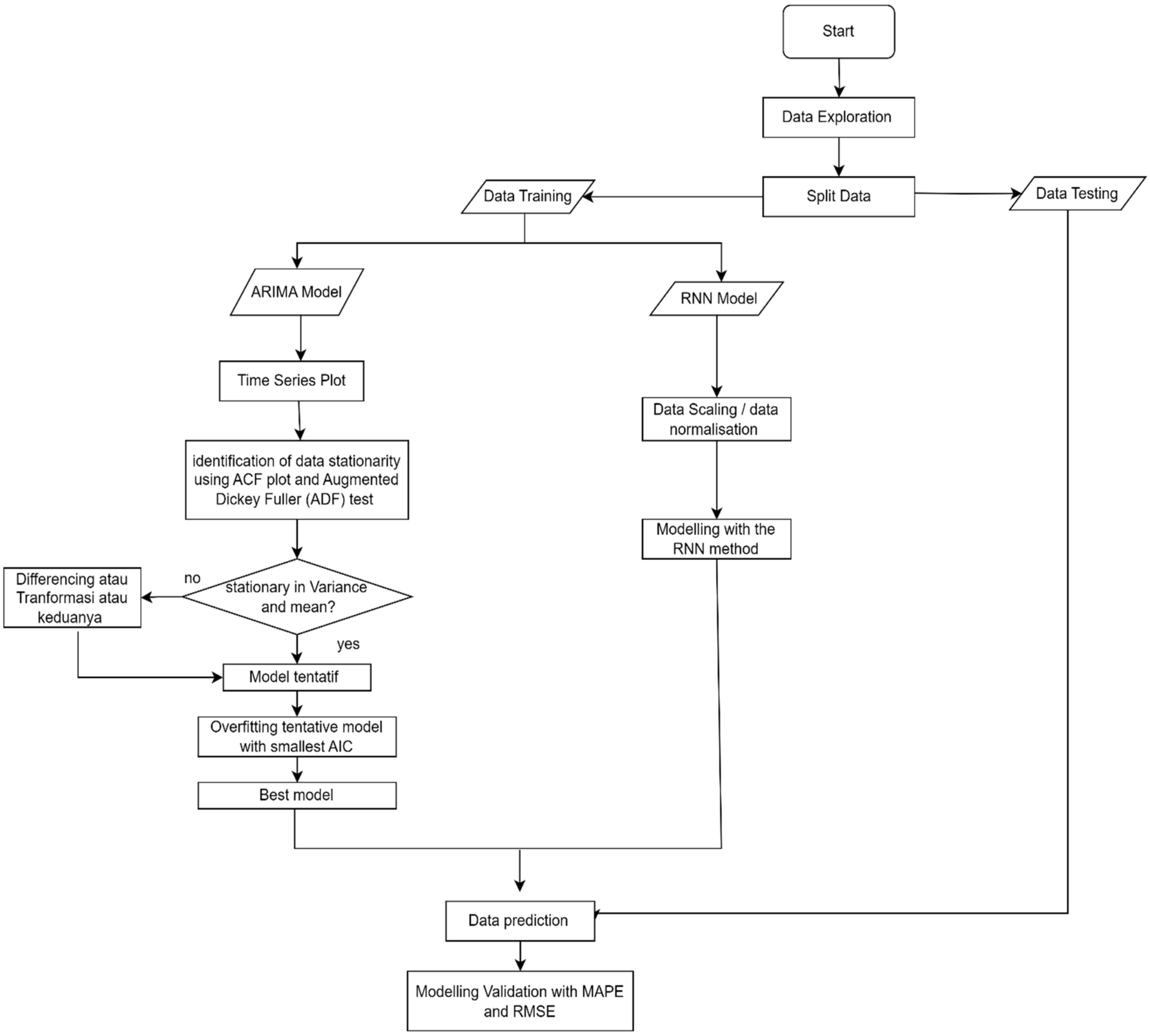

Figure 2. Flowchart of Forecasting using the ARIMA and RNN Models

3. RESULTS AND DISCUSSION

3.1 ARIMA Model

a. Data Splitting and Visualization

The exploration phase involves splitting the gold futures closing price data into training and testing sets. The training data consists of 86% of the total data, from January 1, 2021, to September 20, 2023, while the testing data comprises 14% of the total data, from September 13, 2023, to February 29, 2024. Below is the graph depicting the actual gold futures closing price data after being divided into training and testing sets:

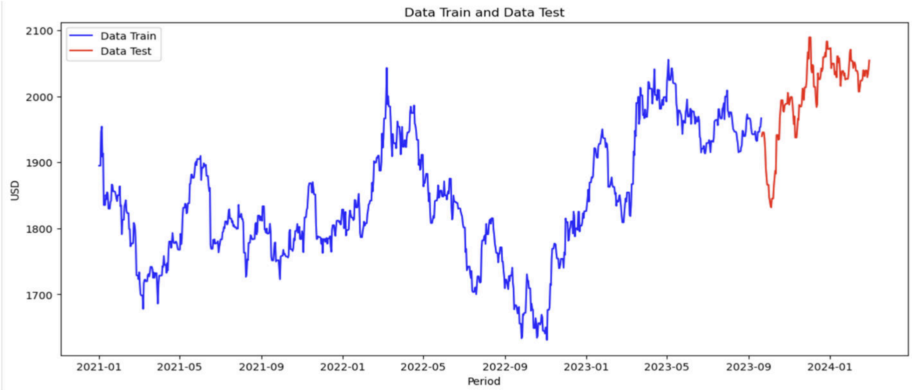

Figure 3. Actual Gold Futures Closing Price Data

Based on **Figure 3**, the training data marked by the blue graph and the testing data marked by the red graph. The pattern observed in the graph indicates that the gold futures closing price data is non-stationary, characterized by a tendency towards upward or downward trends.

b. Stationarity of Data

Plotting the Autocorrelation Function (ACF) and conducting the Augmented Dickey-Fuller (ADF) test are useful methods for assessing the stationarity of data. If the data's mean is not stationary, a differencing process can be applied. If the data's variance is not stationary, a transformation process can be used. In **Figure 3**, it is evident that the data is stationary in terms of variance. The next step is to examine the stationarity of the data in terms of its mean value. Below is the ACF plot of the training data for gold futures closing prices:

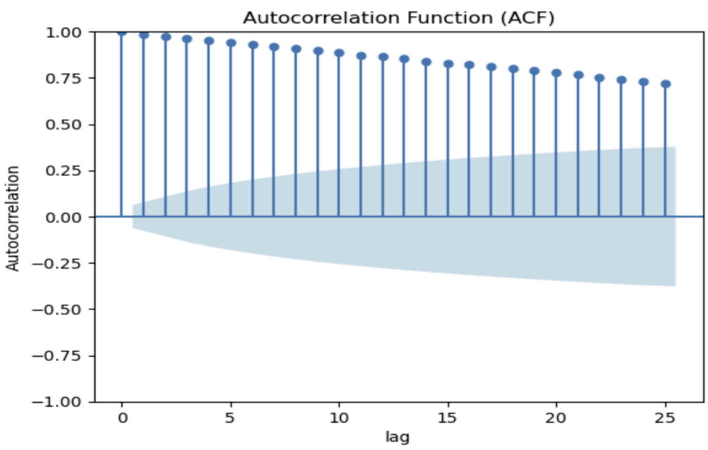

Figure 4. Plot ACF of Training Data for Closing Price of Gold Futures

Figure 4 shows an ACF plot indicating non-stationarity in the data, with a gradual decrease or tails off, lag-lags on the ACF plot outside the standard error interval lines. Additionally, An ADF test was also conducted to reinforce the testing for non-stationarity of the data, yielding a p-Value of 0.374, indicating that the data is not stationary at the 5% significance level (0.374 > 0.05). Since this p-Value is greater than the 5% significance level (0.374 > 0.05), it confirms that the data is not stationary at the 5% significance level.

These findings suggest that the data is non-stationary with respect to the mean. Therefore, differencing is necessary to make the data stationary with respect to the mean. Below are the results of the data plot after differencing:

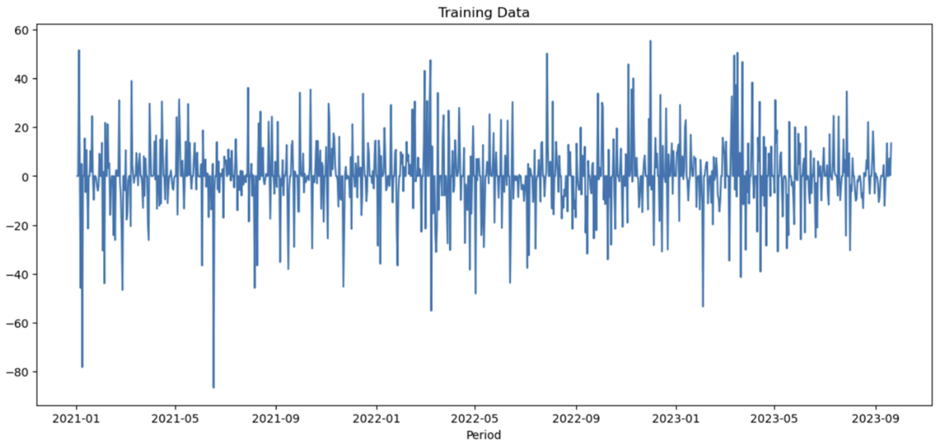

Figure 5. Training Data of Gold Futures Prices After Differencing

After applying differencing, the Augmented Dickey-Fuller (ADF) test was conducted again to evaluate the stationarity of the data concerning its mean. The ADF test statistic after differencing is 0, indicating that the data is now stationary in terms of its mean value.

c. Model Identification and Parameter Estimation

Model identification for stationary data involves analyzing the PACF (Partial Autocorrelation) and ACF (Autocorrelation) plots. The PACF plot helps determine the maximum order of AR(p), while the ACF plot identifies the maximum order of MA(q). For the differenced data, both plots show no lags outside the confidence intervals. This suggests that the appropriate ARIMA model could be ARIMA (0,1,0). The next step is to select the best ARIMA model by comparing various options using the AIC value. Below are the AIC values for several potential models:

Table 1. Comparison of ARIMA models based on AIC

Model	AIC
ARIMA (0,1,0)	8085.884061
ARIMA (1,1,0)	8083.914606
ARIMA (0,1,1)	8083.850182
ARIMA (1,1,1)	8085.789661

Based on **Table 1**, the AIC values for the ARIMA(0,1,0) and ARIMA(1,1,1) models are very close, as are those for ARIMA(1,1,0) and ARIMA(0,1,1). Among these, the ARIMA(0,1,1) model has the lowest AIC value of 8083.850182, making it the most suitable model for the given data set.

d. Overfitting

The overfitting process was conducted by adding one AR or MA order to the tentative model (ARIMA (0,1,1)). Consequently, two candidate models resulted from this overfitting process: ARIMA (1,1,1) and ARIMA (0,1,2). After overfitting, it was found that the tentative ARIMA (0,1,1) model had the lowest AIC value, which is 8083.850182, compared to the other two models. ARIMA (1,1,1) had an AIC value of 8085.789661, and ARIMA (0,1,2) had an AIC value of 8085.807. However, the overfitting process resulted in some non-significant parameter values in the obtained model. Therefore, this model cannot be used.

e. Model Diagnostics

After selecting the most suitable model, the next step is to perform diagnostic testing. This involves conducting tests for normality, heteroscedasticity and autocorrelation.

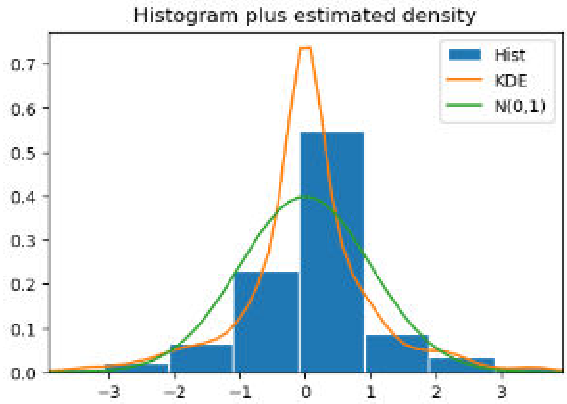

Figure 6. Histogram Plot of Residuals

Based on **Figure 6**, the histogram plot of residuals follows a pattern not consistent with a normal distribution, indicating that the assumption of normality of residuals is not satisfied. However, in time series data analysis, residuals that do not follow a normal distribution can still adequately model the time series as long as the assumptions of white noise and independence are satisfied.

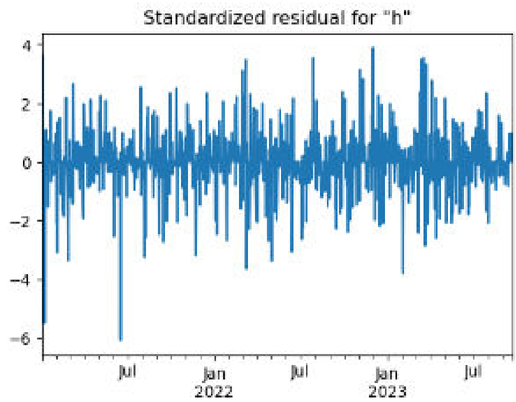

Figure 7. Standarized Residual

Based on the standardized residual plot against time in **Figure 7**, the plot confirms that the residuals' variance is homogenous. Thus, it can be concluded that there is no violation of the assumption of homogeneity of variance.

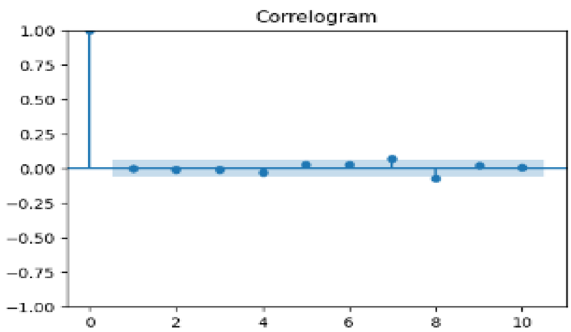

Figure 8. Correlogram

Based on **Figure 8**, the correlogram shows that the autocorrelation values at all lags are within the interval, indicating that the assumption of independence of residuals is met.

f. Model Validation

After conducting diagnostic checks on a model, validating it with test data is essential to ensure its accuracy. For evaluating the forecasted results of training and test data for, two key metrics can be used: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE). two key metrics help quantify the model's prediction accuracy, with lower values indicating better performance. Here is the graph of the ARIMA (0,1,1) validation model:

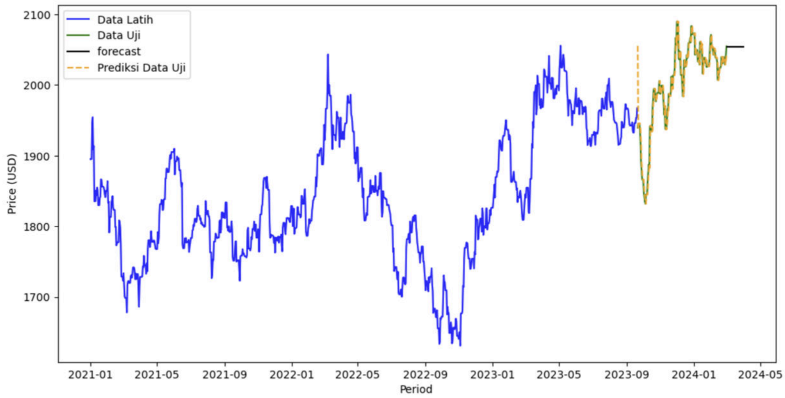

Figure 9. **ARIMA Model Prediction for Training Data and Test Data**

The prediction results for the training data have an accuracy rate of 99.52% based on MAPE, with a MAPE value of 0.48%, indicating excellent prediction results. The RMSE value is 14.38. Similarly, the prediction results for the test data have an accuracy rate of 99.53% based on MAPE, with a MAPE value of 0.47%, indicating excellent prediction results. The RMSE value is 16.12.

g. Forecasting the Closing Price of Gold

The forecasting is conducted using the ARIMA(0,1,1) method for the next 14 days. Below are the forecasted closing prices of gold futures using the ARIMA(0,1,1) method:

Table 2. **The Forecast of ARIMA (0,1,1)**

Period	The Forecast Result (USD)	Period	The Forecast Result (USD)
01-Mar-24	2054.0753	08-Mar-24	2054.0753
02-Mar-24	2054.0753	09-Mar-24	2054.0753
03-Mar-24	2054.0753	10-Mar-24	2054.0753
04-Mar-24	2054.0753	11-Mar-24	2054.0753
05-Mar-24	2054.0753	12-Mar-24	2054.0753
06-Mar-24	2054.0753	13-Mar-24	2054.0753
07-Mar-24	2054.0753	14-Mar-24	2054.0753

Based on **Table 2** above, it indicates the gold futures closing prices remains constant over time after February 2024. This suggests that the gold futures closing prices in the future period does not change. However, in reality, this assumption cannot be relied upon over a sufficiently long period because many factors can cause the gold futures closing prices to change over time.

3.2 Model Recurrent Neural Network (RNN)

The initial stage of the RNN model involves splitting the gold futures closing price data into training and testing datasets. The data will be split into training data, comprising 86% of the total data, from January 1, 2021, to September 20, 2023, and testing data, comprising 14% of the total data, from September 13, 2023, to February 29, 2024. The modeling process of the RNN involves scaling or normalizing the training data of gold futures closing prices using the MinMaxScaler method to ensure that all data have the same range, from 0 to 1. Several parameters used in the RNN modeling are an epoch of 100 and a batch_size of 2. In gradient descent, "epoch" defines how many times the model will pass through the entire training dataset. An epoch means the model has seen every training sample once. "Batch_size," on the other hand, specifies the number of samples the model processes before updating its internal parameters. These parameters help control the training process, affecting how quickly and effectively the model learns.

The RNN model provides fairly good prediction results in forecasting the gold futures closing prices in the training data, as evidenced by the prediction plot in **Figure 9**, which closely approximates the actual data. **Figure 10** illustrates the comparison between the actual data of gold futures closing prices and the predicted closing prices.

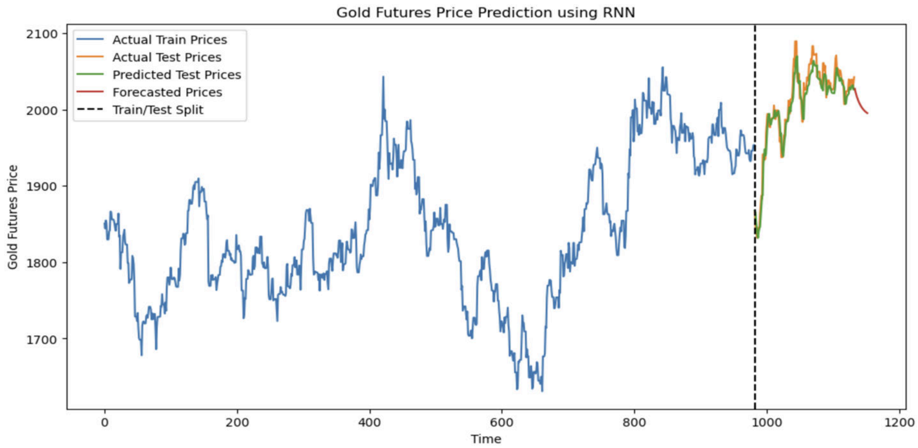

Figure 10. Comparison Graph of Actual and Predicted Gold Futures Prices

In **Figure 10**, the RNN model demonstrates a strong performance, with its prediction line closely following the actual data line. This high accuracy is supported by the Mean Absolute Percentage Error (MAPE) of 0.57%, reflecting a 99.43% accuracy rate. Additionally, the Root Mean Square Error (RMSE) of 15.01% indicates reliable prediction results. The forecast spans the next 14 periods, from March 1, 2024, to March 14, 2024, showing the model's effectiveness in price forecasting. The forecasted gold futures closing prices using the RNN model are presented in **Table 3**.

Table 3. The Forecast Result of RNN

Period	The Forecast Result (USD)	Period	The Forecast Result (USD)
01-Mar-24	2026.76	08-Mar-24	1993.72
02-Mar-24	2019.85	09-Mar-24	1990.10
03-Mar-24	2015.78	10-Mar-24	1986.86
04-Mar-24	2010.21	11-Mar-24	1983.76
05-Mar-24	2005.71	12-Mar-24	1980.84
06-Mar-24	2001.41	13-Mar-24	1978.13
07-Mar-24	1997.49	14-Mar-24	1975.55

The forecast results in **Table 3** indicate a decrease in gold futures closing prices over time after February 2024. The largest decrease occurs on the second day, and in the following days, the magnitude of the decrease diminishes compared to the previous day.

3.3 Comparison of Performance between ARIMA (0,1,1) and RNN Models

Performance comparison between ARIMA and RNN models can be measured by comparing the values of model goodness-of-fit measures, namely MAPE and RMSE. Below is a table comparing the MAPE and RMSE values for the ARIMA (0,1,1) and RNN models.

Table 4. Comparison of Performance Between ARIMA(0,1,1) and RNN Models

Forecasting Models	MAPE	RMSE
ARIMA (0,1,1)	0,47%	16.12
RNN	0.57%	15.01

Based on **Table 4**, the ARIMA(0,1,1) model is better than the RNN model because the ARIMA(0,1,1) model has the smallest goodness-of-fit measure, which is MAPE, compared to the RNN model. However, in terms of RMSE value, the RNN model is better than ARIMA The ARIMA(0,1,1) model is considered superior in this context because it has a lower Mean Absolute Percentage Error (MAPE) of 0.47% compared to the RNN model, which has a MAPE of 0.57%. According to the book "Forecasting Methods for Management" by Makridakis in 1989, MAPE is a measure of error expressed as a percentage. The smaller the MAPE value, the better the model is at predicting actual values. [16] With a lower MAPE, the ARIMA (0,1,1) model demonstrates higher accuracy and smaller prediction errors relative to the actual data. Although the RNN model has a lower Root Mean Square Error (RMSE), indicating better performance in terms of absolute error, MAPE is often more relevant in many applications because it reflects relative error, which is easier to interpret in practical contexts.

4. CONCLUSIONS

Research by predicting the closing price of gold futures, shows the results that the ARIMA model has a MAPE value of 0.47% and an RMSE value of 16.12 which indicates the ARIMA model performs very well in predicting short-term data, while the RNN model has a MAPE value of 0.57% and an RMSE value of 15.01 which indicates better accuracy in predicting long-term data. However, when comparing the accuracy of both models for the entire dataset, the ARIMA model slightly outperforms the RNN model in short-term accuracy, while the RNN is better suited for long-term predictions.

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