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Exploring the effectiveness of a multilayer neural network model for gold price prediction

***Abstract**. Effective gold price forecasting model is an essential tool for price discovery and benchmarking market changes for mining project across the world. This study presents a model for effective prediction of gold price variation across the world. An experimental analysis was conducted for forecasting monthly US market gold prices from December 1978 to March 2023 using the Autoregressive Integrated Moving Average (ARIMA) model and Multilayer perceptron (MLP) regression model. Optimized hyperparameter search determined the lowest Mean Squared error (MSE) and Mean Absolute (MAE) results with ARIMA (2, 1, 1) and MLP best parameters. The proposed multilayer perceptron (MLP) model demonstrates an improvement in the effective prediction obtained from the experimental analysis.*

Streszczenie.** Efektywny model prognozowania cen złota jest niezbędnym narzędziem do odkrywania cen i porównywania zmian rynkowych dla projektów wydobywczych na całym świecie. W badaniu przedstawiono model skutecznego przewidywania zmian cen złota na świecie. Przeprowadzono analizę eksperymentalną w celu prognozowania miesięcznych cen złota na rynku amerykańskim od grudnia 1978 r. do marca 2023 r., stosując model autoregresyjnej zintegrowanej średniej ruchomej (ARIMA) i model regresji perceptronu wielowarstwowego (MLP). Zoptymalizowane wyszukiwanie hiperparametrów pozwoliło uzyskać najniższe wyniki błędu średniego kwadratowego (MSE) i średniego bezwzględnego (MAE) z najlepszymi parametrami ARIMA (2, 1, 1) i MLP. Zaproponowany model perceptronu wielowarstwowego (MLP) wykazuje poprawę efektywnej predykcji uzyskanej na podstawie analizy eksperymentalnej.* (Badanie efektywności wielowarstwowego modelu sieci neuronowej do przewidywania ceny złota***)

Keywords: Gold price, Prediction, Multilayer Neural Network.
Słowa kluczowe: Cena złota, prognoza, wielowarstwowa sieć neuronowa

Introduction

Gold is a crucial raw resource for industrial manufacturing in addition to being used to embellish and beautify jewellery. Gold is a unique valued item that combines the attributes of a commodity, precious metal, and currency. A significant financial commodity, which is included in the international reserves of the majority of national banks, demonstrating its central place in the world economy, making it the preferred option for investment [1][2]. The standing of the gold market has gradually improved with the growth of the financial market, becoming an equally significant financial investment market to the stock market, futures market, bond market, and so on [1]. However, the gold market's trajectory is nonlinear, and it can alter dramatically depending on a variety of factors, including the value of different currencies, inflation rates, the price of crude oil, copper, and other commodities [3]. Hence, forecasting changes in the price of gold is a major problem for the financial sector, and this is attracting the attention of both academics and the government. In order to minimize the problems faced by market players, particularly in nations whose economy depend on gold, as well as for investors who make investment decisions in the commodity market, it is crucial to develop an accurate prediction model.

There are several methods that have been deployed for gold price prediction. The traditional prediction methods are mostly seen as a time series problem, where gold price variations are statistically modelled as a standard prediction method [4]-[13]. The most widely used traditional methods for gold price predictions are autoregressive integrated moving average (ARIMA) [14], moving average (MA) [15], generalized autoregressive conditional heteroskedasticity GARCH) [16], and autoregressive conditional heteroskedasticity (ARCH) [17]. These traditional methods make use of certain statistical formulas for evaluating whether the model variables are linear [18][19]. The gold price prediction, however, contains complicated, ambiguous, long-memory, nonlinear information. The evolution of artificial intelligence for forecasting gold price has greatly enhanced the accuracy of the gold price prediction owing to its ability to handle uncertain mathematical expression systems, which yield better outcomes in comparison to traditional models [20]. The performance of this intelligence model is influenced by their input variables, model architecture, and internal learning mechanism. In this study, an autonomous, interpretable gold price prediction system is proposed. It makes use of the polarity and sentiment intensity of financial news. The main contributions of this research are:

- A multilayer neural network model is proposed to explore the feasibility of the intelligence system in forecasting the gold price and for determining the efficiency of the accuracy.
- This study also offers a technique for predicting long-term variations in commodity prices.
- Comparison of the accuracy of the multilayer neural network model with the linear mathematical model.
- To increase prediction accuracy, we fully consider relevant variables as inputs to the multilayer neural network model to ascertain their impact on the gold price analysis.

The remaining of this paper is outlined as follows. Section 2 presents the related reviews on gold price prediction. Section 3 introduces the proposed multilayer neural network prediction model, while the data utilized for the empirical study are presented in Section 4. The performance of the suggested model is compared to cutting-edge gold price prediction models in Section 5. Finally, Section 6 provides a summary of the study conclusions.

Literature Review

Globally, it is getting harder to predict future prices for many commodities, especially gold [1][12]. Mining businesses, which must take future pricing into account in their business operations, are similarly impacted by the challenge of price forecasting. Therefore, a reliable prediction model is crucial to the mining businesses and the investment decisions. Data from various research revealed that a wide range of commodities could benefit from the forecasting techniques. The volatility of commodity prices has been predicted using a variety of models. Therefore, this section briefly discussed several forecasting models such as statistical models and artificial intelligence models.

Ref. [21] proposed the use of GARCH-MIDAS models to show the short- and long-term volatility components to model the conditional volatility in the price of gold. A vector error-correction model was used by [2] to construct a model for predicting gold prices in India. The prices of gold, palladium, platinum, and silver were found to have a bidirectional causal relationship using the Granger causality approach [22]. For the purpose of predicting the price of Kijang Emas, the official gold bullion of Malaysia, [23] compared the two methods Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Ref. [24] employed the historical data for iron ore prices from 1982 to 2011 to create iron price simulations using a sequential Gaussian simulation technique. Ref. [25] presented a linear regression model to forecast gold prices based on historical data for the US dollar, crude oil prices, and gold price time series. Ref. [26] proposed a VAR-GARCH model to analyze volatility spillovers between the stock market and the price of gold in China. Ref. [27] proposed the use of linear regression in predicting gold prices. This paper made use of a 15-year historical dataset for gold prices that was obtained from a source that was openly accessible.

Artificial intelligence is one of the most significant categories of machine learning models created for predicting commodities prices. Ref. [28] presented an ANN-based prediction model for the US stock market. The dataset included prices for various indices throughout a 20-year period. According to numerous performance metrics, the proposed model performed well, according to the study's performance evaluation results. A research paper using intelligence system as forecasting models for the values of many precious materials was reported in [29]. Ref. [30] proposed a Multilayer Perceptron network-based model for predicting crude oil prices. A five-year history of publicly accessible crude oil prices was used to validate the MLP. The experimental work demonstrated that MLP is accurate for predicting oil prices. Ref. [31] study the accuracy of Convolution Neural Networks (CNN) for predicting price of gold. CNNs are among the models that work best for nonlinear time series, according to the authors. The experiment's findings, which were based on archival World Gold Council data, revealed that the CNN model is trustworthy. In [32], the ARIMA traditional approach was contrasted with conventional ANN. For their investigation, the authors applied three separate performance metrics: coefficient of determination (R2), MAE and RMS. They did this using archival data from 18 years of gold price data. The findings revealed that ANN beat ARIMA at the training and testing stages for all performance parameters.

Methodology

Artificial neural networks (ANN) are nonparametric mathematical models with intelligence that were influenced by the biological nervous system. The main purpose of ANN is to replicate human reasoning as a powerful approach for computers. In the few decades, the use of ANNs to solving problems with classification, pattern recognition, regression, and forecasting has advanced at an accelerating rate [33], whilst significantly impacting the efficiency of the learning process. The feedforward neural network (FNN) is an architecture for a neural network that resembles the neurons in the human brain and represents knowledge as a series of layers [34]. They are specific form of neural networks. They are made up of a group of thought-processing units called "neurons." These neurons are dispersed throughout multiple stacked layers, each of which is intimately coupled to the one above it. MLP is a variant of the FNN paradigm which transfers data from the input layer to the output layer in a single direction [35]. The MLP architecture can be explained as follows: all layers between the input and output layers are referred to as hidden layers, while the initial layer that feeds the network with input variables is referred to as the input layer [36]. The fundamental structure of an MLP neural network is shown in Fig. 1.

The MLP parameters comprises of the features (input), the weights (w), and the biases (b) and this can be expressed mathematically as follows:

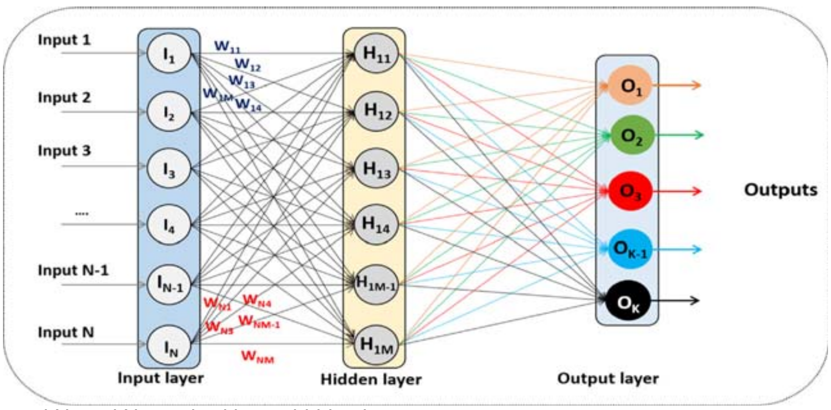

Fig.1. Multilayer Feed-Forward Neural Network with one hidden layer.

(1) $N_x^O = \alpha(\mu_N^x) = \alpha\left\{\sum_{i=1}^{N_x} N_i^{O(x-1)} w_{i,N}^x + w_{0,N}^x\right\}$

$1 \leq x \leq m$

The index x depicts the real layer in the network of *P* non-input layers. $\alpha(\mu_N^x)$ is the activation function for neuron *N* of the real layer *x*. It is typically set up as a linear function to produce the findings of the output layer and a nonlinear tangent hyperbolic function for the intermediate levels, which are also known as hidden layers. N_x represents the number of neurons at real layer *x*. N_x^O is the output of neuron *N* in the real layer *x*. $w_{i,N}^x$ is the weight related to the connections of neuron *i* of layer *x*. $w_{0,N}^x$ depicts the bias of neuron *N* of the real layer *x*.

This study compares the outcomes of the proposed model to those of existing forecasting models in order to confirm the efficiency and accuracy of the suggested model for predicting changes in the price of gold. The MAE and RMSE are two of the many performance indicators used for forecasting models [37]. The MAE and RMSE equations are expressed as:

(2) $$MAE = \frac{\sum_{i=1}^{Z} \epsilon_i^2}{Z}$$

(3) $$RMSE = \sqrt{\frac{1}{Z}\left(\sum_{i=1}^{Z} \epsilon_i^2\right)}$$

These metrics are mostly utilized to evaluate discrepancies between predictions made by prediction models and actual values. The accuracy of the model increases with decreasing error values.

Experimental data and results

In this section, we examined how well the proposed multilayer neural network model can effectively forecast gold prices. The dataset used in this research and their sources are described in the first subsection, while the performance metrics and results are discussed in the second subsection. Notably, we thoroughly contrasted this system with cutting-edge approaches to gold price prediction.

Description of datasets

In this study, the dataset examined are for 532 months, from December 1978 to March 2023 of gold prices. The main trade, producer, and consumer currencies are also indexed by the WGC. There are 532 observations for the monthly average gold price. The initial entry was made on December 31, 1978, and the final entry was made on March 31, 2023. Training and testing data were separated from the WGC dataset in chronological sequence. The testing set covered the period from December 31, 2018, to March 31, 2023, and included 68 observations, whereas the training set had 464 observations from the start of the project to November 30, 2018.

Experimental results and discussion

The results support the strong ability of predictor variables to foretell changes in the price of gold. The substantial association between gold prices and all the predictor variables is caused by such high capacity. In this study, a validation technique was used to assess the effectiveness of the suggested model, and the final 106 observations (20%) served as the validation data.

Globally, inflation has an impact on the price of gold. According to the scholar, the ability of gold to stop inflation is invisible [38][39]. The link between the price of gold and the U.S. Consumer Price Index (CPI) is positive. Figure 2 shows the historical trends of the nominal effective exchange rate of the U.S. and gold price. The average monthly price of gold climbed quickly starting in 2001 and reached over \$1,700.00 by 2011. At the time of this study, it fell to \$1,068 in 2016 and rose once more to \$1,912 in March 2023. In Figure 3, the standard absolute value is greater at the lower and upper boundaries of the standardized residual plot. Consequently, some observations are regarded as outliers. The density map shows a Gaussian distribution, with the majority of the values clustered around 0. Some observation points in the Q-Q plot stray from the straight diagonal line. With all values close to 0, the correlogram determines the statistical randomness of the dataset.

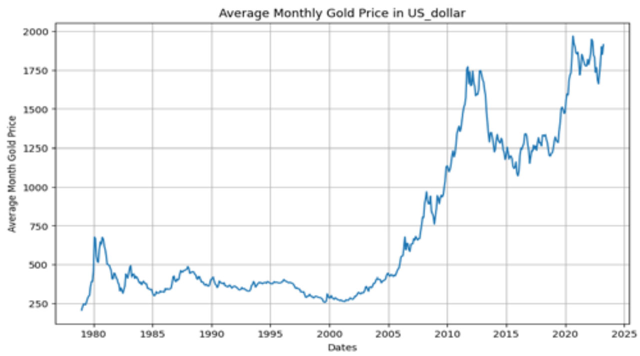

Fig.2. Average monthly gold price plot in US dollars

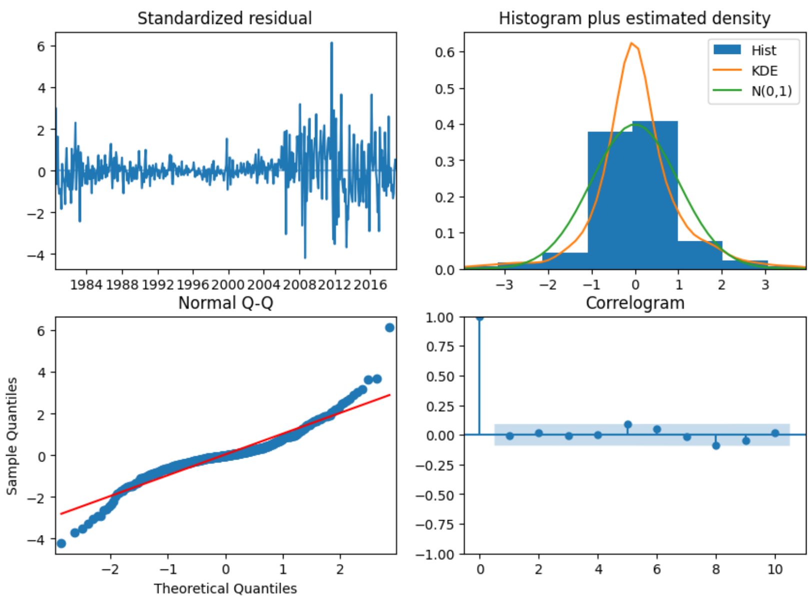

Fig.3. Analysis of average monthly gold price plot in US dollars

Fig.2. Analysis of average monthly gold price plot in US dollars

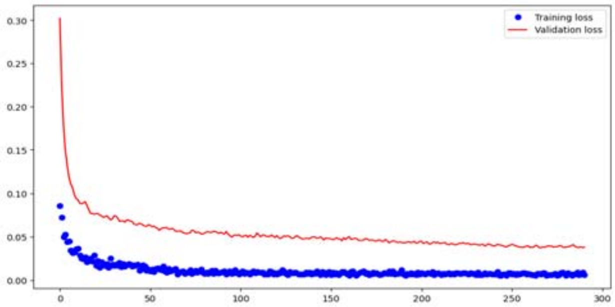

Fig.2. Analysis of average monthly gold price plot in US dollars

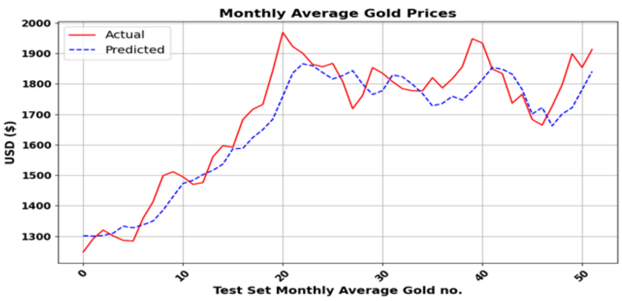

Fig.2. Analysis of average monthly gold price plot in US dollars

Table 1 shows the initial values for the ARIMA component for AR(P), MA(q), and I(d) as 1 for the smallest value and 5 for the highest value. There is no seasonality, and the time series fails the Kwiat-kowski-Phillips-Schmidt-Shin (KPSS) test for stationarity. The stepwise technique was put up in accordance with Hyndman and Khandakar (2008) to determine the ideal model parameters. The stepwise technique fits the model more quickly and is less prone to overfit it.

Table 3 compares the suggested model's prediction ability against the traditional ARMIA using the identical data sets. The MSE and MAE were deployed to compare and contrast the suggested model's performance and accuracy with those of the other forecasting models. As indicated in Table 3, the proposed model has a lower value of MSE and MAE when compared to ARIMA showing the best captures data variability. The area under test saw a sharp increase in the monthly average gold price. The trends cannot be captured using ARIMA (2,1). A linear representation of the test set forecast provided the best outcome. In capturing the sharp trend in the latter average monthly gold price in US dollars, the MLP model unquestionably showed enhanced performance. The variance in the time series models in capturing the trend in the outcome is further supported by the error metrics for the ARIMA (2, 1, 1) and MLP models.

Table 1. Auto ARIMA parameter configuration

Component	Model-Period	Min	Max
ARIMA	AR(p)	1	5
	MA(q)		5
	I(d)		5
Seasonality	False		
Test	KPSS		
Stepwise	True		
Number of fits	50		

Table 2. MLP Model Optimized Hyperparameters

Parameter	Value
learn rate	0.0001
hidden layer two	10
hidden layer one	25
epochs	1000
dropout	0.2
batch size	4

Table 3. Comparison of ARMIA and MLP for model prediction

Heading level	MSE	MAE
ARIMA (2, 1, 1)	264234.26	471.69
MLP	6023.89	60.99

Conclusion

Providing a reliable model for predicting changes in the price of gold aids in predicting future market patterns, giving stakeholders important information for choosing the best course of action to avoid or reduce risks. Despite the fact that there are many forecasting models available, numerous research are ongoing to enhance these models' performance. This study proposed a novel framework for gold price prediction utilizing Multilayer Perceptron neural network technique. The proposed model looks for the top-tier number of weights and biases that can yield precise predictions for gold prices. There were 532 observations for the monthly average gold price. The initial entry was made on December 31, 1978, and the final entry was made on March 31, 2023. Training and testing data were separated from the WGC dataset in chronological sequence. The findings demonstrate that using the attributes in MLP model improves the accuracy of gold price predictions. The results obtained from the proposed model were compared with ARIMA in terms of MSE and MAE, with MLP model showing a strong option for predicting gold prices accurately.

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