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Gold Price Prediction Using the ARIMA and LSTM Models

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Abstract: For some investors who are interested in investing for the long term, gold is one of the promising options because the price of gold has recently continued to increase. In the current condition, gold investors generally use instinct and guesswork in investing in gold because there is a benchmark gold price based on world market prices. Many empirical studies identify factors that affect gold prices to forecast them. Factual and econometric analysis recommend different informative factors. This study investigates the influence of gold prices and five supporting variables in the form of economic indicators, namely crude oil price, federal funds effective rate, consumer price index, effective exchange rate and S&P 500 stock market index between 2002 and 2022. Models were built using ARIMA and LSTM methods, evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE). With a dataset allocation of 80% for training data and 20% for testing data, the comparison of actual gold prices with the predicted values of each model shows that LSTM has the best performance compared to the ARIMA (0,1,1) model where the LSTM model has an RMSE value of 8.124 and a MAPE value of 0.023. The models also show that economic indicators affect the ounce price of gold.

Keywords: Gold Price, Prediction, Economic Indicators, ARIMA, LSTM

INTRODUCTION

Gold may be a valuable metal that is regularly used as a medium of trade in exchange and as a budget standard for various countries (Madonna Yuma, 2018). For some investors who are interested in investing for the long term, gold is one of the promising options because the price of gold has recently continued to increase. To get optimal profits, gold investors must expect to get a low price when buying and an expensive price when selling (John & Latupeirissa, 2021).

In the current condition, gold investors generally use instincts and guesses in investing in gold because there is a benchmark gold price based on world market prices. Many empirical studies identify factors that affect gold prices to forecast them. Factual and econometric analysis recommend different informative factors. The relationship between gold and oil price is usually positive as emergencies tend to extend both (Chen & Xu, 2019). Likewise, (Wang & Chueh, 2013) concludes that the price of gold and oil both increase while interest rates and the US dollar decrease the price of gold. Currency depreciation also makes investors turn to gold, which explains the negative relationship between gold prices and exchange rates (Giannellis & Koukouritakis, 2019).

Gold prices are linked to stock market indices, exchange rates, the consumer price index (CPI), US bond rates and oil prices. Over the long term, there is a positive correlation between US CPI and gold price. Investors prefer gold whenever inflation is high because gold is inflation resistant. So, when the CPI rises, the price of gold also rises (Liu & Li, 2017). (Mensi, Beljid, Boubaker, & Managi, 2013) examined the correlation and volatility transfer of various commodities, such as gold, oil, and the stock market. As a result, it was found that the price of the S&P500 influences the volatility of gold and oil

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prices. To deal with this problem, the prediction process can be done. Prediction can be a guide to efficiently assess what is most probable to happen in the future based on past and current data, so that mistakes (the difference between what happened and what was evaluated) can be minimized (Kafil, 2019).

The ARIMA model is a model used to make predictions on time series data by utilizing the dependent variable of the data. This model is suitable for prediction because it is considered flexible (following data patterns), has high forecasting accuracy, and is reliable for short-term forecasting. However, if used in long-term predictions, the ARIMA model will experience a decrease in accuracy (Kanavos, Kounelis, Iliadis, & Makris, 2021). To overcome this, the LSTM model is the best choice to overcome the shortcomings of the ARIMA method because LSTM implements state cells that make this model able to store information over a long period of time. The drawbacks of LSTM just like most recurrent neural networks are the long training time and complex parameter combinations (Rowan, Muflikhah, & Cholissodin, 2022).

Based on the description above, this research aims to evaluate the performance of the algorithm in predicting gold prices by taking into account several supporting elements or variables related to influencing the value of the gold price itself. The use of ARIMA and LSTM models which are widely used for time series data processing is expected to help investors who want to invest in gold to find out the movement of gold prices in the future so as to minimize losses and optimize gold investment profits.

LITERATURE REVIEW

There have been many studies that discuss forecasting using deep learning. Especially deep learning that is supervised learning. The literature review in this study reviews research using the ARIMA and LSTM models. the objectives, conclusions and suggestions of these studies are presented in Table 1, in addition, a comparison between previous research and the research to be carried out is also presented.

Table 1. Literature review matrix and research position Using ARIMA and LSTM Models

Reference	Title	Conclusion	suggestion	comparison
(Makala & Li, 2021)	*Prediction of Gold Price with ARIMA and SVM*	The prediction results show SVM is better than ARIMA by having RMSE of 0.028 and MAPE of 2.5.	To obtain success in prediction, it is better to use several different models by utilizing machine learning algorithms and this research only uses the gold price variable so that it needs several additional variables that affect changes in gold prices to improve its accuracy.	This research uses ARIMA and SVM models by only using the gold price variable in its dataset to predict gold prices while the research to be carried out uses ARIMA and LSTM models using gold price variables and several supporting variables in the form of economic indicators to predict gold prices.

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(Mohtasham Khani, Vahidnia, & Abbasi, 2021)	*A Deep Learning-Based Method for Forecasting Gold Price with Respect to Pandemics*	Of the four LSTM models used in this study, the prediction results of the LSTM output sequence vector achieved MSEs of 12.31, 17.75 and 2.44 at the validation specified by the format for 1 day, 2 days, and 30 days outperforming other models proposed in the literature.	Social network context can also be explored as a potential feature in prediction models to improve their accuracy as well as their applicability to be reliable in the real world.	This study uses four LSTM models with gold price variables, financial indicators and feature variables such as the COVID-19 case to predict gold prices. While the research to be carried out uses two different models, namely ARIMA and LSTM, using gold price variables and several supporting variables in the form of economic indicators to predict gold prices.
(Yurtsever, 2021)	*Gold Price Forecasting Using LSTM, Bi-LSTM and GRU*	The results of the study using the LSTM, Bi-LSTM and GRU models show that economic indicators affect the price of gold ounces. The LSTM model performed best, with values of 61,728 RMSE, 48.85 MAE and 3.48 MAPE.	It needs to be evaluated related to the hidden layer, the number of epochs, batch size to the division of datasets to improve the accuracy results for predicting gold prices with the model evaluated in this study.	This research considers hidden layer, number of epochs, batch size to dataset sharing with the composition of dataset sharing is 70:30. For the research to be carried out, it is the same but for the distribution of datasets, three scenarios are carried out with the composition of the dataset distribution being 70:30, 80:20 and 90:10.
(Rady, Fawzy, & Fattah, 2021)	*Time Series Forecasting using Tree Based Methods*	The calculation of the RMSE value in this study shows that the RF results are more accurate with the lowest RMSE value of 38.52 for monthly gold price predictions than the DT, GBT and ARIMA (0,1,1) models.	To improve the success results in prediction, we recommend using a different ARIMA model such as Hybrid ARIMA and comparing it with the tree-based method in this study to get the quality benefits of both models.	This research uses tree-based methods namely Decision Tree (DT), Random Forest (RF), Gradient Boosted Trees (GBT) and ARIMA models to predict monthly gold prices. For the research to be carried out using a hybrid model, namely ARIMA-LSTM, to improve the results of success in predicting the monthly price of gold in the future.

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METHOD

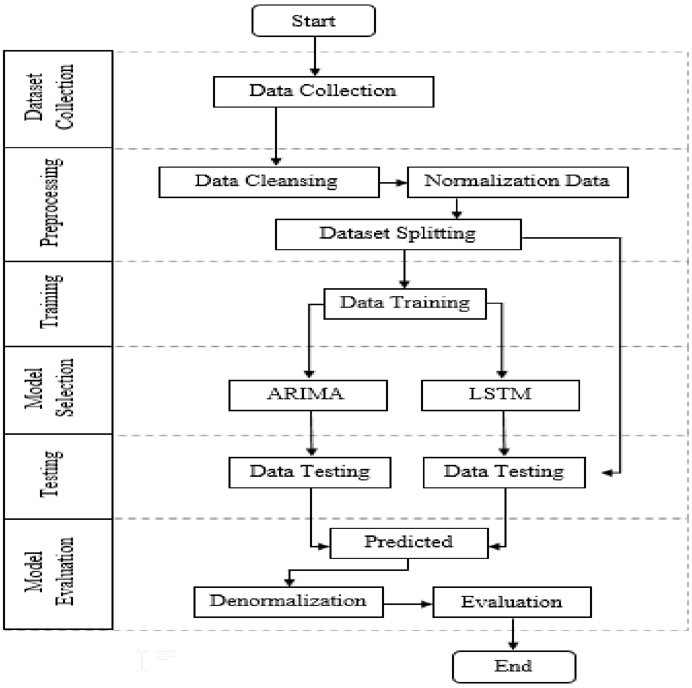

Figure 1. Flow of Research

Figure 1 explains the stages of the research which consists of 5 stages of research. The research stages above will be explained sequentially as follows:

Dataset Collection

The dataset used in this study consists of 20 years (2002-2022) with a monthly data timeline of world gold ounce prices and five supporting variables in the form of economic indicators. The economic indicators used are: gold price data and supporting data were collected from January 2002 to February 2022 through indexmundi.com for gold prices, fred.stlouisfed.org for crude oil prices, effective exchange rate, consumer price index, federal funds effective rate and finance.yahoo.com for S&P 500 stock market index.

Preprocessing

Data that has been collected into a dataset, then preprocessing will be carried out which consists of data cleansing, data normalization and dataset splitting. Data cleansing is done to check for null data in the dataset, then normalize the null data where the data is rescaled between 0 and 1 with the min-max scaling technique. After performing the normalization process, then dataset splitting is performed where the dataset will be allocated to be divided into training data and testing data.

Training and Testing

The scenario of using the dataset in this study was prepared based on the composition of testing data and training data in percentage. The test scenario is presented in Table 2.

Table 2. Dataset Composition

No	Data Training	Data Testing
1	70%	30%
2	75%	25%
3	80%	20%

At this stage, the training data process will be carried out from the world gold ounce price dataset and five supporting variables in the form of economic indicators. The training process is carried out on two models used in this study, namely the ARIMA and LSTM models. The results of each model

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obtained are then used in the prediction process by loading the model file. Data that has been allocated into testing data will be used to obtain predictive values from the results of each model obtained. Furthermore, the denormalization process of the testing data is carried out to obtain the predicted value and the evaluation value of the model performance results.

Model Selection

The predictions in this study utilize ARIMA and LSTM models to predict gold prices.

Autoregressive Integrated Moving Average

Autoregressive Integrated Moving Average or ARIMA model uses past and present data from the dependent variable to obtain accurate short-term predictions. ARIMA is appropriate when time series observations are statistically correlated with each other (dependent) *(Djami & Nanlohy, 2022)*.

ARIMA is a combination of Autoregressive (AR), Moving Average (MA), and differencing models. ARIMA is also known as the Box-Jenkins method. ARIMA can be used if the observations of time series data are interconnected *(Elsaraiti & Merabet, 2021)*. Forecasting can be done with the ARIMA model, namely by determine a good statistical relationship between the variable being forecasted and the historical value of the variable. that variable. In general, ARIMA is expressed with the notation ARIMA (p,d,q) where p is the AR order, d is the differencing order, and q is the MA order *(Cryer & Chan, 2008)*. The ARIMA model can be expressed in the following equation:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)e_t \quad (1)$$

Long Short-Term Memory

Long Short-Term Memory or LSTM is a type of Recurrent Neural Network (RNN) introduced by Hochreiter and Scmidhuber in 1997 to eliminate the weakness of RNN architecture (Gao et al., 2021). The LSTM model stores information on patterns in the data. LSTM can learn which data to keep and which data to discard, because each LSTM neuron has several gates, namely input gate (i_t), output gate (o_t) and forget gate (f_t) as well as the memory cell state value ($\acute{C}_t$) in LSTM which regulates the memory of each neuron itself *(Primananda & Isa, 2021)*. In the LSTM computation process, calculations are performed using the following formula:

$$f_t = \sigma(W_f * [h_{t-1}, X_t] + b_f \quad (2)$$

$$i_t = \sigma(W_i * [h_{t-1}, X_t] + b_i \quad (3)$$

$$\acute{C}_t = tanh\ (W_c * [h_{t-1}, X_t] + b_c \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \acute{C}_t \quad (5)$$

$$o_t = \sigma(W_o * [h_{t-1}, X_t] + b_o \quad (6)$$

Model Evaluation

At this stage, an evaluation of the model used is carried out to determine how large or small the error produced in the prediction process.

RMSE serves as a reliable measure of prediction accuracy, so it is often used as a benchmark indicator to assess model performance. The smaller the RMSE value, the better the model performance *(Lu, Li, Wang, & Qin, 2021)*. The RMSE formula can be seen in equation below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

MAPE is a performance accuracy evaluation method by calculating the average absolute deviation percentage of the actual value divided by the actual value. (Faisal et al., 2022). The MAPE formula can be seen in equation below:

$$MAPE = \left(\sum_{t=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right)\frac{100}{n} \quad (8)$$

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RESULT

The 6×242 dataset covering January 2002 to February 2022 uses world gold ounce price data and five economic indicators. Five economic indicators were used: crude oil price, federal funds effective rate, consumer price index, effective exchange rate and S&P 500 stock market index. In our research, gold ounce price estimation is based on the input indicators. Figure 2 shows the sample dataset used to predict the gold price.

Month	Price	Crude Oil Prices	Consumer Price Index	Real Broad Effective Exchange Rate	Federal Funds Effective Rate	ES=F
2002-01-01	281.51	19.71	0.226372	128.23	1.73	1130.50
2002-02-01	295.50	20.72	0.395257	129.03	1.74	1107.00
2002-03-01	294.06	24.53	0.562430	128.72	1.73	1144.75
2002-04-01	302.68	26.18	0.559284	128.43	1.75	1076.00
2002-05-01	314.49	27.04	0.000000	126.64	1.75	1064.00

Figure 2. Gold Price Prediction Data Samples

In various experiments, the allocation of training and testing data directly affects the prediction accuracy. The allocation of data used is 70/30, 75/25 and 80/20. The models tried when modeling in this study is shown in Table 3. The performance of the models listed in Table 3 is calculated by comparing the estimated results with the actual values. LSTM produces the best RMSE and MAPE values, followed by ARIMA model.

Table 3. Model Performance Result

Model	Allocation Data	RMSE	MAPE
ARIMA (0,1,1)	70/30	42.884	0.186
	75/25	41.991	0.189
	80/20	43.599	0.185
LSTM	70/30	44.753	0.034
	75/25	22.787	0.027
	80/20	8.124	0.023

We will first discuss the ARIMA results. In the ARIMA model to ensure the stationarity of time series data, this study uses the Augmented Dickey-Fuller test to ensure the stationary status of the dataset. The hypothesis in this test is:

H0: There is a unit root

H1: There is not a unit root

When the P-value is greater than the critical value (generally 5%), it fails to reject the null hypothesis. And when the P-value is smaller than 0.05, reject the null hypothesis. From Table 4, it can be seen that the P-value is 0.7899 which is greater than the critical value at all significant levels even though the ADF statistic value is smaller than the critical value. Therefore, this study fails to reject the null hypothesis (simply accepting the null hypothesis), which states that the time series data have unit roots and are non-stationary.

The next step is to perform the first differentiation and check whether it is stationary because stationarity status is very important. If not, then the second differentiation is performed. In ARIMA (p,d,q) the number of differentiations is d, which is also called the lag term. The result of the first differencing obtained a P-value of 0.0000, which means that this study rejects the null hypothesis and accepts the alternative hypothesis so that it can be concluded that the data series does not have a unit root and the data is stationary.

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Table 4. ADF Test Results

		Level (d = 0)	First Different (d=1)
ADF Statistic		-0.8940	-1.2677
P-Value		0.7899	0.0000
Critical Value	1%	-3.4578	-3.4578
	5%	-2.8736	-2.8736
	10%	-2.5732	-2.5732

Based on the results of the previous stationarity test, the stationarity conditions are known after first-order differencing, so the d value of the model is 1. Furthermore, the p and q values need to be identified to detect the ARIMA (p,1, q) model. Through observing the autocorrelation function (ACF) and partial autocorrelation function (PACF), the values of p and q can be obtained. Figure 3 shows that the ACF and PACF do not show significant changes or cuts, so it is considered an ARIMA model.

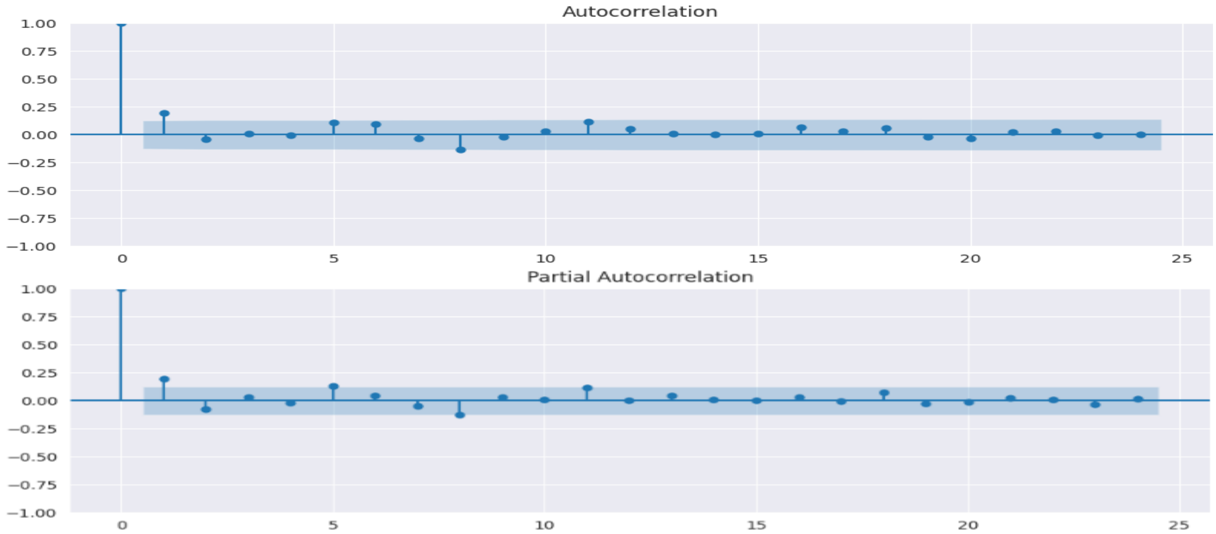

Figure 3. Autocorrelation function and partial auto correlation function

The parameters of the Arima model must be found. In this study, an automatic function is used on the python platform where the most suitable Arima mode is selected based on the smallest AIC and BIC values. In this study, the most suitable Arima is ARIMA (0,1,1) because the AIC value is 2470.678 and the BIC value is 2477.639 which is the minimum value based on model comparison. This shows that the order of auto-regressive development is 0, the order of order of development of the moving average is 1 and the order of difference is 1. Table 5 shows the summary result of the ARIMA model and Figure 4 shows the results of the ARIMA model with 80% dataset allocation for training data and 20% for testing data.

Table 5. Comparison of Different Model Indicators

Model	AIC	BIC
ARIMA (2,1,2)	2473.476	2490.879
ARIMA (0,1,0)	2480.398	2483.879
ARIMA (1,1,0)	2471.707	2478.668
ARIMA (0,1,1)	2470.678	2477.639
ARIMA (1,1,1)	2472.267	2482.709
ARIMA (1,1,2)	2472.455	2482.897
ARIMA (1,1,2)	2473.081	2487.004

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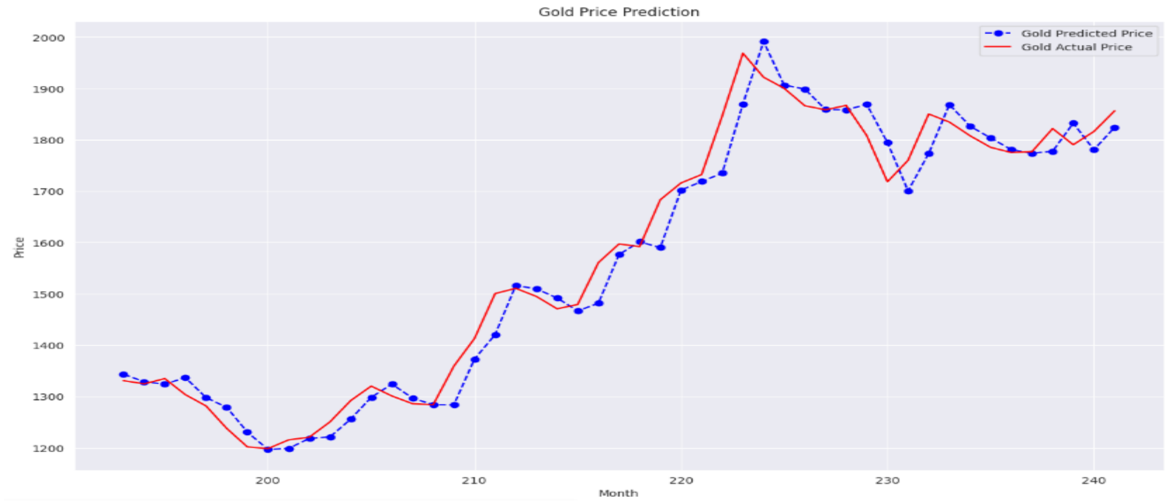

Figure 4. Price Prediction with ARIMA Model

Furthermore, the training of the LSTM model was carried out using the google collaboration tool and the Python programming language. The LSTM model is built using the Keras library for deep learning. The hyperparameters specified in the validation process can be seen in Table 6.

Table 6. Hyperparameters Values

No	Type	Information
1	Layers	2
2	No. of Neurons	50
3	Optimizer	Adam
4	Loss	MSE
5	Epoch	100

The LSTM model created in our research has 2 layers, namely 1 LSTM layer with each layer having 50 neurons which is the input layer and 2 dense layers consisting of 25 neurons and the other with 1 neuron which is also the output layer. The epoch value of the LSTM model used is 100 and the batch size value is 1. To run this model, the research uses the adam optimizer by taking the mean square error (MSE) value as the loss value. Dense layer is used to capture certain changes or patterns of gold price movements while trained on the LSTM layer. Figure 5 shows the results of the LSTM model with 80% dataset allocation for training data and 20% for testing data.

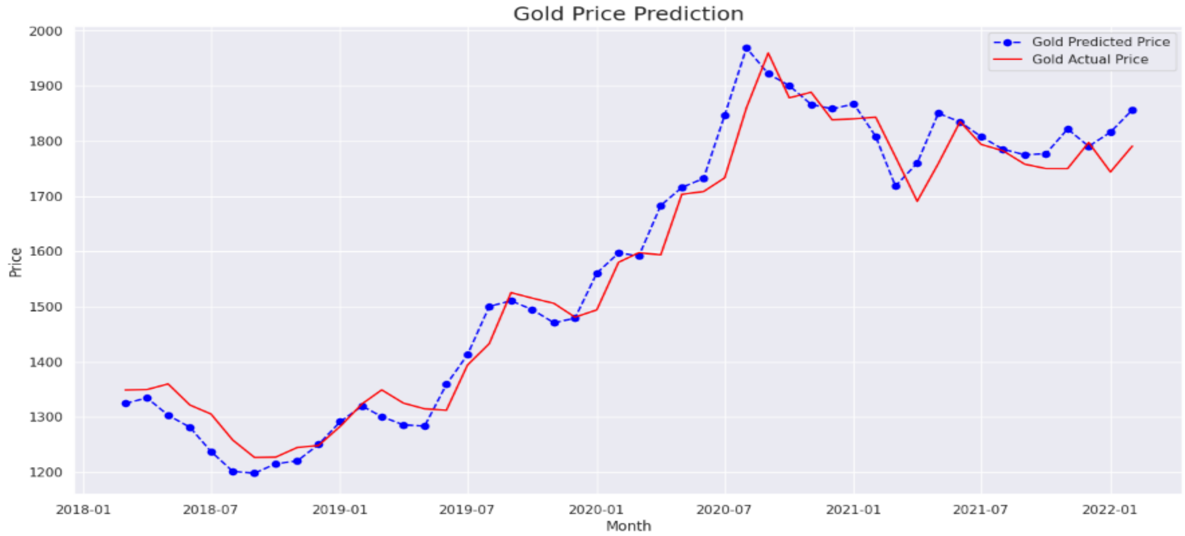

Figure 5. Price Prediction with LSTM Model

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DISCUSSIONS

To compare the performance of the two models (ARIMA and LSTM) can be seen by using the performance metrics used in this study as shown in Table 3. The use of data in predicting the world gold price is made with five economic indicators and the price of ounces of gold using monthly time series data. RMSE measures the accuracy of forecasting where the smaller the RMSE value is the best forecasting. The allocation of training and testing data that produces the best RMSE and MAPE values in both models is with a dataset allocation of 80% for training data and 20% for testing data.

In the results of this study ARIMA (0,1,1) has an RMSE of 43,599 and LSTM with the number of neurons = 50 neurons, batch-size = 1 and epoch = 100 has an RMSE of 8,124. The above performance clearly indicates that LSTM has better performance using RMSE justification. Similarly, using MAPE which measures the average percentage error, shows that the ARIMA (0,1,1) model has a MAPE of 0.185 and the LSTM has a very small MAPE result of 0.023, and the smaller the value, the better the result.

This study has limitations because it only uses a few variables. Therefore, we suggest adding other macroeconomic variables such as global situation uncertainty, inflation and other foreign stock indices for future research. In addition, our research only uses monthly data so a longer and more recent research period can be extended and use daily data samples.

This study is consistent with previous findings that there is a strong conditional correlation between the S&P 500 stock market index and gold prices, so the S&P 500 stock market index affects gold price volatility (Mensi et al., 2013). This study also supports previous findings of (Liu & Li, 2017) that there is a positive correlation between gold prices and the federal funds effective rate, consumer price index, and effective exchange rate. This study is also consistent with previous findings that there is volatility and a positive correlation between crude oil prices and gold prices (Chen & Xu, 2019). Using a different model from previous studies, we combine these economic indicators to predict the world price of gold ounces using ARIMA (0,1,1) and LSTM models, and conduct various training and data allocation tests that directly affect the prediction results. The results show that the LSTM performs best compared to the ARIMA (0,1,1) model where the LSTM model has an RMSE value of 8.124 and a MAPE value of 0.023, with a data allocation used of 80/20.

CONCLUSION

In this work, we compare the performance of ARIMA (0,1,1) and LSTM models for predicting gold prices using monthly time series data. The dataset in the study consists of monthly data of gold ounce prices and five economic indicators from January 2002 to February 2022. To evaluate the accuracy, RMSE and MAPE were used to measure the performance of the two models. Comparison of the actual gold price with the predicted value of each model shows that LSTM has the best performance compared to the ARIMA (0,1,1) model where the LSTM model has an RMSE value of 8.124 and a MAPE value of 0.023, with the allocation of data used is 80/20, number of neurons = 50, batch-size = 1 and epoch = 100. The models also show that economic indicators affect the price of gold ounces, which is consistent with previous findings (Mensi et al., 2013; Liu & Li, 2017;Chen & Xu, 2019). The results show that ARIMA (0,1,1) and LSTM are satisfactory models for the ordinal data used in this study.s

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