

# Investment Instruments: The Power of Neural Networks in Predicting Gold Price Trends

Jakub Horak <sup>1,\*</sup>, Marek Vochozka <sup>2</sup>, Dominik Kaisler <sup>3</sup>

<sup>1</sup> The Institute of Technology and Business, Ceske Budejovice, Czech Republic  
ORCID: 0000-0001-6364-9745  
e-mail: [horak@mail.vstecb.cz](mailto:horak@mail.vstecb.cz)

<sup>2</sup> DTI University, Slovak Republic  
ORCID: 0000-0001-9923-7814  
e-mail: [vochozka@mail.vstecb.cz](mailto:vochozka@mail.vstecb.cz)

<sup>3</sup> The Institute of Technology and Business, Ceske Budejovice, Czech Republic  
ORCID: 0009-0006-7497-1389  
e-mail: [dkaisler@mail.vstecb.cz](mailto:dkaisler@mail.vstecb.cz)

\* Corresponding author: Jakub Horak, [horak@mail.vstecb.cz](mailto:horak@mail.vstecb.cz)

## Abstract

Precious metals, and especially gold, have been inextricably linked to the history of mankind since time immemorial. In modern times, gold has become a key factor in international trade and the global economy. Therefore, for example, oil price fluctuations can be a predictor of gold price movements. Today, gold is seen as an independent financial asset that has become a popular tool for portfolio diversification, as well as a hedge against inflation. For this reason, this topic is considered to be very important and topical worldwide, attracting the attention of a wide range of people, both from the ranks of experts and the lay public. The article's objectives are to determine the position of gold in the commodity market, measure and compare the metal's historical price development from 2000 to March 2023, and, last but not least, assess how well artificial neural networks can forecast the movement of gold's market price. Evaluating whether gold is a good financial resource multiplier or custodian is one of the partial goals. In order to achieve this goal, time series analysis will be performed using artificial neural networks. It is feasible to track how accurately artificial neural networks can forecast changes in market prices by using this technique. The results show that the most common elements influencing the historical development of the price of gold were political, economic, technological, and social aspects. Additionally, it was shown that artificial neural networks are capable of accurately predicting the course of the price of gold and, thus, mimicking the genuine price development curve. Based on the obtained results, future studies might be carried out to compare a more extensive portfolio of commodities in order to build on this work. The contribution is beneficial both on a theoretical and practical level. It can serve investors, analysts, economists, and other authors dealing with this issue.

## Key words

gold, prediction, artificial intelligence, commodity market, investing.

## Cite as:

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## Introduction

Coins were the primary form of money for hundreds of years or possibly more than two millennia, with a few notable exceptions. Given that they were initially struck on a single side in the Lydian Empire, which included parts of modern-day Turkey, circa 660 BC, coins made of precious metals—

especially gold—are frequently regarded as the earliest money in history (Štúr et al., 2014). These coins were referred to as “full-value” coins because their intrinsic value, or the amount of precious metal they contained, matched their purchasing power (Revenda & Arltová, 2022). According to Gutiérrez, Franco & Campuzano (2013), genuine gold trading began in the fourteenth century. The authors go on to say that during the 19th and 20th centuries, gold was used as a means of exchange and as a financial guarantee for printed banknotes. According to Beretta & Peluso (2022), gold has long been regarded as a “haven” or “anchor of stability”. The authors also contend that although gold’s price is susceptible to financial bubbles, the metal itself is not (because of its natural scarcity). The yearly fluctuations in supply and demand have a significant impact on the stability of gold prices. Nonetheless, there are arguments that the “best bubble” has already burst or that gold could trigger a much larger bubble than tech stocks in light of the recent sharp increase in the price of gold. Due to the lengthy and intricate relationship between gold, money, and financial markets, gold is frequently brought up in conversations about money and investments (O’Connor et al., 2015). Due to its negative correlation with stocks and poor correlation with other financial assets, which make it very effective at diversifying a portfolio and lowering its inherent risk and volatility, gold can also be very helpful during stressful times (Lucey et al., 2021). According to Gürgün & Ünalms (2014), domestic investors in the majority of countries can use gold as a haven and a hedge.

Gold demonstrates strong hedging in the US, India, and a diverse function in China. Gold continues to be a valuable investment due to its status as a haven, particularly in nations like China, India, the United States, and the United Kingdom where gold is deeply ingrained in the culture. However, gold still only has a flexible function in growing countries like Malaysia and the United Arab Emirates. The US central bank has 8133.5 tons of gold, or 75.6% of all foreign reserves, making it the nation with the largest official gold reserve. The United States of America is a prominent participant in the gold mining industry, having produced 230 tons of the metal, placing it third in terms of production, after China and Australia (Ghazali et al., 2020). In recent years, China has emerged as the world’s foremost producer and the second-largest consumer of gold, with its gold market experiencing rapid growth. Although China has a long history of mining, dating back to the Xia, Shang, and Zhou dynasties, the “Silk Road” era is considered to be the mining heyday. Even though the nation “officially” states that it produced only 2 tons of gold in the nearly 40 years between 1982 and 1993, there has been a notable upsurge in production in recent years, with an annual rise of 160 tons. With more than 460 tons produced annually, China leads the world in gold output, which has increased dramatically in recent years (Pian & Santosh, 2020). According to Zhang & Wei (2010), the commodities market is primarily represented by the gold and oil markets. As a result, changes in the price of oil can forecast changes in the price of gold (Le & Chang, 2012). For a variety of reasons, it is generally challenging to characterize the price behavior of any commodity (Smiech, 2014). Like any other commodity on the market, the price of precious metals increases with increasing demand and decreases with increasing supply. Due to a variety of factors affecting supply and demand, the price of gold and silver fluctuates and evolves. As a result, everyone who invests in the financial market hopes to time the market and determine how much to purchase. The topicality of this topic results from the global importance of gold and its indisputable position on the commodity markets. This yellow metal had and still has many uses across the world. Be it its use as an indicator of wealth, the use of gold for monetary purposes, decoration and the application of gold in modern times as an integral part in the field of technology, medicine and research. The wide use of this metal is due to its extraordinary chemical and physical properties.

Nowadays, gold is increasingly used as an investment metal, as it serves as a store of value in times of economic recessions, making it an integral part of a diversified portfolio. For this reason, constant attention has been paid to the prediction of gold prices recently.

The purpose of this article is to determine the place of gold in the commodity market, measure and compare the precious metal's historical price development from 2000 to March 2023, and assess the accuracy of artificial neural networks' price predictions. Determining if this commodity may serve as an appropriate multiplier or custodian of financial resources is one of the partial goals. The following research questions are defined to fulfil the stated objectives:

1. What factors historically influenced gold prices on the commodity exchange?
2. How accurately can artificial neural networks predict the gold price time series?

The contribution of the achieved results can be viewed from several angles, both theoretical and practical. The contribution can serve as a theoretical basis for other authors who deal with the same or similar issues, as well as an informative article for potential interested parties who would like to learn more about the given issue. However, this work can bring the greatest benefit especially to potential investors, who, for example, are still deciding whether an investment in gold will lead to safe keeping, and especially to the multiplication of their financial resources, or to analysts, who will thus obtain valuable information.

The paper is further divided as follows: The paper is further divided as follows: A Literature review that provides an overview of several specific research papers dealing with gold price forecasting models. The Methodology describes data collection using the kaggle.com website and describes the application of regression analysis using neural networks, which will be evaluated using the Statistica program. In the Results section, the position of gold on the commodity market is identified, the historical development of its prices over a certain period is measured and compared, and the ability of neural networks to predict the accuracy of the gold price is analyzed. The Discussion summarizes the results and provides answers to the research questions. The Conclusion contains a summary of all findings and recommendations.

## 1. Literature review

Given the importance of precious metals in the financial and industrial sectors, accurate precious metal price forecasting is essential. Lin et al. (2022) adjusted the empirical mode decomposition (MEEMD) method integrated with a long-short-term memory (LSTM) neural network to achieve improved prediction accuracy for precious metal price prediction. MEEMD outperforms ensemble empirical modal decomposition (EEMD) in terms of decomposition effect, according to multi-step permutation entropy analysis. Next, the LSTM is supplied with each intrinsic mode function (IMF) that MEEMD produced in order to make predictions. The final projection results are obtained by adding the forecast values of each IMF. The MEEMD-LSTM forecasting model outperforms the conventional multi-layer perceptual neural network (MLP), support vector regression (SVR), and super learner combined forecasting model in both one-step-ahead and multi-step-ahead forecasting scenarios. To thoroughly and statistically confirm MEEMD-LSTM's best prediction performance, an ensemble test for multi-horizon model credibility is used. They further show that, depending on the training to test set ratio or the economic cycle phase, the model continues to show improved prediction accuracy. This competitive technique for forecasting the price of precious metals holds promise for connected enterprises, investors, and government organizations.

The world's gold price has garnered a lot of attention lately, and, in comparison to previous price movements, the price of gold has increased dramatically. A model to forecast the price of gold was attempted to be developed by Faruk & Hossain (2019). The period from January 1950 to January 2018 was utilized to get sample gold price data (USD per ounce). The forecasting model was constructed using the Box-Jenkin Autoregressive Integrated Moving Average (ARIMA) methodology. ARIMA (1,1,2) (1,1,2)<sub>12</sub>, according to them, is the best model for predicting gold prices. Zhang & Ci (2020) concur, noting that in the past, governments, institutions, and individuals have all taken notice of changes in the price of gold. Reducing the impact of gold market swings and accurately capturing price trends are two benefits of an accurate gold price forecast. Given the complex and non-linear structure of the gold market, this is a difficult job. To forecast the price of gold, they put forth a deep belief network (DBN) model that includes a back-propagation (BP) layer with supervision for fine-tuning and limited Boltzmann machines for pretraining. Comparisons were made between the outcomes and the mathematical linear ARIMA model, the genetic algorithm optimization model for the BP neural network, and the conventional BP neural network model. With the lowest mean squared error, mean absolute error, and mean absolute error as well as the greatest directional statistics, they discovered that the suggested DBN model has outstanding prediction and directional performance. All things considered, the new DBN proves to be a more accurate gold price-predicting technique than both linear models and conventional neural networks.

In an effort to anticipate gold volatility using nation-specific indicators (GPRs), Li et al. (2023) examined the contributions of dimension reduction techniques and integrated prediction models to increase forecast accuracy. For this, several GARCH-MIDAS model extensions are employed. Initially, they discovered that the majority of nation-specific GPR indices regulate gold volatility and that, when predicting gold volatility, it makes sense to take forecast data from several nation-specific GPR indices into account. They also disclosed that combination prediction models are not as predictive as dimension reduction techniques. Furthermore, dimension reduction methods do exceptionally well in forecasting, particularly when gold volatility is minimal. Not to mention, the results remain strong even after adjusting the gold market, in-sample length, model configuration, and evaluation technique. Numerous financial operations worldwide are significantly impacted by the fluctuations in the price of gold. Creating a solid forecasting model may help shed light on the dynamics, volatility, and behavior of the gold price in addition to providing a chance to earn handsomely in the long run. In order to precisely estimate gold prices and fluctuations, Livieris et al. (2020) present a novel forecasting algorithm based on deep learning. The suggested model makes use of the effectiveness of LSTM in identifying short- and long-term dependencies, as well as the powers of convolutional layers, to extract valuable knowledge and understand the internal representation of time series data. They ran a number of tests and compared the suggested model to the most advanced deep learning and machine learning models available. Utilizing LSTM layers in conjunction with other convolutional layers has the potential to greatly enhance prediction performance, according to preliminary experimental data.

In their study, Wang et al. (2021) describe how the price creation mechanism of gold futures, a significant element of the financial market, has drawn the remarkable interest of academics and financiers. However, because gold futures price data is a time series and has chaotic, noisy, and non-stationary features, it is particularly difficult to anticipate. To solve these problems, they suggested a brand-new forecasting model called SGRU-AM, which is based on an attention mechanism (AM) and a specific recurrent unit (SGRU). The rectified recurrent unit (GRU) model known as the SGRU

modifies the memory ratio between the present and past moments by applying a 1-tanh function to the basic GRU's reset gate output. This process changes the reset gate's value range. With its long-range data collection capabilities, SGRU is able to forecast the closing price of gold futures the day after trade. Next, AM is used to alter the SGRU time dimension feature expression in order to increase prediction accuracy, learn the meaning of current local sequence features, and collect more comprehensive feature information for the model. In contrast, Pierdzioch et al. (2023) used a quasi-sampling forecasting experiment to study the predictive power of the short-term real interest rate for the volatility of gold price returns. They used US monthly data for the sample period of 1990/1 to 2022/2 to achieve this. They looked at a shadow real interest rate given the recent extension of the zero floors and a standard real interest rate predicated on sufficient federal funding. They discover that, in numerous forecasting experiment parameters, the real interest rate has a better predictive value for later realized volatility for the shadow real interest rate than for the regular real interest rate. The findings have significant ramifications for portfolio selections made by investors because gold is regarded as a safe-haven asset. Vrbka et al. (2020) state that one of the most often used prognostic techniques is the artificial neural network, which necessitates a more intricate model, employs a greater number of variables, and tends to operate non-linearly. As a result, this approach is appropriate for further modifications in the financial industry, particularly in the stock market. Neural networks yield favorable outcomes, and when solving important company indicators, they perform and are much more accurate than classical statistical techniques (Horák et al., 2023). Network drawbacks include the need for very high-quality data and the potential for artificial neural networks to behave irrationally (Rowland et al., 2021). Predictions made using neural networks can also be used to calculate the exchange rate. Vochozka et al. (2019) used artificial neural networks to predict the exchange rate, and their work produced useful and high-quality outcomes for a number of research projects. The investigation included data on currency exchange rates spanning more than nine years, totaling 3303 input data points. Using neural networks, they carried out regression and produced two sets of networks, the second of which was centered on seasonal changes. Prior to the experiment, there did not seem to be a reason to use categorical variables in the calculation. They discovered that adding more variables to the value measurement—like the year, month, day of the month, and day of the week—improved the precision and order of the time series alignment. The literature search revealed that the subject of gold as an investment was studied by a comparatively large number of scientific scholars. Numerous publications and studies have been released, and a variety of techniques have been employed. Artificial neural networks are widely utilized due to their exceptional accuracy and adaptability, enabling the computation of nearly anything. For this reason, we also selected artificial neural networks for our computations. These will be applied to RQ2, where the accuracy of neural network predictions of the gold price time series will be assessed. Then, we will forecast the price of gold for the following 30 business days. Following this estimate, a validation will be made and the discrepancy between the real and previously mentioned gold prices will be analyzed.

## 2. Methodology

To achieve the desired outcome, the practical part will be split into two sections. The initial stage of this work's practical part will be gathering individual secondary data utilizing the kaggle.com website. This information will be crucial in figuring out how the price of the chosen commodity, particularly the price of gold, has historically changed. In order to provide a more comprehensive historical

perspective of the price development of this precious metal, daily data for the last twenty-three years—that is, from January 4, 2000, to March 30, 2023—will be provided. The ounce will be the unit of mass and the currency for this commodity will be expressed in US dollars. Microsoft Excel data files will be created for the gold price development framework. Data files for gold will contain 5846 input data. For clarity, the created data files will therefore be edited, within which only the relevant data will be overwritten into the table, with which further actions will take place. The obtained data will be presented and evaluated both qualitatively and quantitatively, as well as graphically.

The acquisition of pertinent information appropriate for forecasting the price of the gold commodity will be required in the second stage. These will be made available once more utilizing time series from January 4, 2000, to March 30, 2023, using the kaggle.com website. After that, the data will be processed using Tibco Software Inc.'s Statistica program. As part of the need to answer RQ1, a quantile analysis will be performed with the help of the aforementioned Statistica program, which will lead to obtaining the necessary values for the precious metal, which will be: median, mode, arithmetic mean, standard deviation, range of variation and maximum and minimum value. The general mathematical formula (1) and (2) for the median:

$$\tilde{x} = \frac{x_{(N+1)}}{2}, \text{ if } N \text{ is an odd number} \quad (1)$$

$$\tilde{x} = \frac{x_{(\frac{N}{2})} + x_{(\frac{N}{2}+1)}}{2}, \text{ if } N \text{ is an even number} \quad (2)$$

$\tilde{x}$  – the median is a set of values of size  $N$ , whose elements  $x_i$  are ordered from smallest to largest.

General mathematical formula for mode (3):

$$Mod(X) = \text{the value of } x \text{ with the highest frequency} \quad (3)$$

The general mathematical formula (4) of the arithmetic mean:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i = \frac{x_1 + x_2 + \dots + x_n}{n} \quad (4)$$

$\bar{x}$  – the arithmetic mean is equal to the sum of all values  $x_i$  divided by the total number of statistical units ( $n$ ).

General mathematical formula (5) for standard deviation:

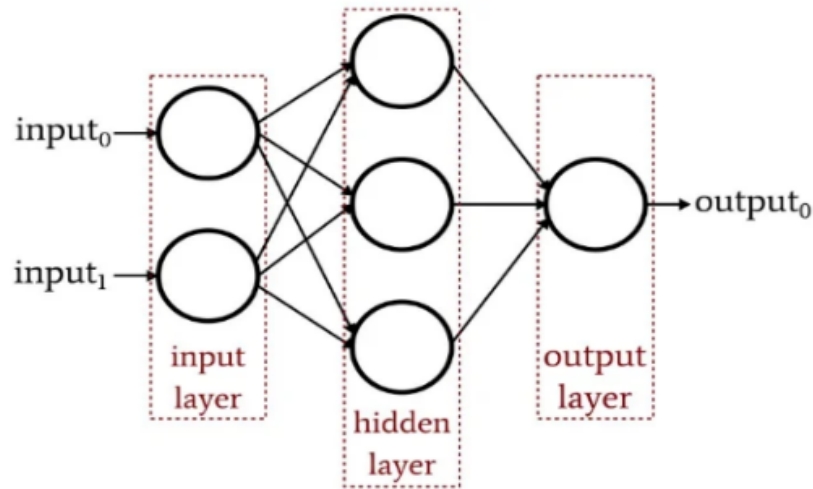
$$Var(X) = \frac{1}{N} ((x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_N - \bar{x})^2) \quad (5)$$

$$\sigma = \sqrt{Var(X)} \quad (6)$$

$Var$  – the square root of the variance, where  $\bar{x}$  is the average value and  $X$  represents the set of values, equals the standard deviation ( $\sigma$ ).

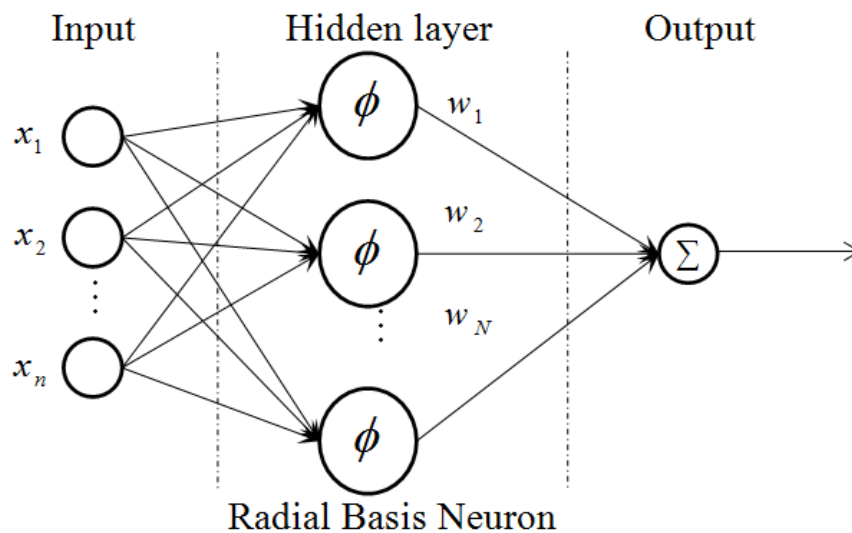
Time series analysis will assist in determining its evolution and, concurrently, the factors that impacted the historical price of gold by comparing similar data in chronological order. Additionally, by applying the comparison method, it will be feasible to evaluate how gold's price fluctuated more during the course of history and, concurrently, determine whether or not these variations had an impact on the price development.

MLP networks and radial basis function (RBF) networks will be employed in the artificial neural network approach to address RQ2. The MLP and RBF neural networks are graphically represented in Figures 1 and 2.



**Figure 1.** MLP neural networks

Source: Keim (2019).



**Figure 2:** RBF neural networks

Source: He et al. (2019).

The MLP neural network then has the following mathematical expression (6) (Kudová, 2001):

$$(\vec{x}) = \sigma(\sum_{i=0}^n w_i x_i) \quad (6)$$

And RBF neural networks then have a mathematical expression (7) like this (Kudová, 2001):

$$y(\vec{x}) = e - \left(\frac{\|\vec{x} - \vec{c}\|}{b}\right)^2 \quad (7)$$

where  $\vec{x}$  represents input values,  $y$  is output;  $\vec{c}$  is centre;  $b$  – width;  $\|\vec{x} - \vec{c}\|$  – the distance calculated using the Euclidean metric;  $\frac{\|\vec{x} - \vec{c}\|}{b}$  – the internal potential of the RBF unit and  $w$  is the weight value.

Time series analysis will be useful, as it compares similar data in chronological order. We will utilize time series regression analysis to forecast gold prices. To use this strategy, though, the correlation coefficient—that is, the gold price's reliance on time—must first be determined. A significance threshold of 0.95 will be selected for this. There will be 5846 input data in the data files with calculations, with time acting as the independent variable and commodity price acting as the dependent variable. The processing of linear regression employing neuron architectures will come when these tasks are finished. The least squares method will be used to build 1000 neural networks in each example, of which the ten best fits for future development prediction will be retained. Time series will be separated into training, test, and validation data based on classification. Seventy percent of the training data will be used to train the neural networks. 15% more of the data will be utilized for testing and validation. The number of neurons in the hidden layer and each neuron's weight in the other layers will be determined by the training. Three layers will make up neural networks. The input layer will be the first layer. The quantity of inputs, representing the value from every day since 2000, will be included in this. The hidden layer, which makes up the second layer, will show how many hidden neurons are there and will be used to build analogies for critical computations. The output layer, which is the final and third layer, is where the final values are obtained. For the MLP hidden and output layer, we will employ the following functions: linear, logistic, Atanh, exponential, and sine. The other settings (automated network creation in the ATS tool) will remain as default. The individual function formulas are displayed in Table 1.

**Table 1.** Formulas of functions

| Function           | Definition                          | Range                |
|--------------------|-------------------------------------|----------------------|
| Identity           | A                                   | $(-\infty; +\infty)$ |
| Logistic sigmoid   | $\frac{1}{1+e^{-a}}$                | $(0;1)$              |
| Hyperbolic tangent | $\frac{e^a - e^{-a}}{e^a + e^{-a}}$ | $(-1;+1)$            |
| Exponential        | $e^{-a}$                            | $(0;+\infty)$        |
| Sine               | $\sin(a)$                           | $[0;1]$              |

Source: Šuleř & Machová (2020)

The mentioned least squares method is used as the error function, which is represented by the following formula (8):

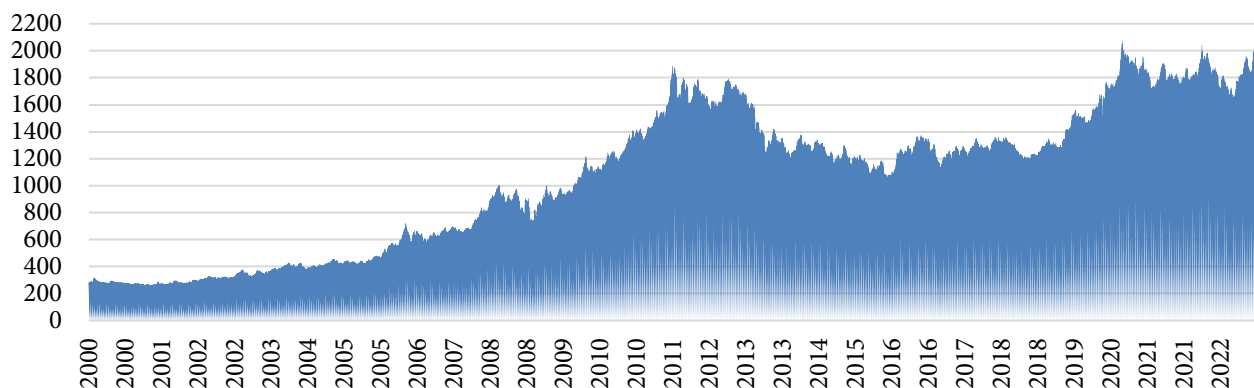
$$E_{sos} = \frac{1}{2N} \sum_{i=1}^N (y_i - t_i)^2 \quad (8)$$

where  $N$  – the number of trained cases,  $y_i$  – the prediction of the target variable  $t_i$  and  $t_i$  is the target variable of the with case.

A prediction will also be made for 30 trading days ahead, where it will be determined if any of the neural networks show any price extremes. Following this prediction, a validation will be created to determine the actual and predicted prices of gold using the residual. If the expected gold price will be the same as the real one, or if it will have different values and by how much.

### 3. Research results

The historical evolution of gold prices from 2000 to March 2023 is shown in the results section. Additionally, the findings pertaining to the commodity's price's future impact are showcased here. The price of gold has fluctuated over time due to a number of variables, including inflation and political and economic developments. These occurrences had a big impact on how the supply and demand for gold developed concurrently. The price of gold fluctuated and went through several periods between 2000 and March 2023. Applying time series analysis, Figure 3 was created from the results, which shows the historical development of gold prices over twenty-one years.



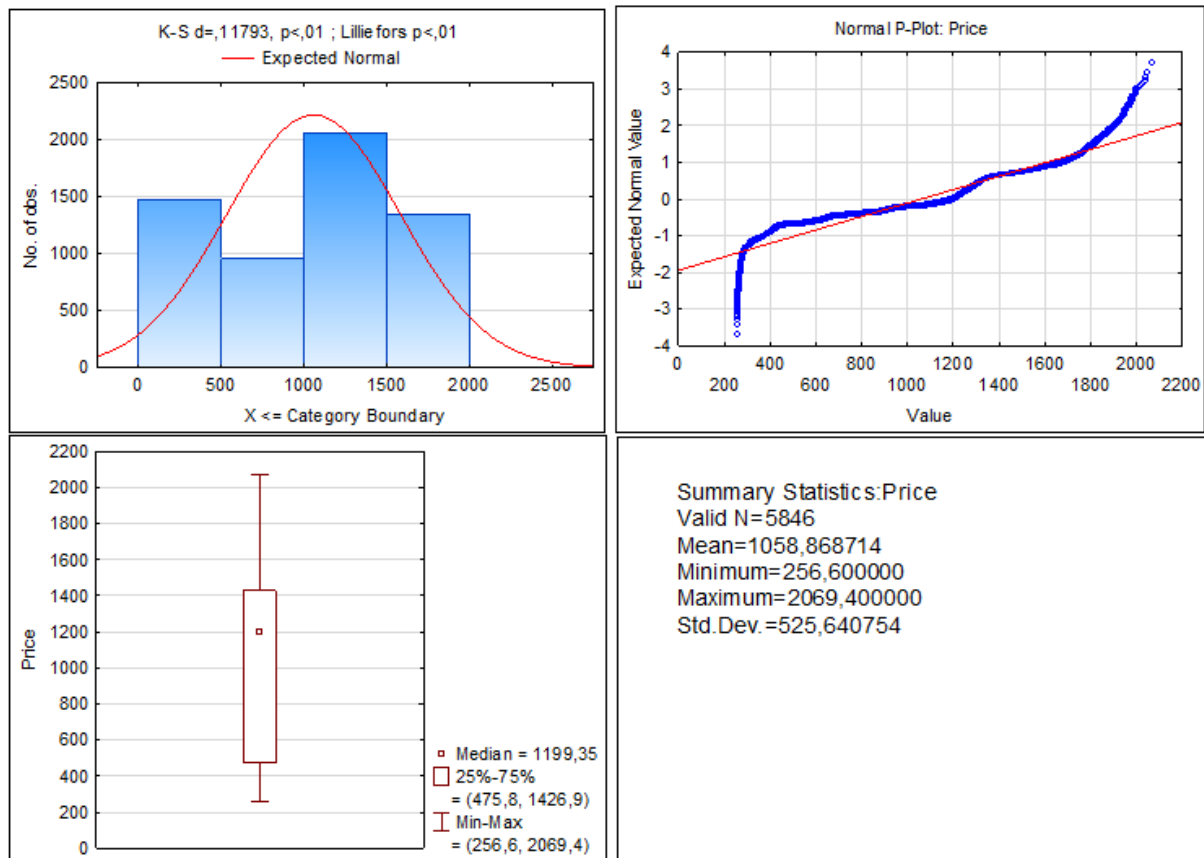
**Figure 3.** Historical development of gold prices from 2000 to March 2023 (in USD/oz t)

Source: developed by the authors.

Figure 3 illustrates how, from an investing perspective, prices developed over the monitored period in a generally positive manner, with very few exceptions. Prices increased. The highest price that gold ever acquired during the monitored period was the amount of 2069.4 USD/oz t reached on August 6, 2020. On the other hand, the lowest amount for which one ounce of gold could be purchased in the monitored period was 256.6 USD/oz t reached on April 2, 2001. Comparing these two values, the difference is 1812.8 USD/oz t, which is roughly a 706% increase in price, which from the investor's point of view appears to be one of the most suitable investment opportunities for the appreciation of your assets. Using the Statistica software, the fundamental statistical properties of the time series were also determined during the monitored period. These included the normality test and analyses of the data set's median, mode, arithmetic mean, standard deviation, and variation range. The results are shown in Figure 4. Throughout the examined time, the average price of gold was 1199.3 USD/oz t. The most frequent price from 2000 to March 2023 was 278.6 USD/oz t. 1058.8 USD/oz t was the average price of gold per ounce, with a 525.6 standard deviation.

The year 2000-2002 was relatively favourable for the development of gold prices. During the year 2000, gold prices were relatively stagnant. In 2001, there was a slight drop in prices, where it is possible to trace the mentioned minimum price of the monitored period, i.e. 256.6 USD/oz t. From this amount

until roughly the middle of 2002, prices rose slightly. The price of gold had a minor decline in the second half of the same year, and by the end of the year, it had reached its maximum point for the time being, or 349.7 USD.



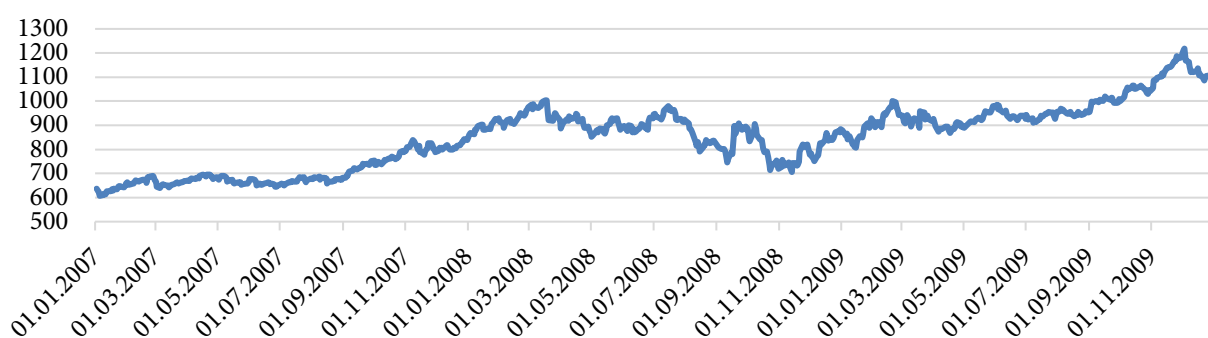
**Figure 4.** Basic statistical characteristics of the development of gold prices

Source: developed by the authors.

During this period, however, no factors appeared that would significantly influence the development of the prices of this investment instrument. In general, it can therefore be concluded that the price of gold did not develop considerably during the period from 2000 to 2002 and, with slight fluctuations, kept a mostly constant price, which ranged from 256.6 to 349.7 USD/oz t., and that with an average price of 288.2 USD/oz t. The beginning of 2003 followed the rise in prices from 2002. But then there was the first significant drop in prices, which reached the lowest possible price of gold, i.e. 322.2 USD/oz t, in the given year. This fall did not last long, and after a while, prices began to slowly rise again when towards the end of 2003, gold first crossed the threshold of USD 400/oz t and thus reached the highest possible price of USD 417.2/oz t. On the other hand, the average gold price did not differ much from 2002, i.e. in 2003; it acquired a moderate amount of 364.3 USD/oz t. In 2004, gold prices developed at a relatively similar pace as in previous periods. Despite slight price fluctuations, prices were mainly stagnant. Compared to 2003, the highest possible price for gold in 2004 differed only by 40.6 USD/oz t and the lowest possible price by 52.7 USD/oz t. The average price for that year was 410.4 USD/oz t. According to the data thus far, there appears to be a consistent pattern in which gold prices generally experience a small decline at the beginning of the year before rapidly rising. 2005 was the first time in history that gold prices did not fall below the 400 USD/oz t mark. Even this year, the gold

price reached a significant milestone when it attacked and broke the 500 USD/oz t mark. During this year, gold prices fluctuated negligibly, while at the end of this period, gold began to acquire a faster price growth rate. To clarify, the maximum value achieved for 2005 was 531.5 USD/oz t, and the minimum value achieved was 414.3 USD/oz t. This shows that investing in this precious metal was a very attractive year. The average value then reached the amount of 447.1 USD/oz t. 2006 was a turbulent year for gold as an investment vehicle. Prices at the beginning of the year soared at an extreme rate above the 700 USD/oz t mark, a difference of almost 200 USD/oz t compared to the highest possible amount so far in 2005. However, this amount did not have a long-term impact and immediately fell sharply below the 600 mark USD/oz t. Gold prices rose again during the rest of the year, but only below the 700 USD/oz t mark. Therefore, in 2006, gold could be purchased at the lowest possible amount of 527.8 USD/oz t, which was almost the highest 2005 possible amount per ounce of gold. The average price for 2006 was 608.2 USD/oz t. The period between 2007-2009 was one of the most significant in the development of gold prices, see Figure 5. During 2007, gold prices were largely stagnant, averaging 701.4 USD/oz t. But a turning point came at the end of that year when gold prices shot up again to record highs, and since then, gold has never traded below an amount of more than USD 700/oz t. At the beginning of 2008, with the economic crisis in full swing, prices continued to rocket and thus subsequently reached another essential historical milestone when they crossed the threshold of 1000 USD/oz t. Immediately, as in the case of the development of gold prices known, prices fell sharply again at the end of 2008, down to 705 USD/oz.t, which meant a price drop of almost 300 USD/oz.t. The year 2009 was very favourable for the development of gold prices. In the course of this year, except for minor fluctuations, prices mostly rose, and at the end of the year, they even reached another milestone, i.e. the border of 1200 USD/oz t.

When 611.4 USD/oz t was the difference between the lowest and maximum conceivable value, gold prices increased by up to 101% year over year. The price of gold in the ensuing years stayed at a maximum of \$1,000 USD/oz t.

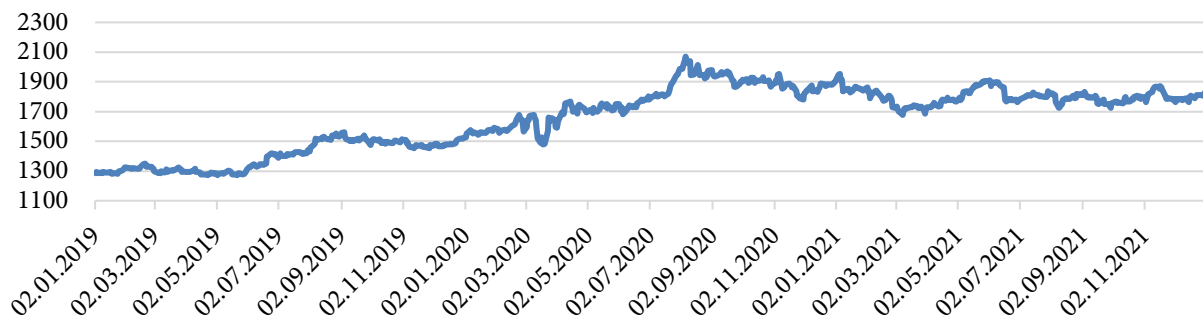


**Figure 5.** Historical development of gold prices during the economic crisis (in USD/oz t)

Source: developed by the authors.

From 2010 to 2012, gold became increasingly popular, increasing its investment value. At the beginning of 2010, gold traded at USD 1052.8/oz t, the lowest price for gold in years. From this amount, the price of gold increased rapidly, reaching a new maximum milestone in mid-2011, namely the amount of 1891.9 USD/oz t. However, the price of gold fell once more near the end of 2011 and stayed just below the 1800 USD/oz t level. Given that the price of gold remained within the range of 1536.6

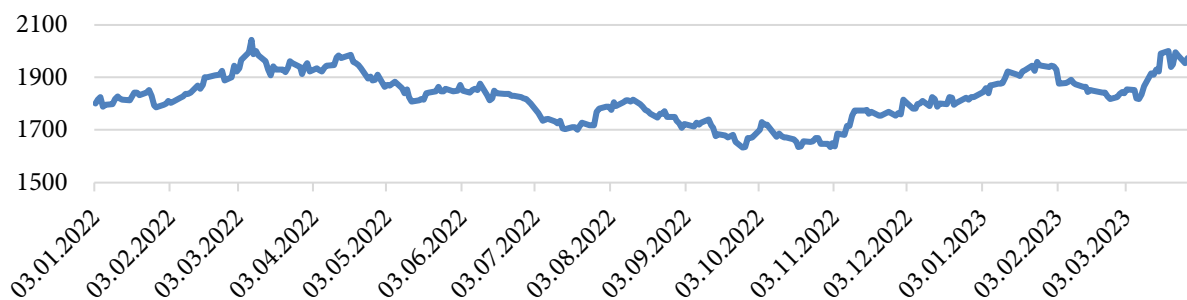
to 1796.5 USD/oz t during 2012, the year could have been more favourable in terms of price development. A notable decline in the price of gold occurred between 2013 and 2015. The price of gold decreased by up to 61% throughout the measured period, from 1693.2 USD/oz t to 1049.6 USD/oz t. Up until the end of 2018, gold prices remained mostly unchanged since then. Consequently, the average price of gold traded for between 2013 and 2018 was USD 1269.5/oz t. With the start of the global COVID-19 pandemic in 2019, gold prices started to rise once more quickly, as seen in Figure 6.



**Figure 6.** Historical development of gold prices during the Covid-19 pandemic (in USD/oz t)

Source: developed by the authors according to data on [Kaggle.com/Gold](https://www.kaggle.com/datasets/gold-price) (2023).

From the beginning of 2019, the price was still around 1300 USD/oz t. However, a turning point occurred around May, when prices gradually increased. In September, this precious metal again crossed the 1500 USD/oz t mark, which meant that after six years of stagnation, the first significant increase in prices. Gold maintained its increasing pace in 2020 when on August 6, it reached the highest possible price in history, i.e. 2069.4 USD/oz t, which has just been surpassed today. Since this milestone, gold prices have been falling, but not at a devastating pace, thus staying around the 1800 USD/oz mark. Based on the war conflict in Ukraine, which began at the beginning of 2022, gold prices rose again, and thus for the second time in the period monitored by us from 2000 to March 2023, they exceeded the maximum limit of 2000 USD/oz t (Figure 7).



**Figure 7.** Historical development of gold prices during the war conflict in Ukraine (in USD/oz t)

Source: developed by the authors.

However, as the year progressed, the tradable price continued to decrease, and in 2022 it fell to the limit of 1600 USD/oz t. Towards the end of 2022, gold prices strengthened again to the limit of 1800 USD/oz t, which began to stagnate. At the beginning of 2023, the development of gold prices began to

strengthen, with which prices once again climbed to just below the tradable level of 2000 USD/oz t. A thousand neural networks were generated in accordance with the chosen procedure. An overview of the top 10 neural networks with the best parameters over the whole range of neural structures that have been developed is provided in Table 2.

**Table 2.** Summary of active neural networks (gold data for the period 2000-2023)

| In-<br>dex | Net. name  | Training<br>perf. | Test perf. | Validation<br>perf. | Training<br>error | Test error | Validation<br>error | Training<br>algorithm | Error<br>function | Hidden<br>activa-<br>tion | Output<br>activation |
|------------|------------|-------------------|------------|---------------------|-------------------|------------|---------------------|-----------------------|-------------------|---------------------------|----------------------|
| 1          | MLP 1-13-1 | 0.994971          | 0.994654   | 0.995185            | 1370.996          | 1517.278   | 1351.208            | BFGS 1863             | SOS               | Logistic                  | Identity             |
| 2          | MLP 1-15-1 | 0.994681          | 0.994785   | 0.994942            | 1450.012          | 1478.377   | 1419.372            | BFGS 512              | SOS               | Tanh                      | Tanh                 |
| 3          | MLP 1-18-1 | 0.994608          | 0.994417   | 0.994843            | 1469.946          | 1583.477   | 1450.820            | BFGS 607              | SOS               | Logistic                  | Logistic             |
| 4          | MLP 1-16-1 | 0.994267          | 0.994500   | 0.994836            | 1567.147          | 1567.667   | 1448.968            | BFGS 565              | SOS               | Tanh                      | Exponen-<br>tial     |
| 5          | MLP 1-18-1 | 0.994622          | 0.994575   | 0.994780            | 1465.840          | 1538.583   | 1466.187            | BFGS 310              | SOS               | Logistic                  | Logistic             |
| 6          | MLP 1-20-1 | 0.994835          | 0.994702   | 0.994995            | 1407.905          | 1501.754   | 1406.403            | BFGS 509              | SOS               | Logistic                  | Identity             |
| 7          | MLP 1-17-1 | 0.994582          | 0.994116   | 0.994773            | 1476.733          | 1665.180   | 1466.995            | BFGS 312              | SOS               | Tanh                      | Sine                 |
| 8          | MLP 1-17-1 | 0.995600          | 0.995424   | 0.996026            | 1199.960          | 1296.604   | 1117.151            | BFGS 704              | SOS               | Tanh                      | Exponen-<br>tial     |
| 9          | MLP 1-9-1  | 0.994691          | 0.994343   | 0.995247            | 1446.999          | 1600.613   | 1335.542            | BFGS 8337             | SOS               | Tanh                      | Tanh                 |
| 10         | MLP 1-15-1 | 0.994661          | 0.994303   | 0.994779            | 1455.493          | 1612.432   | 1465.189            | BFGS 325              | SOS               | Tanh                      | Tanh                 |

Source: developed by the authors.

The table shows that only MLP networks are present, outperforming biased and inefficient RBF networks. The top ten structures were created using the BFGS (Broyden-Fletcher-Goldfarb-Shanno) variant training algorithm and had 12 to 20 neurons in the hidden layer. There is only one neuron in each of the input and output layers. At the same time, the input layer is a variable that represents time, and the output layer is also a variable, but here it is already the final price of gold. The hidden neural layers activated two functions, one of which was the hyperbolic tangent and the other a logistic function. The output layers formed the following five functions: identical, hyperbolic tangent, logistic, exponential and sine. Network performance is more closely represented by the correlation coefficient (Table 3).

**Table 3.** Correlation coefficients (Gold – daily data 2000-2023)

|              | Price    | Price    | Price    |               | Price    | Price    | Price    |
|--------------|----------|----------|----------|---------------|----------|----------|----------|
| 1.MLP 1-13-1 | 0.994971 | 0.994654 | 0.995185 | 6.MLP 1-20-1  | 0.994835 | 0.994702 | 0.994995 |
| 2.MLP 1-15-1 | 0.994681 | 0.994785 | 0.994942 | 7.MLP 1-17-1  | 0.994582 | 0.994116 | 0.994773 |
| 3.MLP 1-18-1 | 0.994608 | 0.994417 | 0.994843 | 8.MLP 1-17-1  | 0.995600 | 0.995424 | 0.996026 |
| 4.MLP 1-16-1 | 0.994267 | 0.994500 | 0.994836 | 9.MLP 1-9-1   | 0.994691 | 0.994343 | 0.995247 |
| 5.MLP 1-18-1 | 0.994622 | 0.994575 | 0.994780 | 10.MLP 1-15-1 | 0.994661 | 0.994303 | 0.994779 |

Source: developed by the authors.

Table 3 summarizes the values of individual datasets according to particular neural networks. The goal is to identify a network whose performance is preferably the same in all sets—training, testing, and validation. The correlation coefficient, which is a measure of the datasets' performance, should equal 1 while looking for the best possible network. Given that the other two datasets confirmed the validity of the structures in the training set, all three datasets performed identically. The table shows that all neural structures and data sets have correlation coefficients higher than 0.994, indicating negligible differences between individual networks. Thus, based on these findings, there is a high degree of performance, which is further supported by the value of each individual network, which

consistently rises over the value of 0.9. More specifically, each set's coefficients always fall between 0.994 and 0.996. The detailed prediction statistics of each unique preserved MLP network are displayed in Table 4.

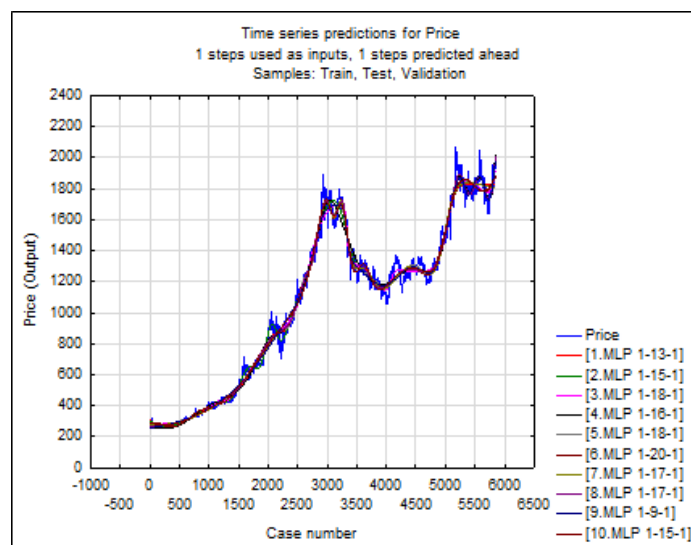
**Table 4.** Predictions statistics (Oil – daily data 2000-2023)

| Statistics           | 1.MLP 1-13-1 | 2.MLP 1-15-1 | 3.MLP 1-18-1 | 4.MLP 1-16-1 | 5.MLP 1-18-1 | 6.MLP 1-20-1 | 7.MLP 1-17-1 | 8.MLP 1-17-1 | 9.MLP 1-9-1 | 10.MLP 1-15-1 |
|----------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|---------------|
| Min. p. (Train)      | 267.839      | 267.268      | 279.277      | 256.600      | 266.532      | 262.971      | 274.674      | 267.570      | 256.399     | 272.107       |
| Max. p. (Train)      | 1827.006     | 1834.998     | 1918.163     | 2019.305     | 1865.446     | 1888.018     | 1836.241     | 2008.971     | 1977.842    | 1873.402      |
| Min. p. (Test)       | 267.842      | 267.276      | 279.278      | 256.600      | 266.508      | 262.971      | 274.676      | 267.552      | 256.358     | 272.110       |
| Max. p. (Test)       | 1827.007     | 1834.998     | 1919.538     | 2023.698     | 1865.849     | 1888.808     | 1836.240     | 2013.038     | 1979.836    | 1873.886      |
| Min. p. (Validation) | 267.840      | 267.268      | 279.278      | 256.600      | 267.190      | 262.972      | 274.675      | 268.041      | 257.487     | 272.108       |
| Max. p. (Validation) | 1827.004     | 1834.997     | 1907.225     | 1985.641     | 1862.221     | 1881.803     | 1836.224     | 1977.803     | 1961.384    | 1869.545      |
| Min. r. (Train)      | -209.241     | -210.248     | -203.745     | -218.071     | -201.018     | -185.328     | -212.590     | -189.865     | -199.183    | -202.149      |
| Max. r. (Train)      | 281.875      | 276.613      | 293.624      | 254.185      | 275.481      | 285.974      | 275.194      | 217.608      | 270.766     | 266.816       |
| Min. r. (Test)       | -208.917     | -209.936     | -203.626     | -211.037     | -200.655     | -184.926     | -212.248     | -189.954     | -199.013    | -201.883      |
| Max. r. (Test)       | 251.386      | 246.049      | 250.298      | 201.650      | 244.621      | 254.930      | 244.614      | 186.127      | 227.638     | 235.944       |
| Min. r. (Validation) | -196.282     | -200.276     | -189.970     | -223.800     | -188.241     | -172.717     | -199.711     | -175.312     | -185.647    | -188.980      |
| Max. r. (Validation) | 234.278      | 229.091      | 215.866      | 172.759      | 228.254      | 238.929      | 227.687      | 171.024      | 197.541     | 219.603       |

Note: Min. p. – Minimum prediction; Max. p. – Maximum prediction; Min. r. – Minimum residual; Max. r. – Maximum residual.

Source: developed by the authors.

It is evident from the data in Table 4 that there is little variation in the values between different neural structures and between different sets of neural network data. While some variations exist between these files, they are not substantial enough to establish the most effective network. To elucidate and identify the most effective network, consult Figure 8, which depicts the real evolution of expected gold prices and prices produced by individual neural networks.



**Figure 8.** Development of gold prices

Source: developed by the authors.

The graph makes it evident that all of these networks forecast gold prices in a fairly similar way, with only minor variations from the actual trend in gold prices initially apparent. On the other hand, resemblance to the actual evolution of gold prices is more important than resemblance to the evolution of individual networks. The coloured curves show the top ten brain structures that have been best preserved, while the basic blue curve shows the history of the real gold price. From this vantage point, the most effective structures functioned rather precisely, allowing them to replicate the real evolution of the gold price movement curve. Even though it was the application of the most powerful neural networks according to the correlation coefficients, there is still a problem with capturing the fundamental minimum and maximum price fluctuations, which is a crucial factor in this prediction. At the beginning of the monitored period, the price prediction was accurate and did not differ from the actual price. On 30 May 2006, the first major fluctuation in the prediction occurred, but still almost negligible. Subsequently, the predicted development was again favourable until 21 December 2007, when the neural networks failed to record an increase in prices to the value of 2100 and immediately afterwards a slight decrease to 2250. During the economic crisis, when gold prices rose rapidly, neural networks proved this fact very well. On the other hand, the prediction of the neural networks differed from reality at 2900 (July 18, 2011), when gold reached its first-ever maximum price milestone. From this time on, the development of the prediction was again accurate, and the neural networks could capture even a sudden drop in prices. Prices fluctuated somewhat from April 30, 2013, to April 17, 2018. While very few neural networks were able to accurately estimate the price in this instance, the differences between their predictions and the real gold prices were negligible. Gold prices surged when the COVID-19 epidemic struck, and neural networks accurately predicted this development. During the pandemic and the war in Ukraine, the prediction was the least accurate for the entire period. At 5200 (2/9/2020) and 5600 (5/4/2022), none of the top 10 neural networks could determine the record gold price. These networks also did not record for the period from 27 January 2021 to 29 August 2022 price drops, but on a minor scale. Despite several undetected fluctuations, it was a very accurate prediction, and all these networks are applicable in practice. Following the training of the neural networks, forecasts on the movement of the gold price over the following thirty trading days were generated. Table 5 illustrates the price movement for the specified 30-day trading period.

**Table 5.** Gold price prediction for April – May 2023

| Date       | 1.MLP<br>1-13-1 | 2.MLP 1-<br>15-1 | 3.MLP<br>1-18-1 | 4.MLP 1-<br>16-1 | 5.MLP<br>1-18-1 | 6.MLP<br>1-20-1 | 7.MLP 1-<br>17-1 | 8.MLP<br>1-17-1 | 9.MLP<br>1-9-1 | 10.MLP<br>1-15-1 |
|------------|-----------------|------------------|-----------------|------------------|-----------------|-----------------|------------------|-----------------|----------------|------------------|
| 31.03.2023 | 1825.27         | 1802.93          | 1919.54         | 2023.70          | 1865.85         | 1888.81         | 1801.98          | 2013.04         | 1979.84        | 1873.89          |
| 03.04.2023 | 1825.27         | 1802.74          | 1923.67         | 2037.13          | 1867.06         | 1891.20         | 1801.81          | 2025.48         | 1985.72        | 1875.34          |
| 04.04.2023 | 1825.26         | 1802.67          | 1925.05         | 2041.69          | 1867.46         | 1892.00         | 1801.75          | 2029.70         | 1987.65        | 1875.83          |
| 05.04.2023 | 1825.26         | 1802.61          | 1926.43         | 2046.29          | 1867.87         | 1892.80         | 1801.70          | 2033.97         | 1989.56        | 1876.32          |
| 06.04.2023 | 1825.26         | 1802.54          | 1927.80         | 2050.94          | 1868.27         | 1893.61         | 1801.64          | 2038.27         | 1991.46        | 1876.80          |
| 10.04.2023 | 1825.25         | 1802.28          | 1933.32         | 2069.95          | 1869.89         | 1896.87         | 1801.42          | 2055.90         | 1998.84        | 1878.76          |
| 11.04.2023 | 1825.25         | 1802.21          | 1934.70         | 2074.82          | 1870.30         | 1897.69         | 1801.37          | 2060.41         | 2000.64        | 1879.25          |
| 12.04.2023 | 1825.25         | 1802.15          | 1936.07         | 2079.72          | 1870.70         | 1898.51         | 1801.31          | 2064.96         | 2002.42        | 1879.74          |
| 13.04.2023 | 1825.25         | 1802.08          | 1937.45         | 2084.67          | 1871.10         | 1899.34         | 1801.25          | 2069.55         | 2004.17        | 1880.23          |
| 14.04.2023 | 1825.25         | 1802.02          | 1938.83         | 2089.67          | 1871.51         | 1900.17         | 1801.20          | 2074.19         | 2005.90        | 1880.72          |
| 17.04.2023 | 1825.24         | 1801.82          | 1942.94         | 2104.93          | 1872.72         | 1902.68         | 1801.03          | 2088.35         | 2010.97        | 1882.20          |
| 18.04.2023 | 1825.24         | 1801.75          | 1944.31         | 2110.10          | 1873.13         | 1903.52         | 1800.98          | 2093.16         | 2012.61        | 1882.69          |
| 19.04.2023 | 1825.24         | 1801.69          | 1945.68         | 2115.33          | 1873.53         | 1904.36         | 1800.92          | 2098.01         | 2014.23        | 1883.18          |
| 20.04.2023 | 1825.23         | 1801.62          | 1947.04         | 2120.59          | 1873.94         | 1905.21         | 1800.86          | 2102.90         | 2015.83        | 1883.67          |
| 21.04.2023 | 1825.23         | 1801.56          | 1948.40         | 2125.91          | 1874.34         | 1906.06         | 1800.81          | 2107.84         | 2017.40        | 1884.17          |
| 24.04.2023 | 1825.23         | 1801.36          | 1952.47         | 2142.13          | 1875.55         | 1908.63         | 1800.64          | 2122.92         | 2021.97        | 1885.65          |
| 25.04.2023 | 1825.22         | 1801.29          | 1953.82         | 2147.63          | 1875.96         | 1909.49         | 1800.59          | 2128.04         | 2023.45        | 1886.15          |

| Date       | 1.MLP<br>1-13-1 | 2.MLP 1-<br>15-1 | 3.MLP<br>1-18-1 | 4.MLP 1-<br>16-1 | 5.MLP<br>1-18-1 | 6.MLP<br>1-20-1 | 7.MLP 1-<br>17-1 | 8.MLP<br>1-17-1 | 9.MLP<br>1-9-1 | 10.MLP<br>1-15-1 |
|------------|-----------------|------------------|-----------------|------------------|-----------------|-----------------|------------------|-----------------|----------------|------------------|
| 26.04.2023 | 1825.22         | 1801.23          | 1955.17         | 2153.18          | 1876.36         | 1910.36         | 1800.53          | 2133.20         | 2024.89        | 1886.64          |
| 27.04.2023 | 1825.22         | 1801.16          | 1956.51         | 2158.78          | 1876.77         | 1911.22         | 1800.48          | 2138.41         | 2026.32        | 1887.14          |
| 28.04.2023 | 1825.22         | 1801.09          | 1957.85         | 2164.42          | 1877.17         | 1912.10         | 1800.42          | 2143.67         | 2027.71        | 1887.63          |
| 01.05.2023 | 1825.21         | 1800.89          | 1961.85         | 2181.64          | 1878.38         | 1914.72         | 1800.25          | 2159.71         | 2031.75        | 1889.12          |
| 02.05.2023 | 1825.21         | 1800.83          | 1963.17         | 2187.48          | 1878.79         | 1915.60         | 1800.20          | 2165.15         | 2033.04        | 1889.62          |
| 03.05.2023 | 1825.21         | 1800.76          | 1964.49         | 2193.36          | 1879.19         | 1916.49         | 1800.14          | 2170.64         | 2034.30        | 1890.11          |
| 04.05.2023 | 1825.21         | 1800.70          | 1965.80         | 2199.30          | 1879.59         | 1917.38         | 1800.09          | 2176.18         | 2035.54        | 1890.61          |
| 05.05.2023 | 1825.21         | 1800.63          | 1967.11         | 2205.28          | 1880.00         | 1918.27         | 1800.03          | 2181.77         | 2036.76        | 1891.11          |
| 08.05.2023 | 1825.20         | 1800.43          | 1971.01         | 2223.54          | 1881.21         | 1920.95         | 1799.86          | 2198.82         | 2040.23        | 1892.60          |
| 09.05.2023 | 1825.20         | 1800.36          | 1972.30         | 2229.73          | 1881.61         | 1921.86         | 1799.81          | 2204.60         | 2041.34        | 1893.10          |
| 10.05.2023 | 1825.20         | 1800.30          | 1973.58         | 2235.96          | 1882.01         | 1922.76         | 1799.75          | 2210.44         | 2042.42        | 1893.60          |
| 11.05.2023 | 1825.20         | 1800.23          | 1974.86         | 2242.25          | 1882.41         | 1923.67         | 1799.70          | 2216.32         | 2043.47        | 1894.10          |
| 12.05.2023 | 1825.19         | 1800.16          | 1976.13         | 2248.59          | 1882.82         | 1924.58         | 1799.64          | 2222.25         | 2044.49        | 1894.59          |

Source: developed by the authors.

Table 5 shows how the price of gold will move from 31.3.2023 to 12.5.2023. It can be seen that none of the networks shows any extreme fluctuations. The price of all networks either rises slightly or falls slightly during the monitored period, but no price shock is visible for any of the networks. The actual price of gold throughout the observed time is shown in Table 6.

**Table 6.** The real price of gold

| Date       | The real price of gold | Date       | The real price of gold |
|------------|------------------------|------------|------------------------|
| 31.03.2023 | 1969                   | 24.04.2023 | 1999.8                 |
| 03.04.2023 | 1983.9                 | 25.04.2023 | 2004.5                 |
| 04.04.2023 | 2022.2                 | 26.04.2023 | 1996                   |
| 05.04.2023 | 2020.9                 | 27.04.2023 | 1999                   |
| 06.04.2023 | 2026.4                 | 28.04.2023 | 1999.1                 |
| 10.04.2023 | 2003.8                 | 01.05.2023 | 1992.2                 |
| 11.04.2023 | 2019                   | 02.05.2023 | 2023.3                 |
| 12.04.2023 | 2024.9                 | 03.05.2023 | 2037                   |
| 13.04.2023 | 2055.3                 | 04.05.2023 | 2055.7                 |
| 14.04.2023 | 2015.8                 | 05.05.2023 | 2024.8                 |
| 17.04.2023 | 2007                   | 08.05.2023 | 2033.2                 |
| 18.04.2023 | 2019.7                 | 09.05.2023 | 2042.9                 |
| 19.04.2023 | 2007.3                 | 10.05.2023 | 2037.1                 |
| 20.04.2023 | 2019.1                 | 11.05.2023 | 2020.5                 |
| 21.04.2023 | 1990.5                 | 12.05.2023 | 2019.8                 |

Source: developed by the authors.

Table 6 shows that the actual price of gold was not as linear as the neural networks predicted. It can be seen here that it rose and fell again during the observed period, but not by any extreme values. It's always been in the tens of dollars, but there are also extreme price jumps. At the beginning of the monitored period, we can see that the price of gold started to rise, but on 10.4. In 2023, there was a big jump in the price, so the very next day, the price of gold rose again to almost its original value. The big price jump came on April 21, 2023, when the price of gold fell from the value of 2019 to the value of 1990. After that, the price of gold began to rise and fall again, and this was the case for almost the entire monitored period. In the observed period, there was another price jump, this time in an upward direction, specifically on 2/5/2023, when the price of gold rose from its value of 1992 to 2023. The residuals between the actual and forecast prices of gold are displayed in Table 7. It shows that the 9th neural network came out as the best, which was the only one with values that approached the value of 0. Not only its total value but also the mean and the median approach the value of 0.

**Table 7.** The residual between the actual gold price and the predicted one

| Date        | 1.MLP 1-<br>13-1 | 2.MLP 1-<br>15-1 | 3.MLP 1-<br>18-1 | 4.MLP 1-<br>16-1 | 5.MLP 1-<br>18-1 | 6.MLP 1-<br>20-1 | 7.MLP 1-<br>17-1 | 8.MLP 1-17-1 | 9.MLP 1-<br>9-1 | 10.MLP 1-<br>15-1 |
|-------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|--------------|-----------------|-------------------|
| 31.03.2023  | 143.73           | 166.07           | 49.46            | -54.70           | 103.15           | 80.19            | 167.02           | -44.04       | -10.84          | 95.11             |
| 03.04.2023  | 158.63           | 181.16           | 60.23            | -53.23           | 116.84           | 92.70            | 182.09           | -41.58       | -1.82           | 108.56            |
| 04.04.2023  | 196.94           | 219.53           | 97.15            | -19.49           | 154.74           | 130.20           | 220.45           | -7.50        | 34.55           | 146.37            |
| 05.04.2023  | 195.64           | 218.29           | 94.47            | -25.39           | 153.03           | 128.10           | 219.20           | -13.07       | 31.34           | 144.58            |
| 06.04.2023  | 201.14           | 223.86           | 98.60            | -24.54           | 158.13           | 132.79           | 224.76           | -11.87       | 34.94           | 149.60            |
| 10.04.2023  | 178.55           | 201.52           | 70.48            | -66.15           | 133.91           | 106.93           | 202.38           | -52.10       | 4.96            | 125.04            |
| 11.04.2023  | 193.75           | 216.79           | 84.30            | -55.82           | 148.70           | 121.31           | 217.63           | -41.41       | 18.36           | 139.75            |
| 12.04.2023  | 199.65           | 222.75           | 88.83            | -54.82           | 154.20           | 126.39           | 223.59           | -40.06       | 22.48           | 145.16            |
| 13.04.2023  | 230.05           | 253.22           | 117.85           | -29.37           | 184.20           | 155.96           | 254.05           | -14.25       | 51.13           | 175.07            |
| 14.04.2023  | 190.55           | 213.78           | 76.97            | -73.87           | 144.29           | 115.63           | 214.60           | -58.39       | 9.90            | 135.08            |
| 17.04.2023  | 181.76           | 205.18           | 64.06            | -97.93           | 134.28           | 104.32           | 205.97           | -81.35       | -3.97           | 124.80            |
| 18.04.2023  | 194.46           | 217.95           | 75.39            | -90.40           | 146.57           | 116.18           | 218.72           | -73.46       | 7.09            | 137.01            |
| 19.04.2023  | 182.06           | 205.61           | 61.62            | -108.03          | 133.77           | 102.94           | 206.38           | -90.71       | -6.93           | 124.12            |
| 20.04.2023  | 193.87           | 217.48           | 72.06            | -101.49          | 145.16           | 113.89           | 218.24           | -83.80       | 3.27            | 135.43            |
| 21.04.2023  | 165.27           | 188.94           | 42.10            | -135.41          | 116.16           | 84.44            | 189.69           | -117.34      | -26.90          | 106.33            |
| 24.04.2023  | 174.57           | 198.44           | 47.33            | -142.33          | 124.25           | 91.17            | 199.16           | -123.12      | -22.17          | 114.15            |
| 25.04.2023  | 179.28           | 203.21           | 50.68            | -143.13          | 128.54           | 95.01            | 203.91           | -123.54      | -18.95          | 118.35            |
| 26.04.2023  | 170.78           | 194.77           | 40.83            | -157.18          | 119.64           | 85.64            | 195.47           | -137.20      | -28.89          | 109.36            |
| 27.04.2023  | 173.78           | 197.84           | 42.49            | -159.78          | 122.23           | 87.78            | 198.52           | -139.41      | -27.32          | 111.86            |
| 28.04.2023  | 173.88           | 198.01           | 41.25            | -165.32          | 121.93           | 87.00            | 198.68           | -144.57      | -28.61          | 111.47            |
| 01.05.2023  | 166.99           | 191.31           | 30.35            | -189.44          | 113.82           | 77.48            | 191.95           | -167.51      | -39.55          | 103.08            |
| 02.05.2023  | 198.09           | 222.47           | 60.13            | -164.18          | 144.51           | 107.70           | 223.10           | -141.85      | -9.74           | 133.68            |
| 03.05.2023  | 211.79           | 236.24           | 72.51            | -156.36          | 157.81           | 120.51           | 236.86           | -133.64      | 2.70            | 146.89            |
| 04.05.2023  | 230.49           | 255.00           | 89.90            | -143.60          | 176.11           | 138.32           | 255.61           | -120.48      | 20.16           | 165.09            |
| 05.05.2023  | 199.59           | 224.17           | 57.69            | -180.48          | 144.80           | 106.53           | 224.77           | -156.97      | -11.96          | 133.69            |
| 08.05.2023  | 208.00           | 232.77           | 62.19            | -190.34          | 151.99           | 112.25           | 233.34           | -165.62      | -7.03           | 140.60            |
| 09.05.2023  | 217.70           | 242.54           | 70.60            | -186.83          | 161.29           | 121.04           | 243.09           | -161.70      | 1.56            | 149.80            |
| 10.05.2023  | 211.90           | 236.80           | 63.52            | -198.86          | 155.09           | 114.34           | 237.35           | -173.34      | -5.32           | 143.50            |
| 11.05.2023  | 195.30           | 220.27           | 45.64            | -221.75          | 138.09           | 96.83            | 220.80           | -195.82      | -22.97          | 126.40            |
| 12.05.2023  | 194.61           | 219.64           | 43.67            | -228.79          | 136.98           | 95.22            | 220.16           | -202.45      | -24.69          | 125.21            |
| Total value | 5712.81          | 6425.60          | 1972.36          | -3619.01         | 4224.22          | 3248.79          | 6447.55          | -3058.15     | -55.23          | 3925.15           |
| Mean        | 190.42           | 214.19           | 65.75            | -120.63          | 140.81           | 108.29           | 214.92           | -101.94      | -1.84           | 130.84            |
| Median      | 194.16           | 217.71           | 62.85            | -138.87          | 144.40           | 107.31           | 218.48           | -118.91      | -4.64           | 133.69            |

Source: developed by the authors.

This network also had two days where their actual value was close to the most predicted value. These were specifically on 3/4/2023 and 9/5/2023. On the contrary, the 7th and 2nd neural networks did the worst, most distant from the value 0. The 1st neural network did not do much better, whose total value was around 5712. In turn, the 4th and 8th neural networks predicted a much lower price of gold than was a fact; therefore, their total value also came out negatively. The table shows that, overall, the expected price of gold for the observed time was almost off from reality.

The results obtained through this research are particularly important for economic practice, as they provide new knowledge in the field of gold price prediction, which can be perceived as very beneficial due to its indisputable importance. In general, predicting gold prices can be considered a very challenging task, which is also confirmed by this research. This is mainly due to the fact that the price of gold on the market is influenced by a number of factors, including supply and demand, speculation on the financial markets, political events and the like. Gold has long been considered one of the traditional means of investment. There are several reasons why investors consider gold as part of their investment portfolio. Gold has a long history as a store of value. For thousands of years, it has been considered a medium of exchange and storage of wealth. Its value is generally independent of monetary policies and economic cycles. A common perception of gold is as an inflation hedge. Gold often

increases in value when prices are rising, and the currency's purchasing power is falling. Investors believe holding gold can help preserve their assets' value when the currency depreciates. Gold is considered a haven in geopolitical uncertainty and financial market instability.

#### 4. Discussion

Gold has been an important factor in human history since time immemorial. The significance of the mining and processing of this precious metal has been carried over to the present day. Its demand is increasing yearly, and the mining associated with it is increasing. However, it is necessary to consider that the occurrence of gold is rare and limited, and its deposits are not infinite. Within a few decades, it can therefore be assumed that the occurrence of this deposit will become lower and lower, thereby increasing the total value of this precious metal. Before the answers to the research questions are provided, it is possible to list several surveys dealing with similar issues. For example, a paper by Li & Diao (2013) shows the dynamics of gold prices on the New York Gold Exchange using a dataset that includes global macroeconomic indicators, financial market indices, and energy product quantities and prices. The authors extract common factors from panel data series and estimate a factor-augmented vector auto-regression for gold prices. This paper has two main contributions. First, all the factors affecting the gold market were divided into three groups, namely the gold reserve and prices of energy products, financial market indices, global macroeconomic indicators. The results show that the influence of financial market indices and macroeconomic indicators on the price of gold is negative, the influence of the gold reserve and energy product prices on the price of gold is positive. Second, they apply the FAVAR model to analyze the factors affecting the price of gold and the price trend. The aim of the study by Gaspareniene et al. (2018), in turn, was to determine whether ARIMA models are suitable for determining short-term gold price volatility. The calculations show that the ARIMA model is only suitable for short-term gold price forecasts (max. 1 year). Therefore, it is necessary to apply other models (multiregression), which can also reveal the relationship between the price of gold and its determinants. Chen et al. (2016) state that future gold price fluctuations are not only influenced by quantitative variables, but also by many non-quantifiable factors such as wars, international relations and terrorist attacks. The aim of their study is to compare the accuracy of gold price forecasts using artificial neural networks and the ARIMA model. The historical gold futures prices from 1999 to 2008 were used as training data and testing data, and the prices of 2009 were used to examine the effectiveness of the proposed model. The results of empirical analysis showed that an artificial neural network forecasted gold futures prices better than ARIMA models did.

In the study E et al. (2019) a novel combination technique is put forward based on independent component analysis (ICA) and gate recurrent unit neural network (GRUNN) methods, which called ICA-GRUNN. In the first place, due to the ICA is multichannel mixed signal analysis technique, variational mode decomposition (VMD) technique is utilized to decompose the original temporal series into virtual multichannel mixed-signal. Next, statistically independent components (ICs) are separated out from the time sequence via ICA, and then, the influence factors of the gold price are analyzed from the aspect of ICs. The results demonstrate that the fluctuation of the gold price will be interrupted by long-term trends, cyclic recurrent factors and random events. Thirdly, applying GRUNN on ICs to acquire the prediction series of independent components (ICPs) and the forecasting result of the gold price is the combination of the ICPs. Finally, comparison experiments indicate that ICA-GRUNN provides prediction with high accuracy and outperforms the benchmark methods, autoregressive

integrated moving average (ARIMA), radial basis function neural network (RBFNN), long short term memory neural network (LSTM), GRUNN and ICA-LSTM.

All of the predetermined research questions can now be answered based on the outcomes of time series analysis and the artificial neural network approach.

RQ1: What factors have historically influenced gold prices on the commodity exchange?

The first crucial aspect that has a considerable impact on how the price of this commodity develops is the existence of gold reserves and the process of extracting them. The mining capacity expanded with the discovery of new resources, which in turn boosted the availability of the material on the market and caused a decrease in price. On the other hand, when deposits were mined and production was reduced, the supply of gold on the commodity exchange fell, which caused the price to rise considerably. Economic instability and inflation are other influential factors involved in price development. For example, during the global financial crisis between 2008-2011, there was great uncertainty in the financial markets. For this reason, many investors were looking for a safe and more stable haven to keep their funds. At this moment, gold appeared with its high potential as one of the safest investments, and therefore the demand was increasing, which caused the price to rise. Also, the demand for precious metals and their corresponding price increased in tandem with inflation. According to Salisu and Adediran's research (2020), investors "pour" money into gold in order to fend off growing inflation, which drives up the metal's price.

Gold prices are influenced by global political instability and conflicts as well. For instance, prices increased on September 11, 2001, the day of the terrorist attacks on the Pentagon and the World Trade Center in New York. The invasion of Iraq in 2003, the armed conflict in Crimea between Russia and the West in 2014, the UK's exit from the European Union (Brexit), tense relations between the US and China between 2018 and 2020, the COVID-19 global pandemic that started in 2019, and the current war conflict in Ukraine are some other political instabilities and conflicts that had a significant impact on price developments. All these events have created uncertainty among investors. Thus, they became confused about the future of preserving their financial assets and began looking for more stable investment options. The demand for gold and silver thus increased again, and so did their tradable price.

The dollar influenced price development as one of the most important world currencies. Because gold is usually traded in dollars, its value tends to fall when the dollar strengthens and to rise when it weakens. Erdogdu (2017) thus confirmed that gold prices combined with the US dollar (USD) strengthened for many years. Central banks had a role in how this commodity's price evolved as well. First, the price of gold increased as a result of banks cutting interest rates, which also decreased the worth of the currency. For example, 2008, the US central bank cut its interest rates to zero. This caused an increase in inflation and, at the same time, a decrease in the dollar's value, subsequently increasing the price of this precious metal. Second, banks build up large reserves by buying gold to maintain stability if the currency collapses. This means that if banks sold these reserves, prices developed negatively, and conversely when reserves were created, prices developed positively.

The last major factor that significantly affects the price of gold is the interest of investors in these precious metals and the associated speculation. Speculators influence the development of precious metal prices for three reasons. First, speculators often buy gold for the sole purpose of holding the precious metal, thus contributing to the rise in price. Secondly, during market instability, speculators often spread so-called fake news, which causes panic among other investors, and thus the price can

rise sharply. Thirdly, speculators have the power to pique prospective investors' attention, which could raise demand and, ultimately, drive up price.

RQ2: How can artificial neural networks accurately predict the gold price time series?

The top 10 neural networks with the best potential for forecasting the movement of the gold price were chosen in order to respond to this research question. The obtained results demonstrate that just MLP-type networks were employed in the price prediction process. In this instance, it can be said that in all three sets (i.e., testing, training, and validation), the RBF networks' performance was insufficient to equal the MLP networks' 99% accuracy inside the framework of gold. The prediction accuracy of the MLP networks for gold was almost flawless, with a few exceptions, of course. The only moment when the networks showed reduced accuracy in prediction was when reaching local minimum and maximum values, where it would be necessary to train the neural networks further. The networks could analyse these local extremes, but each to a different extent and at a different time. For this reason, it is impossible to determine with precision which of the 10 MLP networks is the most accurate. Therefore, further training of these neural networks is also necessary to obtain even more accurate results.

In conclusion, it can be said that all ten of the maintained MLP networks for gold were able to accurately and without any issues replicate the real price development curve for this commodity. Therefore, they can be considered applicable and reliable in practice. This statement is also confirmed by the research of Söylemez (2020), who predicted the price of gold with different variables using artificial neural networks. The study then resulted in a model that could predict gold prices with 98.44% accuracy. Gold, through ANN, was also investigated by Brabenec et al. (2020). The purpose of their study was to predict how the price of gold would evolve in the future and ascertain whether it rises during recessions. The authors examined daily data on gold prices between 2006 and July 2020. The survey was created using five different techniques for smoothing time series: neural networks, decision trees, gradient boosted trees, linear regression, and nearest neighbours. The training data set was used to apply the algorithms, and the test data set was used to evaluate the final model. Together with a histogram of the probability density, a plot of the residuals from the test data sets, and a histogram of the training data set, the residuals of the corresponding models were displayed graphically. It was projected how the price of gold would move in the upcoming year. According to the survey results, market participants maintain the value of their assets by purchasing gold during the early stages of an economic downturn. They are compelled to sell the gold once more since they are short on cash. An analogous progression was anticipated for the upcoming timeframe. A worldwide economic downturn is likely. The need for borrowers to sell their investments will result in a sharp decline in the price of gold. Artificial neural networks and linear regression were utilized by Machová et al. (2020) to conduct a regression analysis of the evolution of the afternoon gold price on the New York Stock Exchange. Out of the 1,000 neuron architectures they produced, they retained the five that had the finest features. The curve derived from the spline function best represents the evolution of the gold price in terms of basic linear regression. Nonetheless, all five maintained neural networks produce superior outcomes.

## Conclusions

In times of political crises or global economic upheavals, gold can act as a vehicle to help protect investments. The price of gold can be very volatile. While it can serve as the cornerstone of a stable portfolio, its value can fluctuate rapidly. Gold itself does not generate any returns. Its value is based largely on market supply and demand. The main way to get gold is by mining. It must be considered

that mining gold can be expensive and difficult, affecting its price. It is crucial to remember that gold's value is subject to fluctuation. Investing in gold should be done with sufficient risk awareness and as part of a broader investment plan considering individual financial goals and risk tolerance. One use of AI and machine learning in the financial sector is the prediction of gold prices with neural networks. Neural networks can analyse and detect complex patterns and patterns in historical data and use them to predict future trends. It is important to note that gold price prediction, like any financial market prediction, is not entirely accurate. The price of gold is subject to numerous variables, many of which are constantly shifting. Furthermore, while neural networks are capable of identifying patterns in data, their accuracy cannot be guaranteed under all circumstances. Prior to predicting gold prices with neural networks or other machine learning methods, it is crucial to conduct a thorough study, confirm the model's performance and dependability, and take other aspects like investment diversification and long-term investment horizon into account.

Thus, investing in commodities, especially precious metals, comes to the fore. The main goal of this work was, therefore, to identify how gold and silver stand on the commodity market, to further measure and compare their historic price development in the period from 2000 to March 2023 and, last but not least, to analyse the accuracy with which artificial neural networks can predict the price. The partial goal was to evaluate whether gold is offered as a suitable custodian or multiplier of financial resources. Research questions were already defined in the introduction to help the work reach its purpose. To answer all the research questions, a literature review was created at the beginning of the work, with the help of which suitable methods applicable to the research were found. Individual historical daily gold and silver price data from 2000 to March 2023 was collected via kaggle.com. RQ1 was subsequently evaluated using quantile analysis and time series analysis. After that, RQ2 was assessed using the Statistica software and the artificial neural network approach. A 30-trading day ahead prediction was also made where none of the networks showed extreme swings. The price of all networks rose or fell slightly during the monitored period, but no price shock was recorded for any of the networks. After the prediction, a validation of the actual gold price with the predicted one was created, from which it came out as the best MLP 1-9-1 network since it was the only one that could have the most values approaching zero. Overall, it was found that the predicted price of gold for the monitored period almost did not correspond to reality. Based on the results, it was found that during twenty-three years, the price of gold mainly increased. It goes without saying that during the historical development of the price, many fluctuations were caused by the action of many factors. With the help of research, the most common factors affecting gold prices on the commodity exchange were defined in particular: the effects of world political instability and war conflicts, as well as the influence of ever-increasing inflation and economic instability, the number of deposits with these precious metals and associated mining, monetary policy and the behaviour of central world banks, the rate of industrial use of gold and, as a last but very important influencing factor, is the very demand and supply on the commodity market. Last but not least, the application of the method of artificial neural networks proved that these networks could predict with great accuracy and thus imitate the real development of the price of gold.

Gold shows high potential and thus offers itself as a safe depository of financial assets, even in times of global instability or uncertainty. This precious metal can bridge financial crises very well and, therefore, can serve as a suitable custodian or multiplier of wealth. Therefore, it can be concluded that gold holds a high position in the commodity market, and that is why many investors increasingly include it in their investment portfolios.

A significant limitation of this research can be seen in the applied data, as it turns out that in some cases the use of a long time series for the purpose of analysis through neural networks is not always an ideal solution. The limit can also be seen in the use of a low number of types of neural networks or in the fact that no comparison with other methods was taken into account. However, it is necessary to point out that the use of several types of neural networks or several methods would not be possible to include within one article, if only because of the limited scope of the article. As for proposals for the future direction of research, it is possible, for example, to further train the best trained network on new data and thereby increase its success rate in predicting gold. Furthermore, it is possible to devote more time to working with time series delays or with the amount of input data for calculations. In the case of comparison, other neural network models (LSTM, PNN and their various variants, etc.) or completely different methods (ARIMA, VAR, etc.) can be used.

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