UNIVERSITY OF INFORMATION TECHNOLOGY
**FACULTY OF INFORMATION SYSTEMS**

# Predict gold price by Linear regression, Non-linear regression, ARIMA, LSTM and Boosting model


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# Predict gold price by Linear regression, Non-linear regression, ARIMA, LSTM and Boosting model


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***Abstract*—Gold is a precious metal and has great value in the market. Forecasting is a function to help us make better decisions in investing. It will forecast gold price for the next days and henceforth. Buyers estimate the future gold price.In this report we will apply the method Multiple Linear Regression, Nonlinear Regression, ARIMA, LSTM, Boosting Model method to predict the trend of gold price movement.**



***Keywords—Gold price, prediction, ARIMA, linear regression, non-linear regression, boosting model, LSTM***


## I. INTRODUCTION

Among metals, gold holds a distinct place. It is the first metal that people have used, it is the most valuable, it was the ultimate goal of alchemists, and it is kept in bank vaults. It also happens to be the earliest metal that humans have used. Numerous other uses for gold include gilding and the creation of burial masks. Gold is regarded as a priceless item that is always in demand. Gold is a rare yet extremely liquid asset. Four basic roles for gold in the investment world.A source of long-term profit.

- A diversification tool that can minimize losses in times of market stress.
- A liquid asset with no credit risk has outperformed fiat currency.
- A means of enhancing overall portfolio performance

In terms of market and economic value, gold is valued for its permanence. The law of supply and demand hardly applies to gold because its supply is always increasing and will never decrease. Even when the demand for gold decreases, the supply never decreases. Even the price of gold is rarely affected by the law of supply and demand. Gold is becoming more mainstream. Since 2001, worldwide investment demand for gold has increased by an average of 15% per year.

The share of non-conventional assets in global pension funds has grown from 15% in 2007 to 25% in 2017. And in the US, the figure is close to 30%. . Gold has delivered positive returns over the long term, outperforming major asset classes

World Gold Council research data shows that since 2001, worldwide investment demand for gold has increased by about 15% per year, according to the latest Gold Retail Market Survey Report 2019, in in terms of investment products that investors have ever purchased, gold ranks first with 46%, followed by savings accounts (78%) and life insurance (54%). The total amount of gold purchases by central banks in 2018 was 651 tons, an increase of 74% compared to the same period last year.

Became the highest level of central bank gold since the collapse of the Bretton Woods system in the 1970s. in the first half of 2019, global central banks bought 374.1 tons of gold, a year-on-year growth of 57%. The demand for gold by central banks is increasing. Gold plays more of an important role in a reserve asset.[1]

In this study, we first present the forecasting model for predicting future gold price using Multiple Linear Regression, Nonlinear Regression, ARIMA, Boosting Model method, LSTM. Then, we discussed the performance of the selected model and finally, the comparison between the final model and a benchmark model is presented.

## II. RELATED WORK

The most relevant approach to understanding the gold price is the Multivariable Linear Regression (MLR) model. MLR is the study of the relationship between a single dependent variable and one or more independent variables, as is the case with gold price as the only dependent variable. The MLR fit model will be used to predict future gold prices. Z.ismail and [2] (2009) in their paper "Forecasting Gold Prices Using Multiple Linear Regression Method" has applied Mutiple Linear Regression Method based on based on economic factors such as inflation, currency price movements and other.

Ref Xiaohui Yang [3] in their paper "The Prediction of Gold Price Using ARIMA Model" establishment of ARIMA model. This study also uses AC, PAC, AIC, BIC to estimate the accuracy of models. Empirical outcomes demonstrate that ARIMA (3, 1, 2) is the finest model to predict the gold price of USD.

The paper "Gold Price Forecast based on LSTM-CNN Model" written by Zhanhong,.. The LSTM component enables to harness the sequential order of daily gold price. Meanwhile, the

Attention Mechanism assigns different attention weights on the new encoding method from LSTM component to enhance the extraction of the temporal and spatial features.[4]

Ioannis E.Livierisa, Emmanuel Pintelas and Panagiotis Pintelas with their paper "A CNN–LSTM model for gold price time-series forecasting" .She ran a number of tests and compared the suggested model to deep learning and machine learning methods. The experimental analysis showed that the addition of extra convolutional layers and the use of LSTM layers might significantly improve forecasting ability. [5]

The paper "Forecasting gold price using a novel hybrid model with ICEEMDAN and LSTM-CNN-CBAM" Yanhui Liang, Yu Lin. It shows that the ICEEMDAN method in the suggested model could successfully capture the essence of a sequence. LSTM could extract the long-term effect of the gold price. CNN could mine the deep features of the gold price data. CBAM could enhance the network's ability to extract features. [6]

The author of "Daily Gold price forecasting using LSTM cells and Attention Mechanism" Kalliopi Anastasia (Lilian) Kourti. They consider RNNs for this task because of their ability of finding hidden patterns in timeseries of stock prices. [7]

Sami Ben Jabeur [8] "Forecasting gold price with the XGBoost algorithm and SHAP interaction values" proposes an innovative approach to accurately forecast gold price movements and to interpret predictions. The results illustrate that the use of XGBoost can provide a significant boost in gold price forecasting performance.

Extreme Gradient Boosting (XGBoost), a machine learning technique, first proposed by Chen and Guestrin [9], has performed well in numerous data mining competitions due to its ability to analyze certain important parameters in the model and easily interpret the predicted output. The XGBoost-based model is a massively parallel boosted tree mode and is currently the fastest and best-boosted tree model. It is more than 10 times faster than ordinary models and has been widely used in many fields.

The XGBoost algorithm utilizes many classification and regression trees (CARTs) to solve regression and classification problems. In this study, the prediction of the relative density of SLMed Ti-6Al-4V parts is a logistic regression problem. The XGBoost model is a strong regressor fused by many CART regression tree models. As shown in Figure 1, the structure of XGBoost includes multiple root nodes, internal nodes, leaf nodes, and branches. In this structure, the i-th parameter xi is input and passed to all root nodes of all CARTs to make the original decisions. Then, the internal nodes make subsequent decisions, the branch points point directly to the decision to be made, and the leaf nodes represent the prediction results of a single CART. Finally, the results of all leaf-pointing nodes are combined to obtain the prediction results of the XGBoost model [9].

According to several research, XGBoost improves other algorithms in dealing with tabular datasets, such as artificial neural networks (ANN) and support vector regression (SVR), which typically require large-scale datasets in the form of images or videos.[10] [11].

In a more recent study, Duan et al. predicted the compressive strength of recycled aggregate concrete using XGBoost, ANN, and SVR. They found that XGBoost outperformed other algorithms and that the XGBoost decision tree algorithm is excellent at solving nonlinear regression issues.[12]

Because of its established precision, XGBoost has recently been applied to additive manufacturing. For instance, Zhang et al. used LSTM with XGBoost to precisely estimate the temperature of a molten pool.[13]

## III. DATA AND METHODOLOGY

### *A. Data sources*

We get data from the website Finance.yahoo.com.

The gold price data from 3/1/2017 to 31/12/2021.

After retrieving the data, we reviewed, edited, and deleted the data at the date of incomplete information.

Google training data has information from January 3, 2017, to December 31, 2021. There are five columns. The Open column shows the price at which the stock started trading when the market opened on a particular day. The Close column refers to the cost of an individual stock when the stock exchange closes the need for the day. The High column describes the highest price at which a gold stock has traded over time. The Low column shows the lowest price of the period. Volume is the total amount of trading activity over some time.

Below is the data after data collection and editing is done.

| | Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|---|
| 0 | 1/3/2017 | 1155.2 | 1160.8 | 1146.5 | 1160.4 | 1160.4 | 52 |
| 1 | 1/4/2017 | 1156.3 | 1165.0 | 1156.3 | 1163.8 | 1163.8 | 36 |
| 2 | 1/5/2017 | 1172.0 | 1183.3 | 1171.5 | 1179.7 | 1179.7 | 500 |
| 3 | 1/6/2017 | 1176.5 | 1176.5 | 1171.9 | 1171.9 | 1171.9 | 16 |
| 4 | 1/9/2017 | 1173.9 | 1183.6 | 1173.0 | 1183.5 | 1183.5 | 62 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 1231 | 12/27/2021 | 1810.0 | 1812.1 | 1807.0 | 1808.1 | 1808.1 | 150 |
| 1232 | 12/28/2021 | 1812.0 | 1818.0 | 1805.5 | 1810.2 | 1810.2 | 146 |
| 1233 | 12/29/2021 | 1803.2 | 1805.1 | 1791.4 | 1805.1 | 1805.1 | 623 |
| 1234 | 12/30/2021 | 1801.7 | 1816.0 | 1796.0 | 1812.7 | 1812.7 | 306 |
| 1235 | 12/31/2021 | 1825.1 | 1827.8 | 1821.4 | 1827.5 | 1827.5 | 80 |

*Figure 1. Gold data table (2017-2021)*

### *B. Linear Regression*

According to the research of the paper "A study on multiple linear regression analysis" written by Gulden Kaya Uyanik [14], Regression analysis is a statistical technique for estimating the relationship among variables which have reason and result relation. Focus of univariate regression is analyzing the relationship between a dependent variable and one independent variable and formulates the linear relation equation between dependent and independent variable. Regression models with one dependent variable and more than one independent variable are called multilinear regression.

In multivariate regression analysis, an attempt is made to account for the variation of the independent variables in the dependent variable synchronically (Unver & Gamgam, 1999). Multivariate regression analysis model is formulated as in the following:

$$y = \beta_0 + \beta_1 + \cdots + \beta_n x_n + \varepsilon$$

$y = dependent\ variable$

$x_i = independent\ variable$

$\beta_i = parameter$

$\varepsilon = error$

Examples where multiple linear regression may be used include:

- Trying to predict an individual's income given several socio-economic characteristics.
- Trying to predict the overall examination performance of pupils in 'A' levels, given the values of a set of exam scores at age 16.
- Trying to estimate systolic or diastolic blood pressure, given a variety of socioeconomic and behavioral characteristics (occupation, drinking smoking, age etc).

As is the case with simple linear regression and correlation, this analysis does not allow us to make causal inferences, but it does allow us to investigate how a set of explanatory variables is associated with a dependent variable of interest.

In terms of a hypothesis test, for the case of a simple linear regression the null hypothesis, H0 is that the coefficient relating the explanatory (x) variable to the dependent (y) variable is 0. In other words that there is no relationship between the explanatory variable and the dependent variable. The alternative hypothesis H1 is that the coefficient relating the x variable to the y variable is not equal to zero. In other words there is some kind of relationship between x and y.

In summary, we would write the null and alternative hypotheses as follows:

$H_0\colon\ \beta_1 = 0$

$H_1\colon\ \beta_1 \neq 0$

### *C. ARIMA*

According to Box and Jenkins (1976) [15], the ARIMA model is one of the widely used models for predicting the price of gold.

This model tries to make the connection between historical value and current value and future value of time series data feasible. Analysts, exporters, importers, multinational corporations, speculators, and traders in the foreign exchange market all hold the belief that historical patterns can give a short-term inference of future action.

The three main steps in the ARIMA Model Development process are time series preprocessing, identification, estimation, diagnostic testing, and prediction. The Augmented Dickey-Fuller (ADF) unit test determines if gold prices are stable in a one-variable model.

Model definition: ARIMA model applies only to static series Models can be represent as AR, MA, or ARMA. The method of determining the model is usually do by studying the direction of change of the autocorrelation function ACF or the partial autocorrelation function PACF.

Non-stationary ARIMA series: needs to be convert to stationary series before calculating the least squares parameter estimate. It is do by calculating the difference between the observed values based on the assumption of different parts of the parameters. Time series are all treat similarly, except for the mean. If the conversion fails, other types of conversions (for example, logarithmic transformations) will be apply. Parameter estimation: computes initial estimates for the parameters a0, a1... ap. b1... bq, of the intended model. The final estimates are then construct using a set-up process.

Accuracy test: After the parameters of the general model have been build, we check the accuracy and fit of the model with the data. We test the residuals (Yt- Y^t) and have the significance as well as the relationship of the parameters. If any of the tests is not satisfied, the model will re-identify the steps above to be perform again.

Forecast: When the model is suitable for the found data, we will make the prediction. at the next time t. Therefore, the ARMA (p.q) model:

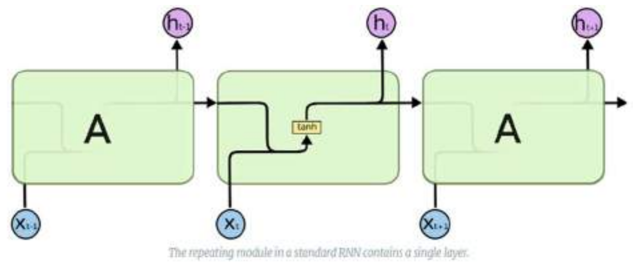
$$\begin{aligned} y(t+1) = a_0 + a_1 y(t) + \cdots + a_p y(t-p+1) + e(t+1) \\ + b_1 e(t) + \cdots + b_q e(t-q+1) \end{aligned}$$

### *D. LSTM*

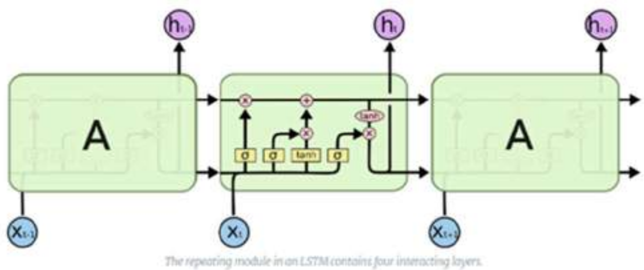
Long Short Term Memory networks, commonly known as LSTMs - are a special type of RNN that is capable of learning distant dependencies. LSTM was introduce by Hochreiter & Schmidhuber (1997), and has since been refined and popularized by many people in the industry. They work extremely effectively on many different problems, so they have gradually become as popular as they are today.

LSTM is designed to avoid the problem of long-term dependency. Remembering information for a long time is their default property, we don't need to train it to be able to remember it. That is, its internals can already be memorized without any intervention.

Every recurrent network takes the form of a sequence of repeating modules of a neural network. With standard RNNs, these modules have a very simple structure, usually a single layer.

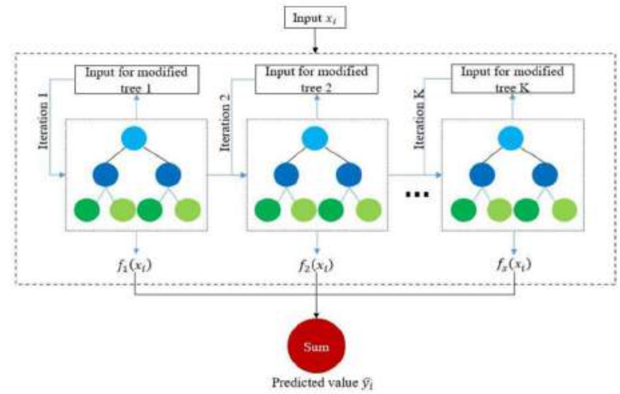



The LSTM also has the same chained architecture, but its modules have a different structure from that of a standard RNN. Instead of just one layer of neural networks, they have up to four layers that interact with each other in a very special way.




### *E. Boosting Model method*

To address classification and regression issues, the XGBoost method makes extensive use of classification and regression trees (CARTs). In this study, a logistic regression problem is used to predict the relative density of SLMed Ti-6Al-4V components. A number of CART regression tree models combine the powerful regressor of the XGBoost model. The topology of XGBoost is depicted in Figure 1 and consists of several root nodes, internal nodes, leaf nodes, and branches. To make the initial decisions, all root nodes of all CARTs receive the i-th parameter's value, xi, as input. Then, the leaf nodes indicate the forecast outcomes of a single CART, the interior nodes create following decisions, the branch points directly point to the decision to be made, and so on. The prediction results of the XGBoost model are then obtained by combining the outcomes of all leaf-pointing nodes [16].




As an example, in the i-th set (xi, yi) (xi is the input data with multiple features, yi is the real value of the trial), the XGBoost regression tree model is expressed mathematically as: [17]

$$\hat{y}_i = \alpha \sum_{k=1}^{k} fk(xi)$$

Where yˆi is the predicted value corresponding to input xi, α is the learning rate of the individual regression tree, K is the total number of CARTs being used, and fk is the output of the k-th regression tree.

$$L = \sum_{i}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_x)$$

The objective function consists of two parts: (1) The loss function l, measuring the loss between yˆi and yi and (2) the regularization item **Ω**, determining the complexity of the regression tree structure. For a CART, **Ω** was expressed as

$$\Omega(\mathrm{f}) = \gamma \mathrm{T} + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega^2{}_j$$

## IV. MODEL SETTING

### *A. Data analysis*

#### *1. Close Price*

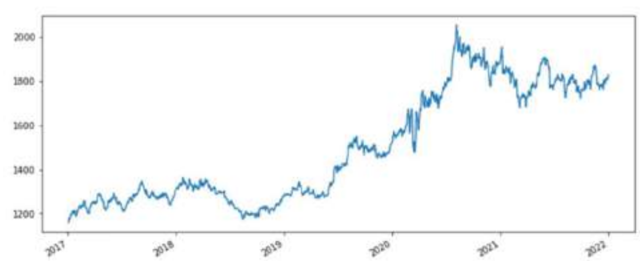



*Figure 3. Graph of Close Price of gold (2017-2021)*

2. *Train Graph*

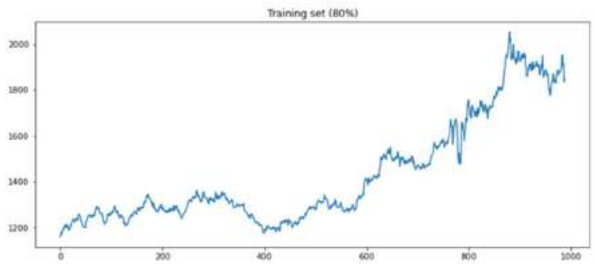



*Figure 4. Graph of train (80%)*

3. *Test Graph*

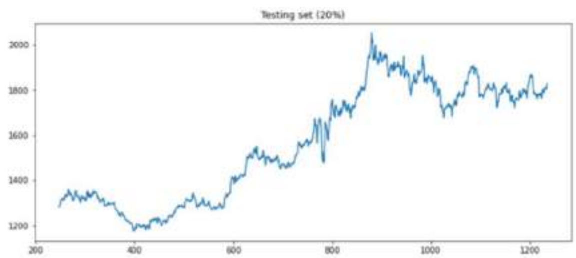



*Figure 5. Graph of test (20%)*

### *B. MAPE, RMSE*

**MAPE**

Mean Absolute Error (MAE) measures the average error in a set of predictions without considering their direction. In other words, the MAE is the mean absolute value of the deviations between the prediction and the actual data, where all individual deviations are weighted equally. The formula for MAE is defined by (3.2).

$$\text{MAE} = \frac{1}{\text{n}}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

In statistics, the mean absolute percentage error (MAPE), also referred to as the mean absolute percentage deviation (MAPD), is a metric for forecasting method accuracy. The accuracy is often expressed as a ratio determined by the following formula:

$$\text{MAPE} = \frac{100\%}{\text{n}}\sum_{t=1}^{n} |\frac{A_t - F_t}{A_t}|$$

Advantages:

•Since absolute values are taken, all errors are calculated on the same linear scale, so no weight is given to outliers.

• Easy comparison between different models.

Disadvantage:

• If the model is heavily influenced by outliers, MAE will be ineffective. Large errors coming from outliers will be weighted identically to smaller errors. This can result in the model being able to often make good predictions, but also often to make some very poor predictions.

**RMSE**

Root Mean Squared Error (RMSE) calculates the square root of the mean squared error between the predicted and actual values of the sample.

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

Advantages:

• RMSE ensures that the limited model predicts outliers with large errors, because RMSE places more weight on large errors due to the squared part of the calculation formula.

Disadvantages:

• If the model gives a very bad prediction, the squared portion of the function will overstate the error. In many practical cases, however, don't pay much attention to these outliers and aim for a comprehensive model that works well enough for the masses.

The similarity of MAE and RMSE is that both are non-negative values, and lower values are better. The important difference between the RMSE and the MAE is that since the errors are squared before averaging, the RMSE gives a relatively high weight to large errors. This means that RMSE is more useful when it comes to large errors.

### *B. Linear Regression*

*Train-test (90% - 10%)*

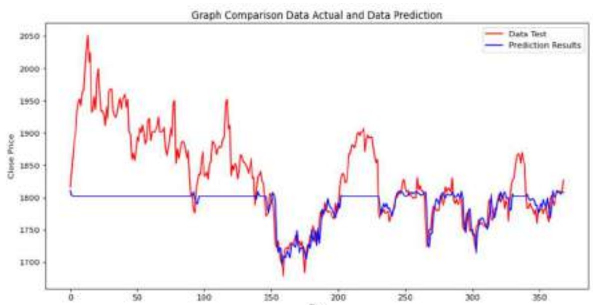

*Train-test (80%-20%)*

*Train-test (70%-30%)*

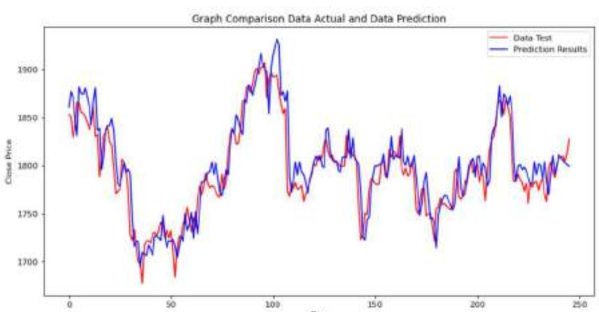

*Figure 6. Compare the actual value and predicted value in Linear Regression*

## *C. Non-Linear Regression*

*Train-test (70%-30%)*




*Train-test (80%-20%)*




*Train-test (90%-10%)*

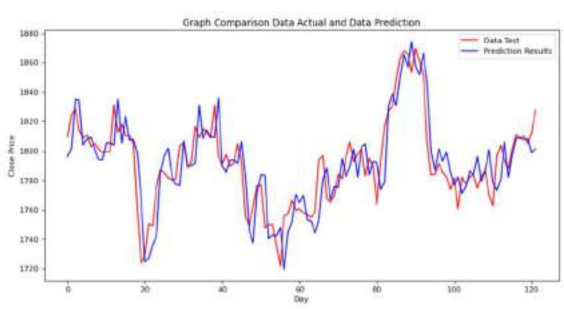



*Figure 7. Compare the actual value and predicted value in Non-Linear Regression*

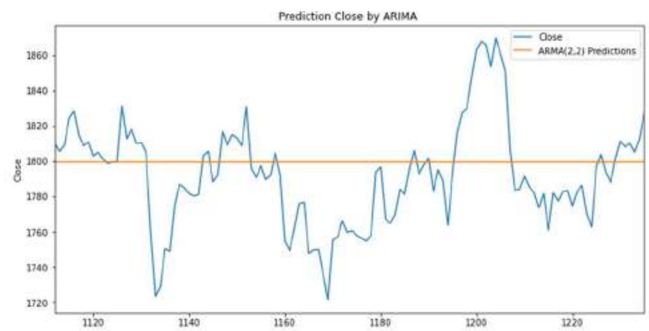
## *D. ARIMA*

*Train-test (90%-10%)*

| | | | |
|---|---|---|---|
| Dep. Variable: | Close | No. Observations: | 1112 |
| Model: | ARIMA(0, 1, 0) | Log Likelihood | -4575.100 |
| Date: | Mon, 02 Jan 2023 | AIC | 9152.201 |
| Time: | 20:50:01 | BIC | 9157.214 |
| Sample: | 0 | HQIC | 9154.096 |
| | - 1112 | | |
| Covariance Type: | opg | | |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| sigma2 | 220.9937 | 4.064 | 54.375 | 0.000 | 213.028 | 228.960 |

| | | | |
|---|---|---|---|
| Ljung-Box (L1) (Q): | 0.40 | Jarque-Bera (JB): | 3606.88 |
| Prob(Q): | 0.53 | Prob(JB): | 0.00 |
| Heteroskedasticity (H): | 6.67 | Skew: | -0.56 |
| Prob(H) (two-sided): | 0.00 | Kurtosis: | 11.76 |




*Train-Test (80%-20%)*

| | | | |
|---|---|---|---|
| Dep. Variable: | Close | No. Observations: | 989 |
| Model: | ARIMA(0, 1, 0) | Log Likelihood | -4053.419 |
| Date: | Mon, 02 Jan 2023 | AIC | 8108.837 |
| Time: | 20:49:47 | BIC | 8113.733 |
| Sample: | 0 | HQIC | 8110.699 |
| | - 989 | | |
| Covariance Type: | opg | | |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| sigma2 | 214.3118 | 4.066 | 52.706 | 0.000 | 206.342 | 222.281 |

| | | | |
|---|---|---|---|
| Ljung-Box (L1) (Q): | 0.53 | Jarque-Bera (JB): | 3645.10 |
| Prob(Q): | 0.47 | Prob(JB): | 0.00 |
| Heteroskedasticity (H): | 6.36 | Skew: | -0.43 |
| Prob(H) (two-sided): | 0.00 | Kurtosis: | 12.37 |


*Train-test (70%-30%)*

| | | | |
|---|---|---|---|
| Dep. Variable: | Close | No. Observations: | 865 |
| Model: | ARIMA(0, 1, 0) | Log Likelihood | -3418.671 |
| Date: | Mon, 02 Jan 2023 | AIC | 6839.341 |
| Time: | 20:49:54 | BIC | 6844.103 |
| Sample: | 0 | HQIC | 6841.164 |
| | - 865 | | |
| Covariance Type: | opg | | |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| sigma2 | 160.0882 | 3.105 | 51.561 | 0.000 | 154.003 | 166.174 |

| | | | |
|---|---|---|---|
| Ljung-Box (L1) (Q): | 0.19 | Jarque-Bera (JB): | 3828.15 |
| Prob(Q): | 0.66 | Prob(JB): | 0.00 |
| Heteroskedasticity (H): | 4.78 | Skew: | 0.48 |
| Prob(H) (two-sided): | 0.00 | Kurtosis: | 13.27 |

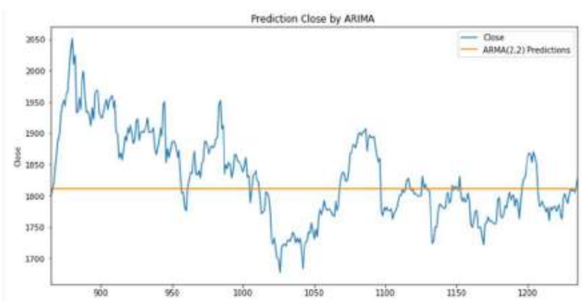
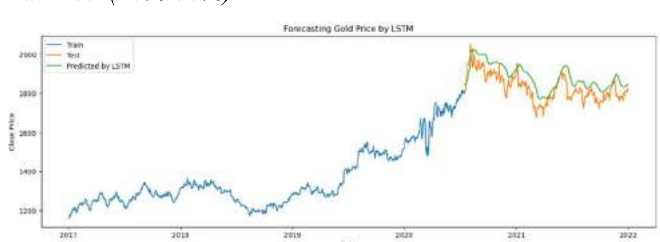


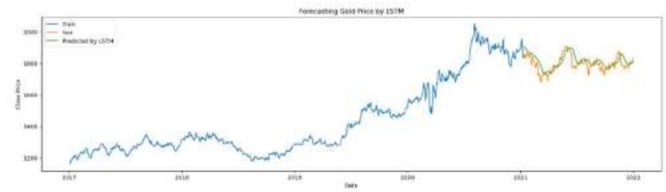

*Figure 8. Compare the actual value and predicted value in ARIMA*

***E. LSTM***

*Train-test (70%-30%)*




*Train-test (80%-20%)*



*Train-test (90%-10%)*

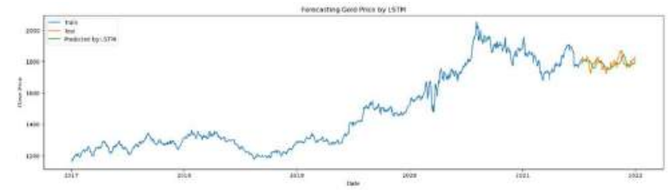


*Figure 9. Compare the actual value and predicted value in LSTM*

***F. Boosting Model***

*Train-test (70%-30%)*


*Train-test (80%-20%)*


*Train-test (90%-10%)*


*Figure 10. Compare the actual value and predicted value in XGBoost*

## V. CONCLUSION

<table>
<tr><th>Model</th><th>Train-test</th><th>RMSE</th><th>MAPE</th></tr>
<tr><td rowspan="3">ARIMA</td><td>7,3</td><td>71.94306149</td><td>3.151558548</td></tr>
<tr><td>8,2</td><td>71.60130532</td><td>3.344174208</td></tr>
<tr><td>9,1</td><td>30.19852993</td><td>1.288772057</td></tr>
<tr><td rowspan="3">LR</td><td>7,3</td><td>430.0357666</td><td>27.62256299</td></tr>
<tr><td>8,2</td><td>404.262886</td><td>25.93407631</td></tr>
<tr><td>9,1</td><td>368.5502813</td><td>22.53881069</td></tr>
<tr><td rowspan="3">NLR</td><td>7,3</td><td>0.078814652</td><td>6.755713089</td></tr>
<tr><td>8,2</td><td>0.022892604</td><td>2.44382116</td></tr>
<tr><td>9,1</td><td>0.018797069</td><td>2.058789629</td></tr>
<tr><td rowspan="3">LSTM</td><td>7,3</td><td>66.16465975</td><td>3.132303067</td></tr>
<tr><td>8,2</td><td>38.37400094</td><td>1.614817844</td></tr>
<tr><td>9,1</td><td>28.04114466</td><td>1.230366687</td></tr>
<tr><td rowspan="3">XGBoost</td><td>7,3</td><td>72.51854746</td><td>3.097124185</td></tr>
<tr><td>8,2</td><td>117.0247615</td><td>5.482490781</td></tr>
<tr><td>9,1</td><td>47.0880027</td><td>1.886239484</td></tr>
</table>

According to the result table:

- ARIMA method has a train-test (9-1) that gives the lowest MAPE. (1.288772057)
- *LR* method has a train-test (9-1) that gives the lowest MAPE. (22.53881069)
- NLR method has a train-test (9-1) that gives the lowest MAPE. (2.058789629)
- LSTM method has a train-test (9-1) that gives the lowest MAPE. (1.230366687)
- XGBoost method has a train-test (9-1) that gives the lowest MAPE. (1.886239484)

In conclusion, we can see that the LSTM method has a train-test (9-1) that gives the lowest MAPE. Therefore, we will use LSTM method to predict the gold price for next 30 days.

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