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Artificial intelligence techniques recruitment for gold ore (Crude gold) price prediction

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Abstract: Due to its unique characteristics, the gold price has a strong influence on almost all sectors. Professionals and scholars have devoted a great deal of attention to forecasting the gold price because of this reason. Using the robust model for the accurate prediction of gold prices, this paper examined the factors that affect IRAQ's gold prices. Using Bayesian Vector Autoregression and random forest models, significant associations were detected between dependent and independent variables over the course of a decade starting in 2013 and ending in 2023. Inflation, crude oil price, and exchange rate are three independent variables that influence gold prices. Crude oil prices are positively impacted by inflation and exchange rates, while gold prices are negatively impacted by inflation and exchange rates. In addition to academics and investors, the study results have practical applications. The Bayesian VAR and Random Forest models are used to analyze the gold price time series. To deliver correct predictions of experimental data, weights are assigned to the models. There are three types of errors to measure: root mean squared error, average error, and average percentage error.
Keywords: *Artificial Intelligence, Bayesian vector autoregression (Bayesian VAR), Gold Ore, Prediction, Random forest model.*

1. Introduction

The value of crude gold has a significant impact on financial markets globally. This has led to a great deal of interest from both investors and scholars, as the fluctuations in gold prices have an effect on various financial markets, such as bonds and shares. To anticipate and prepare for changes in gold prices, central banks and politicians of different countries closely monitor accurate forecasts of gold prices [1]. Accurately predicting the price of crude gold is therefore crucial. There are various conceptual approaches that can be used for forecasting and predicting the gold price. These approaches can be divided into two main categories. The first category includes methods such as random walk (RW), GARCH model, Bayesian VAR, error checking methods (ECM), autoregressive combined moving average (ARIMA), exponential smoothing model (ESM), and error checking methods (ECM). These methods do not consider the nonlinear properties of crude gold and are used to capture the linear relationships in time series [2].

Algorithms have recommended a solution to this problem. Scholars have been interested in ANNs, adaptive neuro-fuzzy inference systems, and genetic algorithms for their strong learning abilities.

Data from the past was used to forecast time series models. This is how the two models are used together. A linear or nonlinear relationship in a correlation may sometimes appear difficult to distinguish, even if it is not impossible [3][4].

Based on existing literature, it is evident that there is no one forecasting method that can consistently yield exceptional results in all situations, as each real-world problem possesses its own unique complexities. Therefore, it is recommended to utilize multiple models instead of relying on a

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single one. Hybrid models have shown to be effective in improving prediction accuracy. With the use of various forecasting models, time series data can now be more easily correlated. However, traditional statistical methods that excel in predicting linear time series may struggle with nonlinear and non-stationary data. As such, several machine learning techniques have been employed to forecast gold ore prices.

Machine learning can use any regression approach for price forecasting since it is a regression or prediction problem. SVR and NN are two of the most popular ML methods. To boost the performance of nonlinear estimates, wavelet neural networks and random effective functions were used [6].

Both BPNN and SVR were outperformed by the method in the experiments. When used for forecasting, SVR outperformed ARIMA and BPNN according to Xie et al. To forecast the ore gold price, a few authors used GA to fine-tune an extended version of SVR called least squares SVR (LSSVR).
Competing models were unable to match the accuracy and efficiency of the predictions made by the system. Another type of ML model used in this field is DFNPMs (data fluctuation net prediction models). There are many other models used in this field, such as hidden Markov models, MLRs, deep learning, and MLRs [7].

2. Problem Statement

Metal exchanges are exposed to multiple and sharp fluctuations due to their being affected by many external factors that affect various aspects of economic activity, including political and economic turmoil and globalization. Due to the diversity of these factors, the problem of difficulty in predicting the future path of gold prices arises using traditional methods and does not give accurate results. Hence, the following question can be formulated: Will studying historical data for gold prices using data mining approximation algorithms contribute to building a model to predict their prices the next day with the lowest possible error rate and high accuracy?

3. Research Objectives

The research aims to predict the price of gold with high accuracy using several artificial intelligence techniques, namely the random forest model and the Bayesian VAR model, in order to compare them to choose the most accurate technique and help the investor reduce uncertainty and make the appropriate decision.

4. Article Distinctive Aspects

To distinguish the manuscript, conduct a comparison process between artificial intelligence techniques by using two methods, the Random Forest Model and the Bayesian VAR Model, to determine the best algorithm for predicting gold prices for the period extending to 10 years from 2013 until 2023.

5. Metals

Metal prices have fluctuated significantly over time, especially since the early 21st century. This fluctuation is due to three main factors that affect the direction of prices, which are as follows:

(1) Supply, which is affected by many factors, including mine production and recycling rates.

(2) Demand, which is affected by economic growth rates and industrial production in the world as a whole.

(3) Speculation by commodity traders and asset managers [8][9][10].

6. Impact of Factories on Gold Price

The study of gold prices and markets is a complex and intriguing aspect of international finance. In order to make informed decisions and maximize profits, potential gold buyers must have a thorough understanding of the factors that influence gold rates. Researchers have also delved into the behavior of gold in order to develop more precise prediction methods. In the following chapter, we will delve into various intricate techniques used in this field. Gold tends to perform well in times of high inflation, making it a popular hedge for banks. Additionally, interest rates on savings also impact gold prices. When interest rates are high, people tend to invest in currency, but when they are low, they turn to purchasing gold. Wang, Lee, and Thi have reported that gold is not always a reliable inflation hedge [11]. The timing and selection of the market are crucial elements in hedging against inflation. To effectively hedge against inflation, investors should choose periods of high momentum or when gold prices are more responsive to inflation. On the other hand, during low momentum periods, gold cannot serve as an inflation hedge. Market selection is also important in hedging against inflation. The value of gold increases when the dominant currency is unstable, as people seek to acquire more gold as a safe investment, driving up its price. During uncertain times, gold investors closely monitor geopolitical developments, such as those in Iraq and Ukraine. For instance, during the Soviet invasion of Afghanistan in 1980 and the US embassy hostage crisis in Tehran, the price of gold reached its peak at $850 per ounce. Similarly, during the Arab Spring and the Euro crisis, gold reached its peak in 2011 at $1,920 per ounce [12][13].

According to studies, the cost of production for gold has an impact on its price, despite being perceived as insignificant. This is just one of the many factors that affect the price of gold. In theory, gold miners increase the price of gold when production costs rise in order to maintain their profits. However, research shows that the price of gold does have an effect on the production of gold mines. Blose and Shieh [15] discovered a positive relationship between the returns of mining companies and the price of gold, while McDonald and Solnick [14] found a similar correlation. Blose and Shieh [15] also developed a model to estimate the gold elasticity of mining stocks and predicted that companies primarily involved in operating gold mines would have an elasticity of more than one. This was tested using 23 gold mining stocks from 1981 to 1990, which supported their model despite the seemingly insignificant production costs of gold. In contrast, while miners may theoretically maintain their profits by selling gold for a higher price when production costs increase, the researchers found that it is actually the price of gold that affects the production of mines. McDonald and Solnick [14] also found a positive correlation between the returns of 25 South African and 10 North American mining companies and the price of gold, further supporting the idea that the value of gold mining companies is sensitive to gold price movements. Blose and Shieh [16] also concluded that their model, developed in a previous study [17], accurately predicts that companies with primarily gold-mining assets would have a gold elasticity of more than one. This was confirmed through their test using 23 gold mining stocks from 1981 to 1990.

7. Dataset

Data for this research was collected from various sources between January 2005 and September 2016. Our team obtained information on oil prices, the New York Stock Exchange, the Standard & Poor's 500 index, US bond rates (10 years), and EuroUSD exchange rates. Additionally, we gathered data from multiple government central banks and five major companies with large investments in gold. The analysis also considered the price of precious metals during this time [18][19]. The sources used for this data are mentioned in Table I. All relevant attributes are listed in Table II. Our forecast is based on the price of gold in US Dollars. The dataset was thoroughly cleaned and preprocessed, with missing values handled appropriately. Daily fluctuations in gold prices are also influenced by major global events. As seen in Figure 1[20], there has been a significant increase in gold rates over the past few years.

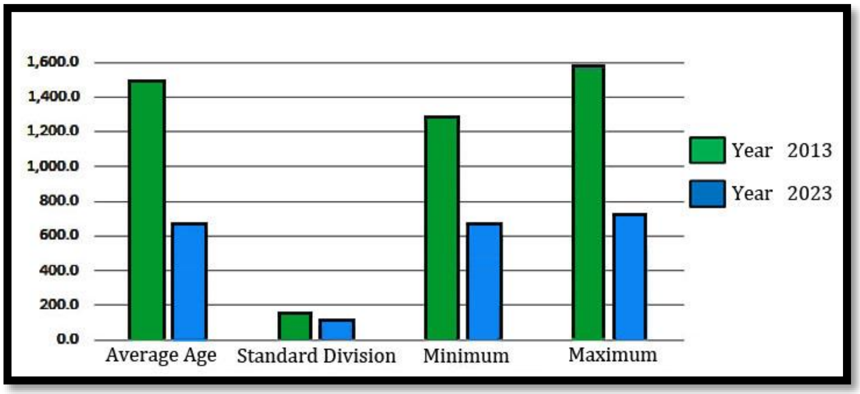

Figure 1.
Gold prices rising rate in recent years.

To handle the substantial difference in cost, it was decided that the dataset would be split in a consecutive manner rather than via random sampling. This led to the selection of the most recent 25% of the data as the test set, while the earliest 75% was designated for training. Consequently, the initial 2295 records were utilized for training and the last 770 rows were used for testing. Due to the significant variations in the value of gold over time, it was considered more appropriate to use recent data for forecasting future trends. As a result, the training set was further divided into four versions: the first version including records from 0% to 75%, the second version including records from 15% to 75%, the third version including records from 30% to 75%, and the final version including records from 45% to 75% of the complete dataset [21][22].

8. Performing an Analysis of Correlations

Our analysis revealed a strong relationship between the price of gold and our set of twenty-two attributes. The correlation results are displayed in Figure 3, which offers interesting insights. Surprisingly, the stock price of Silver Wheaton Corporation, the largest company in the precious metals streaming industry, showed the highest correlation with gold rates, rather than the performance of major economies like the US or the prices of other precious metals [23]. The tenth and eleventh most correlated gold producers were Eldorado Gold Corporation and Compania de Minas Buenaventura, respectively. This is the first study to use the values of major gold producers (as shown in Table II) [24][25] to predict gold prices. As expected, the prices of other precious metals, such as silver, and the performance indicators of major economies like the US and UK closely followed Silver Wheaton Corporation. In this study, Russia's interest rate ranked seventh in terms of its impact on gold prices, making it a notable factor. However, China's interest rate did not have a significant effect on gold prices [26].

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Table 1.
Gold rates predicted by attributes.

Parameters	**[1]**	**[4]**	**[5]**	**[6]**	**[9]**	**[10]**	**Proposed**
Period time	**From 2003 to 2016**	**From 2007 to 2021**	**2009**	**From 1979 to 2020**	**From 2012 to 2020**	**From 1996 to 2014**	**From 2012 to 2023**
Spot price of oil	Yes	Yes	No	No	No	Yes	Yes
Futures price of oil	Yes	No	No	No	Yes	No	No
Price of gold at the spot	Yes	Yes	Yes	Yes	Yes	Yes	Yes
The price of gold in the future	No	No	No	No	Yes	No	No
Rate of interest at base	Yes	No	No	No	No	No	No
Prices of silver in the market	Yes	Yes	No	Yes	No	Yes	Yes
The price of silver in the future	No	No	No	No	Yes	No	No
The price of copper in the future	No	No	No	No	Yes	No	No
The price of platinum	Yes	No	No	Yes	No	No	Yes
Index of the standard and poor's 500,	Yes	Yes	Yes	No	Yes	No	Yes
Index of the US dollar	Yes	Yes	Yes	No	Yes	Yes	Yes
Index of CRB	No	No	Yes	No	Yes	No	Yes
Index of the New York stock Exchange	No	No	Yes	No	No	No	No
Index of (AU)	No	No	No	No	No	No	Yes
Index of NASDAQ	No	No	No	No	Yes	No	No
Index of FTSE	No	No	No	No	Yes	No	No
Index of Hang Seng	No	No	No	No	Yes	No	No
Index of Nikkie	No	No	No	No	Yes	No	No
Index of GBP-USD	No	No	No	No	Yes	No	No
Index of JPY-USD	No	No	No	No	Yes	No	No
Index of CNY-USD	No	No	No	No	Yes	Yes	No
Index of Shanghai	No	No	No	No	Yes	Yes	No
Index of KOSPI	No	No	No	No	Yes	No	No
Index of consumer prices (CPI)	Yes	No	No	No	No	No	Yes
Bills issued by the treasury	No	No	No	Yes	No	No	Yes
Price of palladium	No	No	No	Yes	No	No	Yes
Price of rhodium	No	No	No	No	No	No	Yes
Inflation rates (US Dollars)	No	No	No	No	No	No	Yes
(UK) Interest rates (British Pounds)	No	No	No	No	No	No	Yes
China's interest rate (China's interest rate)	No	No	No	No	No	No	Yes
Rate of interest (Russia)	No	No	No	No	No	No	Yes
Eldorado gold corporation) (A gold mining company based in Canada)	No	No	No	No	No	No	Yes
silver wheaton corporation the trading name of Silver Wheaton	No	No	No	No	No	No	Yes

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Corp							
Anglo gold ashanti limited	No	No	No	No	No	No	Yes
Barrick gold corp. (ABX)	No	No	No	No	Yes	Yes	No
Compania de minas	No	No	No	No	Yes	Yes	No
Buenaventura (BVN)	No	No	No	No	Yes	No	No
Rates of the Euro to United States Dollar	No	No	Yes	No	No	No	No
M1 (Monetary supply) (The measure of the money supply.)	No	No	Yes	No	No	No	Yes
The inflation rate	Yes	No	No	No	No	Yes	No
Production of gold in the world	No	No	No	No	No	Yes	No
Bonds issued by the US treasury (10 years)	Yes	No	No	No	No	No	Yes
Bonds issued by the United States (5 years)	No	No	No	No	No	No	No
The Dow Jones industrial average	Yes	No	No	No	Yes	No	Yes
Research bureau of the commodity exchange	No	No	Yes	No	No	No	No

9. Methodology

The amount of crude gold used by researchers was predicted using machine learning techniques. Statistical analysis was conducted before selecting the model for the time series. By examining the p-value of the Augmentation Dickey-Fuller (ADF) test, we can interpret the statistical data using the ADF test, a standardized unit root experiment. If the statistic is less than or equal to 5%, the null hypothesis (that the sequence is stationary but there is no cointegration relationship) is rejected. Whenever p is greater than 5%, the examined data series has an order of integration and is not stationary, requiring differentiation. In all conducted tests, the p-value exceeds the 5% significance threshold, so the null hypothesis cannot be ruled out. A stationarity test was not performed on the time series examined.

9.1. Machine Learning Models

A Bayesian VAR model and a Random Forest model are used as ML models. In essence, machine learning is a subset of artificial intelligence that develops algorithmic models and algorithms to enable computers to perform actions without being programmed. Consequently, these systems process information in a self-contained manner and identify patterns [27]. In statistics, Bayesian VAR models relationships between dependent (class variables) and independent variables (attributes). Predicting continuous-valued attributes can be done using Bayesian VAR. The RapidMiner tool implementation of LR was used. The RMSE performance measure is used to optimize both models [28].

9.2. Bayesian Vector Autoregression (Bayesian VAR)

Vector autoregressive (VAR) models use lags of outcome variables as predictors of relationships between multiple time series, such as unemployment and inflation rates. Using prior unemployment and inflation rates, the current unemployment rate can be modeled. Inflation rates are also at an all-time high right now. With K outcome variables and p lags, VAR models have at least K(pK+1) parameters. Small datasets make it difficult to estimate model parameters reliably [29]. The bayes: var command helps overcome these challenges by incorporating prior information about model parameters into Bayesian VAR models. Parameter estimation is often stabilized this way. Several supported variations of the original Minnesota prior distribution can be used to investigate the influence of a random-walk assumption on the results. Bayesvarstable can be used to test the stability of a parameter assumption. Using bayesfcast and bayesirf, you can create dynamic forecasts and analyze forecast-error variance decomposition (FEVD) and impulse-response function (IRF) [30][31].

Bayesian VAR [26] is a multivariate forecasting algorithm that is highly effective in assessing and predicting financial time series fluctuations. Time series analysis is successful because Bayesian VAR is flexible as well as simple to implement [32]. Bayesian VAR is generally more accurate than univariate time series forecasting models [27]. With Bayesian VAR, all variables are treated as dependents, resulting in a multi-equation system where the number of equations equals the number of variables [33].

Bayesian VAR has the following form at (p) order:

$$\boldsymbol{y_1 = a + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + \cdots \ldots + A_p y_{t-p} + \varepsilon_1} \tag{1}$$

The k-dimensional whitenoise is represented by $\boldsymbol{y_t}$, where is the vector of time series variables, is the vector of intercept terms, and is the coefficient matrix (k×k)..

9.3. Python Programmiing Language

Python is a widely used high-level interpreted language that was first introduced by Guido van Rossum in 1991. Its design emphasizes the use of large white spaces, which promotes readability of the code. With its support for software structures and object-oriented methodologies, Python enables developers to write clear and logical code for both small and large projects. This language is dynamically typed and has automatic garbage collection. It incorporates various programming paradigms such as procedural, object-oriented, and functional programming. Additionally, Python comes with a vast standard library, making it a "battery-included" language [34][35].

$$W = a + bx + t(1) \tag{2}$$

Input and output variables are often analyzed using Bayesian VAR, but this has its drawbacks [16–18]. An explanation of a single variable by Bayesian VAR cannot be complete, just as an explanation by means cannot be complete. The numerous variables are examined using a Bayesian VAR model. The goal (the dependent variable) is affected by several independent variables. It can be described as such when a regression equation includes many variables [36].

$$W = a + f_1 q_1 + f_2 q_2 + f_3 q_3 + t \tag{3}$$

The independent variables $f1;\ f2;\ f3$ are known as the predictors or target variables. In this example, the y-intercept is called s and the coefficients are called $q1;\ q2;\ q3.$

9.4. Random Forest

Based on the findings of multiple decision trees, the random forest is an ensemble learning algorithm initially introduced by [19], [20]. There is no evidence that random forests are susceptible to outliers, disturbances, or overfitting, and they are stable and accurate predictors [37][38].

Using random forest, many unrelated decisions tree types [m (A, L); l = 1, ...] are constructed for training. The classification method uses decision trees to make predictions about categorization of samples. Ultimately, sample classification determines the outcome. Create training sets that aren't related to reducing random forest variance. The random forest model is built using m1(A).... ml(A) sets of classifications derived from sample training. Random forests are based on voting, as shown in Equation (4)[39].

$$M(\alpha) = arg^{max} \sum_{i=1}^{L} D(m_i(a) = Z) \quad (4)$$

Z is the output of the Random Forest model, while (.) is the indicator function. A new training set is generated each time a decision tree sampling is performed. The playback setup has N training subsets, usually a third of the total number of training samples, which is a smaller number than the whole number of training samples [40]. N decision trees are used to construct random forests. The training set generated in the first phase is used to build determination trees for each training subset. Nodes in the decision tree are divided using the CART method. Gini coefficient reduction is applied to randomly selected objects at node t to assign them to class I. Gini coefficient reduction describes how likely it is that our objects are members of class I. Equation E1 represents the possibility of misinterpretation. According to this rule, there are 4[41].

$$Gini = i \neq Jp(i|t)p(j|t) \quad (5)$$

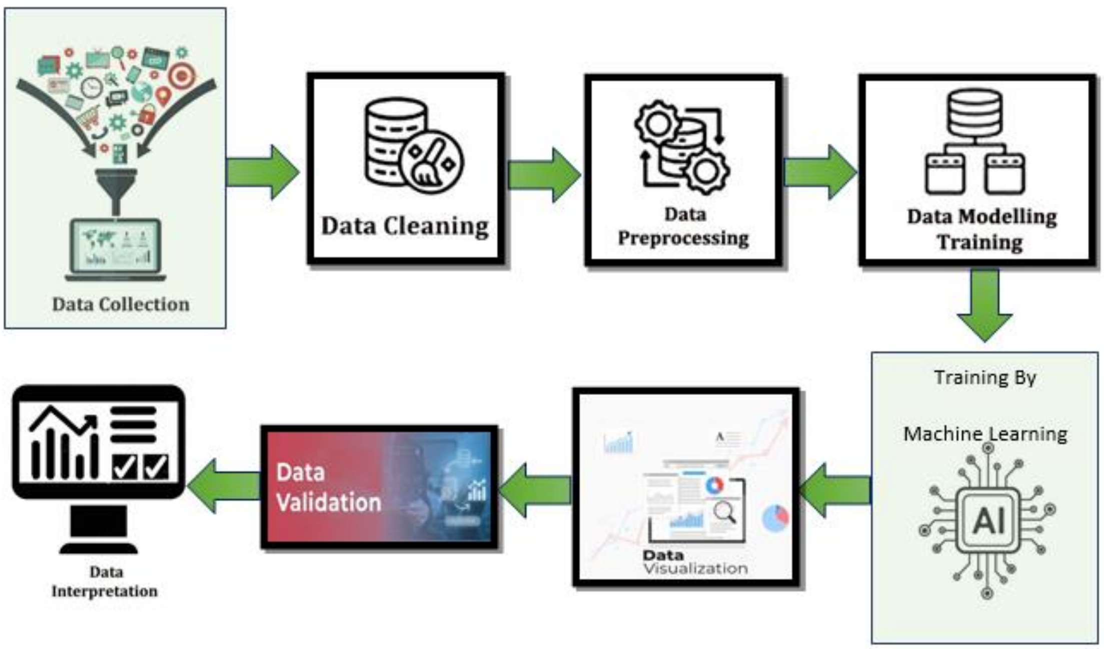

Figure 2.
The proposed methodology schemes.

10. Experimental Datasets

At the moment, a barrel of oil is being traded at a stable range of \$50 to \$55. This period can be considered relatively stable. The demand for oil has decreased between 2016 and 2018 in major economies such as China, India, Russia, and Brazil. However, from the second half of 2018 to the end of 2019, there was a rise in prices. The Brent oil market is prone to price fluctuations and trends. The Brent oil price is a significant factor in the global oil pricing system as it is the benchmark for 68% of the world's oil trade. By analyzing this time frame, more precise and dependable predictions can be made due to the various patterns and spikes that were observed during this period.

A recurring pattern can be defined as seasonality using time-series data. A cyclical trend occurs regularly but does not have a defined duration, unlike stock price fluctuations, which are predictable. Understanding what your data's seasonality trends are will help to evaluate the time-series machine learning algorithm. Data for seasonality and trends are shown in Figure 3. The pairwise relationship in the dataset is shown in Figure 4. In Figure 5, the heat map is shown colored according to the information about the dataset. The correlation heat map in Figure 6 illustrates the correlation between datasets. Figures 7 to 10 present the largest ten statistical probability distribution methods we used in this study.

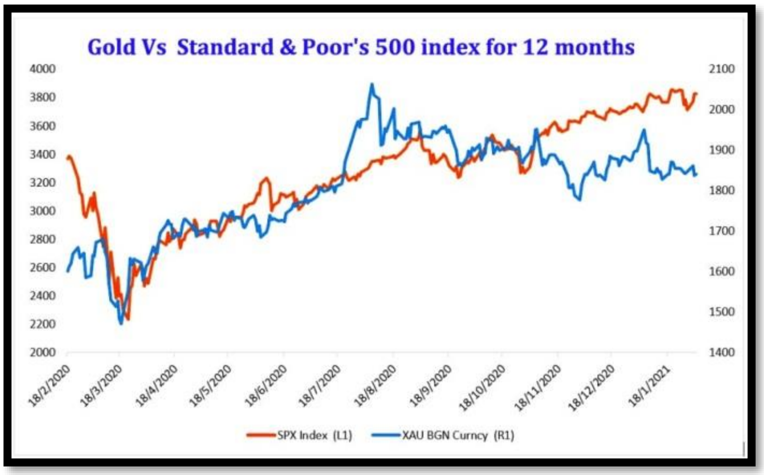

Figure 3.
Reflation hopes of the gold crude of 12 months.

Seasonality refers to a repeating pattern that can be identified through the analysis of time-series data. However, it is important to note that while fluctuations in stock prices can be predicted, they should not be confused with cyclical trends. These trends occur on a regular basis, but do not follow a specific time frame. Being aware of the seasonality patterns in your data can offer valuable insights and act as a reference point for evaluating the performance of your time-series machine learning algorithm. The trend and seasonal data is illustrated in Figure 3, while Figure 4 displays the crude gold yield over a period of 12 months.

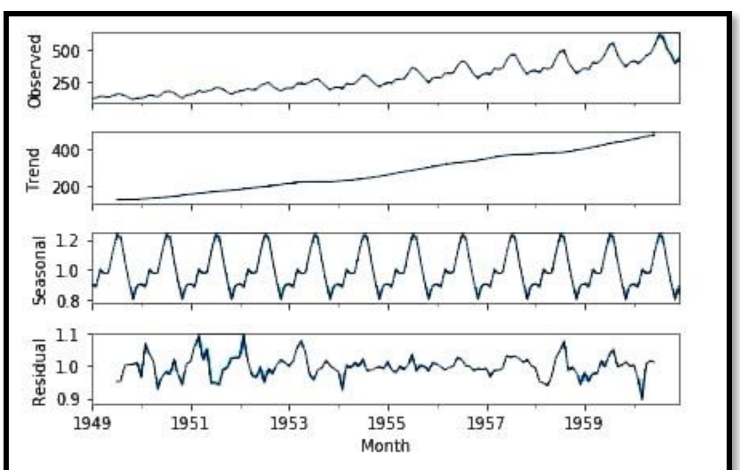

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Figure 4.
Trends and seasonal data.

Figure 5.
Universal crude gold yield 12 months.

10.1. Results

The Bayesian VAR technique is employed to train 67% of the available data. This data is then split into a training set and a testing set of equal proportions (33%), as shown in table 1. Using these coefficients, as presented in table 2, the model is able to make predictions for the next price value in the testing set. In essence, the regression line determines the optimal values for the intercept and slope, resulting in a line that best fits the data. The process of conducting a Bayesian VAR is similar to that of a basic regression, except for the approach used for estimation. This method can be utilized to identify the key factors that have the greatest impact on expected output and their interrelatedness. Figure 11 illustrates the Bayesian VAR model, depicting the actual and predicted values.

The dataset as in Table 1 was used to train the random forest algorithm. Random forest has an accuracy of 0.934. Using Bayesian VAR, the accuracy is 0.99%, while using random forest, it is 0.94%.

Table 2.

	Layer-2	Layer-3	Layer-4	Layer-5
L Rate-1	33.2116	32.5154	32.0512	30.454
L Rate-0.9	33.1405	31.6251	32.0621	31.6252
L Rate-0.8	32.6872	31.5815	31.7453	29.9569
L Rate-0.7	32.5616	32.6435	32.3021	30.35
L Rate-0.6	32.5861	31.4803	32.9001	30.9479

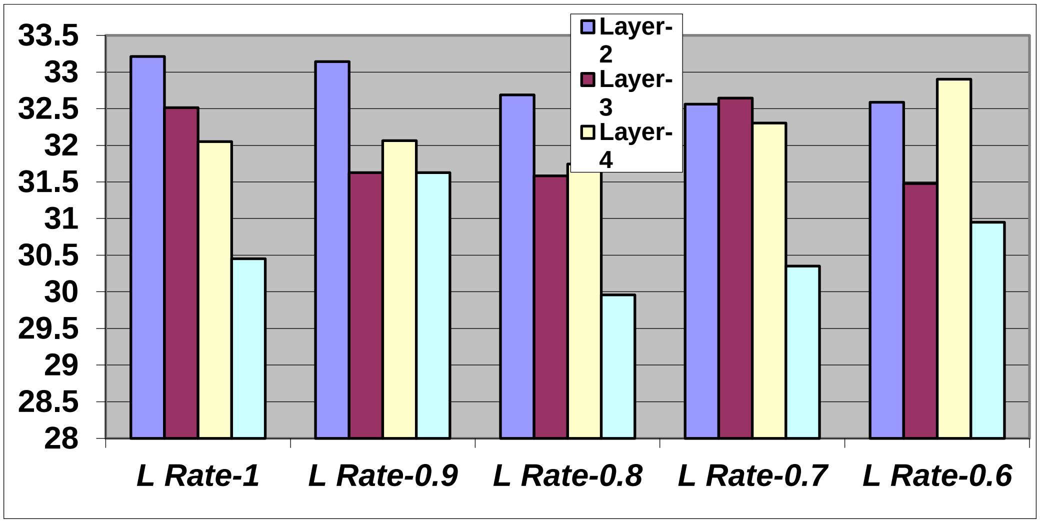

Figure 6.
Error chart on 0-75% training dataset.

11. Conclusion

The crucial impact of crude gold prices on the global economy has led many experts to create precise forecasts for this important economic resource. This is necessary for policymakers to effectively prepare for potential price shocks and minimize their potentially catastrophic consequences. However, analyzing this data is complex due to the presence of lags, nonlinearities, and connections to other markets in the relevant time series. The current literature lacks a suitable model that can accurately capture and optimize these elements. In response, the authors of this paper have developed a Bayesian VAR and a random forest model to forecast crude gold prices. They have gathered daily data on crude gold prices from January 2013 to July 2023 and compared the results of their predictions in pairs.

Throughout history, gold has been regarded as a highly significant commodity. The stability of the global economy relies heavily on the maintenance of gold reserves by central banks. Major companies and investors also allocate a considerable amount of funds towards gold. Despite its complexity, accurately predicting the rate of gold can greatly benefit both investors and central banks in making informed decisions on when to buy and sell, ultimately maximizing profits. In this study, a machine-learning algorithm was utilized to successfully forecast gold rates. By incorporating a variety of economic indicators from different countries and companies, this study is the most comprehensive to date. Additionally, for the first time, interest rates and stock values were used to predict gold rates. Unlike the impact of US economic growth, the stock prices of major companies have a greater influence on the rates of gold. Furthermore, the implementation of ensemble learning and deep learning techniques is expected to further enhance the accuracy of our results in the future.

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