

# Gold Price Prediction Based on Support Vector Regression (SVR) and Artificial Neural Network (ANN) Comparison

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## Abstract:

Gold is the most popular type of investment due to its ease of ownership, low level of risk, and various advantages such as inflation-resistance, high liquidity, and affordability for all groups. Supported by a BPS survey which shows that 58% of people choose gold as the main instrument and an average global price increase trend of 12% in the last 10 years, it is important to predict gold prices to support optimal investment decision-making. This study aims to evaluate and compare the performance of the Support Vector Regression (SVR) and Artificial Neural Network (ANN) models in predicting the price of Indonesian gold. The methods used in this study are SVR and ANN methods with Grid Search Optimization carried out on each method to determine the optimal parameters. The results of this study show that the best model in predicting Indonesian gold prices is the ANN model with an activation function Tanh produced an RMSE value of 44576.672, MAPE of 2.88%, MAE of 38301.776, and AIC amounting to 752,528. The ANN method with the Tanh activation function is the best method for predicting the price of Indonesian gold with smaller RMSE, MAPE, MAE, and AIC values compared to the SVR method.

**Keywords** — Gold price prediction, Artificial Neural Network (ANN), Support Vector Regression (SVR), Time series forecasting.

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## I. INTRODUCTION

Gold is the most popular type of investment because of its ease of ownership and gold is also considered to have a small level of risk so it is an option in the midst of economic uncertainty [1]. A survey conducted by the Central Statistics Agency (BPS) in 2022 showed that 58% of Indonesians view gold as the main investment instrument, especially among the productive generation (aged 25–40 years) [2]. In addition, gold has various advantages as a means of investment, such as security from administrative costs, protection against inflation, high liquidity, durable, easy to move, affordable for all groups, and low risk so that it is suitable for long-term investment [3]. Supported by global market trends, the average increase in gold prices has reached 12% globally in the last 10 years, indicating

stability and promising long-term profit potential [4]. Therefore, it is important to make gold price predictions to help make informed investment decisions. One of the approaches that can be taken in predicting Indonesia's gold price is through the Machine Learning such as the Support Vector Regression (SVR) and Artificial Neural Network (ANN).

SVR is an extension of Support Vector Machine (SVM) and developed based on the Structural Risk Minimization (SRM) [5]. The goal is to estimate a function by minimizing the upper limit of generalization error, so that the SVR is able to cope with Overfitting. SVR can be used to address nonlinear data cases by transforming data into higher spatial dimensions using the Kernel so that they can be separated linearly on Feature Space What's New [6]. In addition to being able to

overcome Overfitting In nonlinear data, the use of SVR also has other advantages, including having options for the choice of functions Kernel and can determine the value of Trade Off on the error value [7]. A study shows that the SVR method is superior to other methods such as linear regression and ANN [8], [9].

ANN or also called Neural Network (NN) is part of the Machine Learning rather Deep Learning, which is based on a numerical algorithm that simulates the behavior of biological systems consisting of Neurons [10]. The system in NN has similar characteristics to biological neural networks [11]. NN includes various types of flexible nonlinear regression models, discriminant models, data reduction models, and nonlinear dynamic systems [12]. This network is a parallel computing system consisting of a large number of basic processing units (Neurons) who are interconnected and able to learn relationships input-output complex linear and nonlinear [13]. One of the advantages of ANN is that it is able to describe both linear and non-linear models with a fairly wide range [14]. Other advantages of use Neural Network if applied to data Time series is that the data do not need to meet the assumption of distribution as in statistical methods [15]. Comparison of model predictions Multi-Layer Perceptron (MLP) which is one of the ANN architectures with the SVR model has been carried out on stock market index data. The results of this study show that the best predictions are made by the MLP model [16].

Research related to the prediction of Indonesian gold price data has been conducted using the SVR method and the results show that the SVR model with a linear kernel is able to predict the price of Indonesian gold well and accurately with an accuracy of 97.41%. Based on the results of this study, it also proves that SVR is able to produce a good prediction on Indonesian gold price data. The research has limitations in the kernel function used, namely the linear kernel function [17]. Therefore, in this study, a comparison of several kernel functions was used.

Other research has also been conducted on gold price data using the ANN method which was able to produce training accuracy of 91.89% and testing of 76.43%. The limitation of the study is that it only uses the sigmoid activation function [18]. Therefore, in this study, a comparison of several activation functions was used.

Based on the findings of previous studies, there has been no study that compares Indonesia's gold price prediction with the comparison of SVR and ANN methods. Therefore, in this study, a comparison of Indonesian gold price data prediction was carried out based on the SVR and ANN methods. This aims to evaluate the performance of both models in predicting gold prices. Thus, this research is expected to determine a more effective and efficient model in handling nonlinear stock price data, as well as provide insights for better investment decision-making.

## **II. METHOD**

### **A. Research Design**

This study is a predictive and comparative quantitative research, which aims to compare the performance of two modeling methods, namely Support Vector Regression (SVR) and Artificial Neural Network (ANN) in predicting gold prices in Indonesia.

### **B. Population and Sample**

The population in this study is all historical data on weekly gold prices in Indonesia and the sample used is historical data on weekly gold prices in Indonesia from the first week of January 2022 to the 2nd week of February 2025.

### **C. Sample Technique**

The sampling technique in this study uses non-probability sampling using the time-series split method with 80% training data and 20% testing data from a total of 163 observations.

### **D. Research Subject**

The subject of this study is historical data on gold prices in Indonesia obtained from [investing.com website](http://investing.com) and used as an object of predictive analysis

by applying SVR and ANN methods to find out the best model in predicting future prices.

**E. Data Analysis Techniques**

The steps of data analysis to form a model and perform forecasting are as follows.

1. Presenting a *time series plot* to visually describe in the form of a *line chart* of the movement of Indonesian gold price data on a weekly basis.
2. Perform an influential lag determination using a PACF plot.
3. Normalize data using *the minmax normalization method*.
4. Adjust the shape of the data according to the results of significant lag in the PACF plot.
5. Modeling and predicting Indonesian gold price data with the SVR approach through the following steps.
  - a. Determine the optimal SVR parameters in the form of  $\gamma$ ,  $C$ ,  $\epsilon$  values and kernel functions used using *walking forward validation*.
  - b. Predicting Indonesian gold price data with *data testing*.
  - c. Denormalize prediction data
  - d. Calculates the evaluation of the SVR model based on RMSE, MAPE, MAE, and AIC values based on the Equation.
6. Modeling Indonesia's gold data using *the Neural Network* method is as follows:
  - a. Determine the optimal *Neural Network* parameters in the form of *hidden\_layer\_sizes* values, types of activation functions, and *learning\_rate* using *walking forward validation*.
  - b. Predicting Indonesian gold price data with *data testing*.
  - c. Denormalize prediction data
  - d. Calculate the evaluation of the ANN model based on the RMSE, MAPE MAE, and AIC values based on the Equation.
7. Comparing the results of predicting Indonesian gold price data from the SVR and ANN methods

based on the values of RMSE, MAPE, MAE, and AIC.

**III. RESULTS AND DISCUSSION**

**A. Descriptive Analysis**

Before making predictions, the first step taken is a descriptive analysis of Indonesia's weekly gold price data. The summary of the weekly data on Indonesian gold prices is presented in Table 1.

TABLE I  
DESCRIPTIVE STATISTICS

Variable	N	Minimum	Maximum
Gold Price	163	794.713	1.538.077
Training	130	794.713	1.247.099
Testing	33	1.241.208	1.538.077

In addition, the weekly time series data of Indonesian gold prices from the first week of January 2022 to the second week of February 2025 is graphically shown in Figure 1.

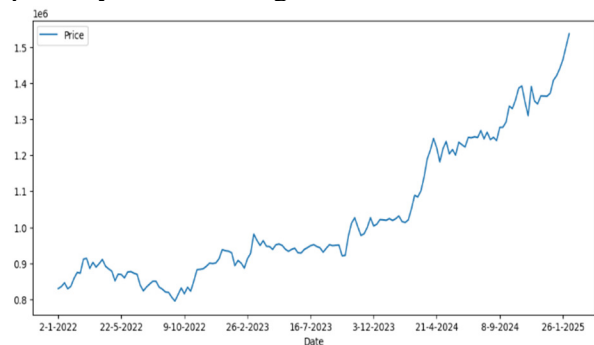


Fig. 1 Plot *Time Series* of Indonesian Gold Price

Based on Figure 1, a significant downward trend can be seen after the stock price reached its highest point, namely 1,538,077 rupiah in the 2nd week of February 2025 until it touched the lowest point of around 794,713 rupiah in the 2nd week of September 2022. The graph also shows fluctuations with *the trend* tending to rise from the beginning to the end of the period.

**B. Optimal Lag Selection**

The selection of autoregressive lag aims to find out the lags that have a significant effect on the actual data. By identifying significant lags, the value of those lags can be used to model the data. The results of the PACF plot of Indonesian gold prices are presented in Figure 2 below.

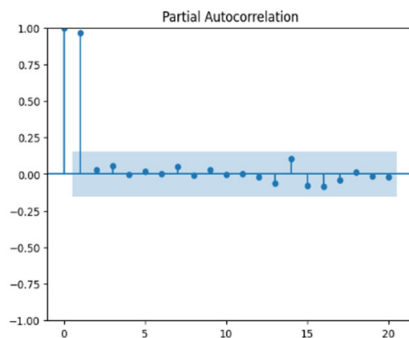


Fig. 2 PACF Plot of Indonesian Gold Price

Based on Figure 2, it shows that the lag that affects is lag 1. So that the data input feature on the model will start at the period  $t = 2$ .

TABLE 2  
Comparison of Kernel Functions on SVR

Kernel Functions	Parameters	RMSE	MAPE(%)	MAE	AIC
Linear	C=100 Epsilon=0.01	18178,165	1,45	13968,352	2552,458
Polynomial	C=0.1 Epsilon=0.1 Degree=2	37336,199	3,28	31342,724	2738,151
RBF	C=10 Epsilon=0.001 Gamma=auto	17582,326	1,38	13307,099	2543,859
Sigmoid	C=10 Epsilon=0.01 Gamma=auto	164005,365	7,07	76974,947	3119,975

Based on the modeling results in Table 2, it can be seen that the best model obtained is the SVR model with the RBF kernel function with parameters  $\gamma=auto$ ,  $C=10$ , and  $\epsilon=0.001$ . This model shows the smallest RMSE, MAPE, MAE, and AIC values compared to other SVR models. Therefore, the next step is to make predictions on the data *testing* using the optimal model obtained. The results of the prediction evaluation in the *data testing* using SVR with the RBF kernel function parameters  $\gamma=auto$ ,  $C=10$ , and  $\epsilon=0.001$  are presented in the following Table 3.

TABLE 3  
Prediction Results of Data Testing Using SVR

RMSE	MAPE(%)	MAE	AIC
93848,561	5,07	70986,720	777,663

The predictive results of the application of the SVR model to data testing are visualized in the plot which shows that the prediction results are not much different from the actual data. In addition, the MAPE

### C. Prediction Using the SVR Model

In the analysis using the SVR method, several kernel functions were used, namely Linear, Polynomial, Radial Base Function (RBF), and Sigmoid functions. The selection of the best kernel function type is based on the smallest RMSE, MAPE, MAE, and AIC values. The following are the results of SVR modeling on training data using four kernel functions to obtain the best model as shown in Table 2 below.

accuracy rate is less than 10% which falls into the category of highly accurate. The plot results of the prediction with actual data for data testing are presented in Figure 3.

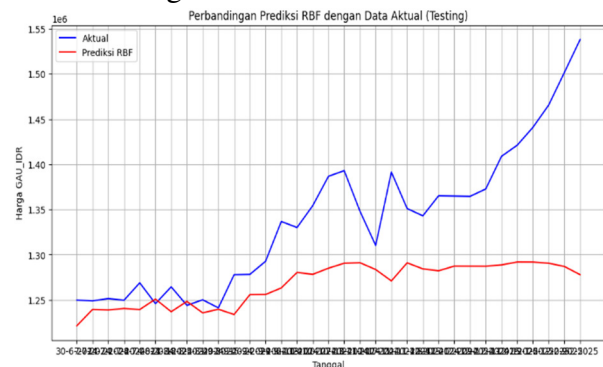


Fig. 3 Plot Comparison of Prediction Data and Actual Data of SVR Method

### D. Prediction Using the ANN Model

In the analysis using the ANN method, activation functions that correspond to nonlinear data are used, namely ReLU, Tanh and Sigmoid functions. The selection of the best type of activation function is

based on the smallest RMSE, MAPE, MAE, and AIC values. Here are the results of the optimal ANN model as shown in Table 4.

TABLE 4  
ANN Optimal Model

Activation Function	Parameters	RMSE	MAPE(%)	MAE	AIC
Tanh	hidden_layer_sizes=(100,50) learning_rate=constant	21621,330	1,63	15826,037	2621,210

Based on Table 4, it can be seen that the optimal model obtained is an ANN model with a Tanh activation function with a number of 100 nodes both in the first hidden layer and 50 nodes in the second hidden layer and the learning rate is constant. Furthermore, predictions are made on testing data using the optimal model obtained. The results of the prediction evaluation in data testing using ANN with the Tanh activation function are presented in Table 5 below.

TABLE 5  
Prediction Results of Data Testing Using ANN

RMSE	MAPE(%)	MAE	AIC
44576,672	2,88	38301,776	752,528

The prediction results of the application of the ANN model to data testing are visualized in the plot which shows that the prediction results are not much different from the actual data. In addition, the MAPE accuracy rate is less than 10% which falls into the category of highly accurate. The plot results of the prediction with actual data for the testing data are presented in Figure 4.

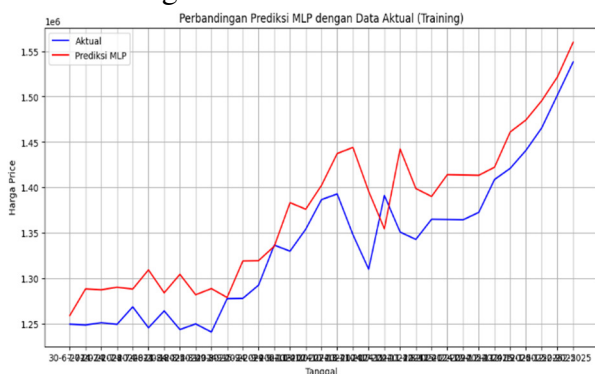


Fig. 4 Plot Comparison of Prediction Data and Actual Data of ANN Method

**E. Prediction Using the SVR Model**

Based on the analysis that has been carried out with two methods, namely SVR and ANN, a

comparison of the best model prediction results for each method is presented in Table 6.

TABLE 6  
Comparison of Prediction Results of Data Testing Using ANN

Method	RMSE	MAPE (%)	MAE	AIC
SVR	93848,561	5,07	70986,720	777,663
ANN	44576,672	2,88	38301,776	752,528

Based on Table 6, it can be seen that the prediction results with the Artificial Neural Network (ANN) approach are more accurate than the Support Vector Regression (SVR) method. Therefore, the ANN method was obtained as the best method in predicting the price of Indonesian gold with the smallest RMSE, MAPE, MAE, and AIC values.

Based on the best model, namely the ANN model with the Tanh activation function, the prediction results for the next ten periods are obtained which are presented in Table 7 as follows.

TABLE 7  
Gold Price Prediction

t	Gold Price (Rp)
164	1559705,368
165	1620355,981
166	1682812,531
167	1746080,258
168	1809011,777
169	1870387,872
170	1929020,628
171	1983861,037
172	2034089,731
173	2079173,194

**IV. CONCLUSIONS**

Based on the results of the analysis that has been carried out on the prediction of Indonesian gold prices using SVR and ANN, it was found that the ANN method with the Tanh activation function produces the smallest RMSE, MAPE, MAE, and

AIC values compared to SVR. The best model obtained resulted in a MAPE value of 2.88% with a very good prediction accuracy category. This method also produces prediction patterns that resemble actual data that tend to fluctuate up and down. Therefore, ANN can be used as the best method to predict Indonesian gold prices for the first week of January 2022 to the second week of February 2025.

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