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Gold Prices Time-Series Forecasting: Comparison of Statistical Techniques

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Abstract

This research confronts the formidable task of predicting gold prices, grappling with the inherent volatility of this precious metal. Employing an array of statistical techniques, including linear regression, naive Bayes, and various smoothing algorithms, the study draws from a robust 70-year dataset sourced from Kaggle. Its core objective is to elevate predictive accuracy and precision, offering tangible insights for investors and the wider public. By conducting a meticulous comparative analysis of these methods, the research contributes significantly to existing knowledge, deepening our understanding of algorithmic efficacy over an extensive time frame. At its essence, this study seeks not only theoretical advancements but practical implications, bridging the gap between the complexities of gold price movements and the need for reliable predictions. The research underscores the superiority of a single exponential smoothing method, substantiated by an impressive Mean Absolute Percentage Error (MAPE) score of 7.12%. Beyond its immediate impact on decision-makers navigating gold markets, this discovery holds broader significance, guiding future research endeavors in financial forecasting. By providing a comprehensive exploration of multiple algorithms and their comparative performance, this research establishes a foundational reference point for scholars and practitioners, advancing the collective understanding of predicting gold prices and enhancing the sophistication of future forecasting methodologies.

Keywords: Time Series, Gold Prices, Linear Regression, Exponential Smoothing

1. Introduction

The fluctuation in gold prices can be influenced by various factors, including monetary policies, interest rates, and global economic conditions. In the long term, gold prices tend to rise in tandem with inflation and economic uncertainty. However, in the short term, gold prices can be highly volatile and are influenced by factors such as changes in industrial demand and market speculation [1][2][3]. In recent years, gold prices have experienced significant increases, driven by concerns about slowing economic growth, high levels of national debt, and geopolitical uncertainty. In 2020, gold prices saw a substantial uptrend, reflecting the uncertain global economic conditions resulting from the Covid-19 pandemic. Simultaneously, loose monetary policies by central banks have further supported the rise in gold prices [4][5].

Generally, gold prices are expected to continue their upward trajectory, although short-term fluctuations are common. Analysts often recommend gold investments as a means of hedging against inflation and economic uncertainty. However, as investors, conducting research and evaluation is essential before making investment decisions [6][7]. Deep learning is one of the technologies that can be used to predict gold prices. Deep learning algorithms employ highly complex neural networks to analyze data and make predictions. In this context, the data used can include historical gold prices, global economic factors, and market news [8][9].

The process of predicting gold prices using deep learning algorithms begins with the collection of relevant data. This data is processed and cleaned to remove noise. Subsequently, the data is used to train neural networks that will be utilized in deep learning algorithms to predict future gold prices [10]. These predictions are based on patterns identified in historical data and global economic factors used during the neural network training. However, it is important to note that these predictions are not always accurate and should be used as a guide in making investment decisions [11].

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This research aims to determine the best algorithm for predicting gold prices using various methods such as Linear Regression (LR), Naive Bayes (NB), Simple Average (SA), Moving Average (MA), Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES). Linear regression is used to find a linear relationship between gold prices and other important variables [12][13], while naive bayes is used for classifying the class of an object based on its attributes [14][15]. Other methods like SES, DES, and TES are employed to calculate the average gold prices from the collected data. The results of the best algorithms used in this study can provide valuable information for investors and gold market participants in making their investment decisions [16].

The primary objective of this research is to address the intricacies of predicting gold prices, a challenge compounded by their inherent volatility. Previous studies, such as those conducted by Zhang and Ci [17], Ben Jabeur et al. [18], Alameer et al. [19], and Liang et al. [30], have made valuable contributions to this field, each employing distinct models and methodologies. The first study, conducted by Zhang and Ci [17], utilized a multivariate GAS model to predict the volatility and correlation between oil and gold prices. While providing insights into the mutual influence of oil and gold prices, this study laid the foundation for employing multivariate models in predicting both prices. Ben Jabeur et al. [16] focused on utilizing a Markov Regime Switching Autoregressive model to predict gold prices in Pakistan, shedding light on the applicability of this model in specific geographical contexts and the impact of market condition changes on prediction outcomes. Alameer et al. [19] and Liang et al. [20] introduced hybrid models, emphasizing their ability to enhance prediction accuracy and their utility in gold price analysis.

However, despite these valuable contributions, a research gap exists. Previous studies typically employed a limited number of algorithms in gold price prediction, potentially leading to less accurate and comprehensive predictions. This research seeks to fill this gap by extending understanding from the aforementioned studies and combining techniques used in those studies to predict gold prices. Additionally, it aims to provide a more in-depth analysis of how external factors, such as economic and political conditions, can influence gold prices. This novel approach, incorporating LR, NB, SA, MA, SES, DES, and TES algorithms, distinguishes our study from previous research, offering a more robust and comprehensive exploration of gold price prediction.

2. Literature Review

2.1. Factors Influencing Gold Prices

Previous research has delved deeply into understanding the intricate web of factors that exert influence on gold prices. Among these, monetary policies, interest rates, and the broader global economic landscape emerge as pivotal determinants shaping the trajectory of gold markets. Over the long term, gold prices demonstrate a discernible positive correlation with inflation and economic uncertainty. This enduring relationship underscores gold's role as a hedge against economic instability. Conversely, in the short term, gold prices experience volatility driven by factors like fluctuations in industrial demand and speculative activities within the market [1][2][3].

The enduring correlation between gold prices and inflation, as well as economic uncertainty, underscores gold's unique position as a long-term hedge. Previous studies have consistently observed that as inflationary pressures mount and economic uncertainty looms large, the value of gold tends to rise. Investors often turn to gold as a store of value during periods of economic turbulence. This long-term perspective provides a nuanced understanding of gold's role beyond mere market dynamics, emphasizing its significance as a stabilizing asset in the face of broader economic challenges.

While gold's long-term relationship with economic factors is well-established, short-term fluctuations tell a different story. The volatility witnessed in gold prices within shorter time frames is intricately linked to the dynamism of market speculation and changes in industrial demand. Investors and market participants keen on understanding the nuances of gold prices in the short term must consider these factors. Recognizing the dual nature of gold prices, influenced by both enduring economic trends and short-term market dynamics, is vital for a comprehensive understanding of gold as a financial instrument [1][2][3].

2.2. Recent Trends in Gold Prices

The dynamic nature of gold prices reveals a responsiveness to significant global events, creating a market environment characterized by volatility. One noteworthy instance of such dynamism occurred in 2020, marked by a substantial

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uptrend in gold prices. This surge was propelled by a confluence of factors, including growing apprehensions surrounding the global economy's deceleration, escalating national debt levels, and the geopolitical uncertainties stemming from the Covid-19 pandemic. Investors sought refuge in gold as a safe-haven asset during these tumultuous times [4][5].

The notable uptrend in gold prices during 2020 can be attributed to several interconnected factors. Firstly, concerns about the economic fallout from the Covid-19 pandemic instilled a sense of uncertainty among investors, prompting a flight to the perceived stability of gold. Additionally, high national debt levels further heightened economic anxieties, pushing investors towards alternative assets like gold. Furthermore, the implementation of loose monetary policies by central banks globally served as a significant driving force behind the surge. The infusion of liquidity into financial markets reinforced gold's appeal as a store of value and contributed to the upward trajectory of its prices [4][5].

The surge in gold prices in 2020 holds implications not only for investors but also for the broader economic landscape. As gold is often considered a barometer of economic uncertainty, its upward movement reflected the prevailing unease in global markets. Investors, recognizing gold's historical role as a hedge against economic volatility, reevaluated their portfolios, seeking a balance that would withstand the challenges posed by the pandemic and its economic repercussions. The consequences of this surge extend beyond the realm of investment, influencing economic policy discussions and shaping perceptions of financial stability in the face of unprecedented global challenges.

2.3. Deep Learning in Gold Price Prediction

To navigate the intricate landscape of gold price prediction, researchers have embraced cutting-edge technologies, placing a specific emphasis on deep learning methodologies. These advanced algorithms utilize intricate neural networks to delve into historical gold prices, global economic conditions, and market news, aiming to extract meaningful patterns and trends [8][9]. The application of deep learning in this context signifies a departure from traditional forecasting methods, offering a more dynamic and adaptable approach to understanding the complexities inherent in the gold market.

The deployment of deep learning algorithms in predicting gold prices involves a meticulous process. Commencing with the collection of relevant data, the subsequent steps include a comprehensive cleaning procedure designed to eliminate extraneous noise that could distort the accuracy of predictions. The heart of this methodology lies in the training of neural networks, where the algorithms are fine-tuned to recognize intricate patterns within the historical data and grasp the nuanced interplay between various global economic factors. This process forms a critical foundation for the subsequent predictive analyses [10].

While deep learning algorithms present a promising avenue for predicting gold prices, it is imperative to approach their outcomes with a degree of caution. Predictions derived from these algorithms are based on historical data patterns and global economic factors, and as such, they are not infallible. The inherent unpredictability of financial markets necessitates a measured interpretation of deep learning predictions, emphasizing the importance of supplementing algorithmic analyses with a comprehensive understanding of the broader economic landscape. This cautionary note underscores the critical role of informed decision-making and thorough evaluation in the realm of gold investments [11].

2.4. Comparative Analysis of Prediction Algorithms

This study significantly enhances the literature by embarking on an extensive comparative analysis of various prediction algorithms, each playing a distinct role in forecasting gold prices. The algorithms scrutinized encompass a diverse range, including Linear Regression (LR), Naive Bayes (NB), Simple Average (SA), Moving Average (MA), Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES). LR, as a key player, is instrumental in establishing linear relationships with crucial variables, offering insights into the directional trends of gold prices [12][13].

Beyond LR, the study delves into the classification expertise of Naive Bayes (NB), shedding light on its ability to categorize objects based on inherent attributes [14][15]. Simultaneously, the research employs traditional methods such as Simple Average (SA), Moving Average (MA), Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES) to compute average gold prices. These techniques provide a nuanced understanding of the broader spectrum of prediction methodologies, each contributing unique analytical perspectives [12][13][14][15].

The comprehensive exploration of these diverse algorithms underscores the study's commitment to advancing the understanding of gold price prediction. By leveraging a combination of linear relationships, classification techniques, and traditional averaging methods, the research aims to uncover nuanced patterns within the data. This multifaceted approach positions the study to contribute valuable insights to investors and market participants seeking a more comprehensive and robust framework for making informed decisions in the dynamic gold market [16].

3. Methodology

This research utilizes Jupyter with LR, NB, SA, MA, SES, DES, and TES algorithms. The research stages are illustrated in Figure 1.

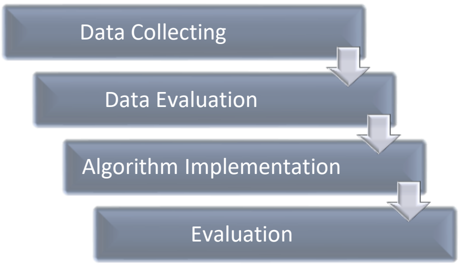

Figure 1. Research Phases

3.1. Data Collection

The dataset used in this research is Gold Prices obtained from Kaggle, consisting of historical annual and monthly gold prices. The quality of the dataset is evaluated, as inaccurate or incomplete data can lead to invalid research results. In this stage, the acquired data is examined and analyzed to assess its accuracy, precision, and completeness. Subsequently, the evaluated data is further processed to simplify it and make it more manageable for analysis. Data is processed by altering data formats, removing unnecessary data, or scaling data. The processed data is then used for analysis and modeling in the following stages.

3.2. Data Evaluation

Data evaluation, or EDA (Exploratory Data Analysis), is a crucial stage in this research process. During this stage, components in the dataset are evaluated. Components that influence gold prices include economic factors such as inflation, interest rates, and stock market conditions.

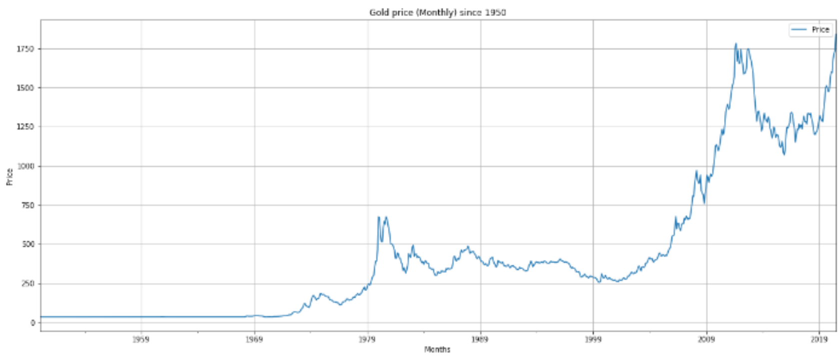

Figure 2. Increase in gold prices (per month) over a 70-year period.

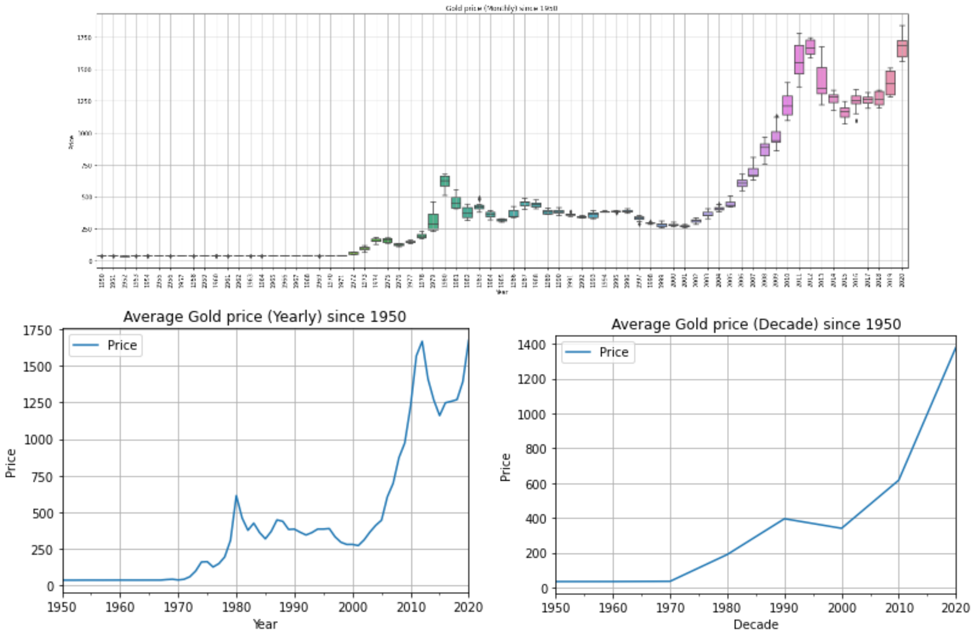

Figure 3. (a) Candle chart of gold price increases from 1950, (b) Average gold price increase per year, and (c) Average gold price increase per decade.

EDA is also used to evaluate the features present in the dataset. Analyzed features include gold prices from various previous periods, trade volume, and the number of investors engaging in gold transactions. The purpose of this stage is to understand the quality and characteristics of the dataset, ensuring it can be effectively used for accurate gold price prediction. Invalid data is removed and replaced with valid data to enhance the accuracy of the analysis. After the EDA stage is completed, a clear understanding of the quality and characteristics of the dataset is obtained, facilitating the subsequent process of creating an accurate and reliable gold price prediction model.

3.3. Algorithm Implementation

This research is implemented using several algorithms, namely LR, NB, SA, MA, SES, DES, and TES. The linear regression algorithm is employed to establish the relationship between independent and dependent variables in the Gold Prices data. The naive bayes algorithm is used to determine the probability of an event based on historical gold price data. The Simple Average algorithm calculates the average gold price from historical data. The Moving Average algorithm computes the average gold price from historical data by shifting the time frame used.

Figure 4. Data partitioning in the time-series prediction process.

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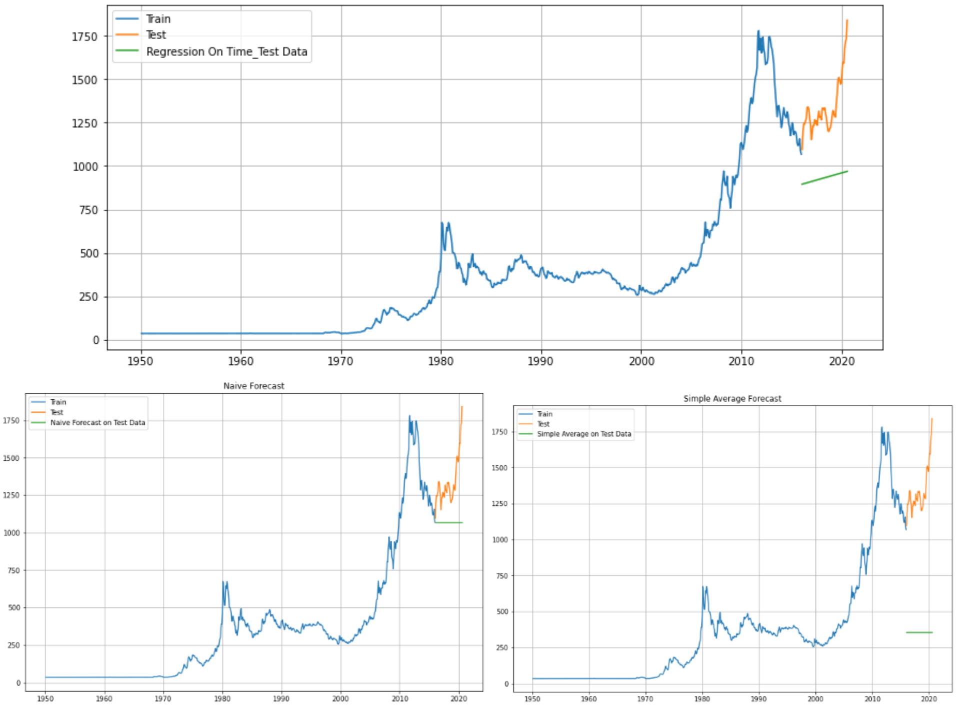


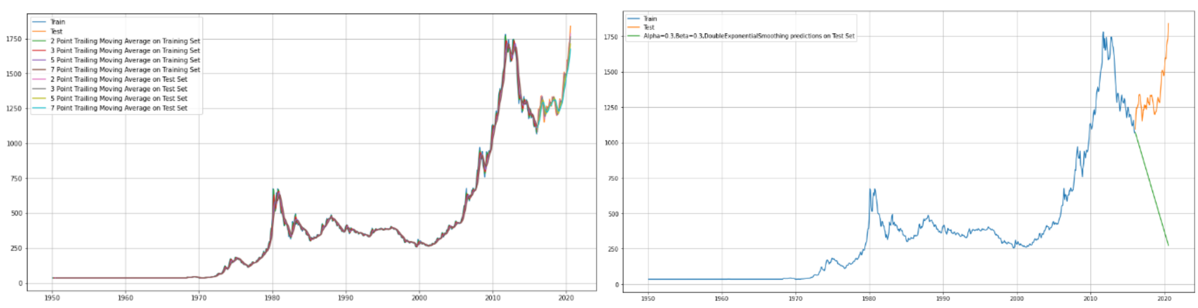
Figure 5. (a) Linear regression test results, (b) Naive Bayes test results, and (c) Simple average forecast test results.

Meanwhile, SES, DES, and TES algorithms are used to calculate the average gold price from historical data using more advanced smoothing methods. By utilizing these algorithms, the predictions of gold prices are more accurate and can serve as a basis for investment decisions.

3.4. Evaluation

In this stage, the results obtained from data analysis are validated and analyzed to determine the accuracy of the gold price predictions made:

1) The results from data analysis need to be validated by checking whether the data used in the research meets the specified criteria.
2) After data validation, it is then analyzed to determine the accuracy of the gold price predictions made using appropriate statistical methods, such as regression or artificial neural network analysis.



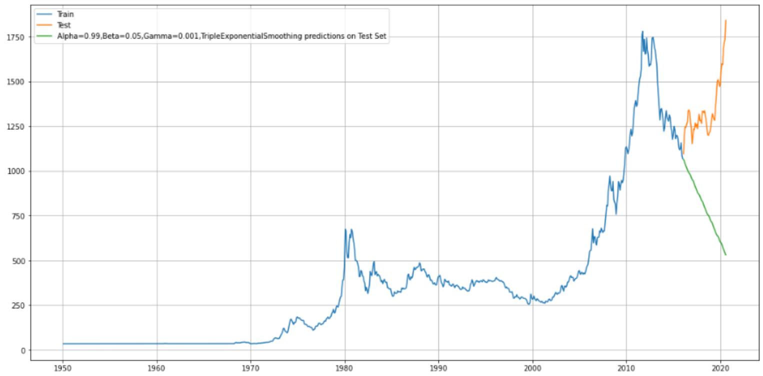


Figure 6. Results of smoothing algorithm testing.

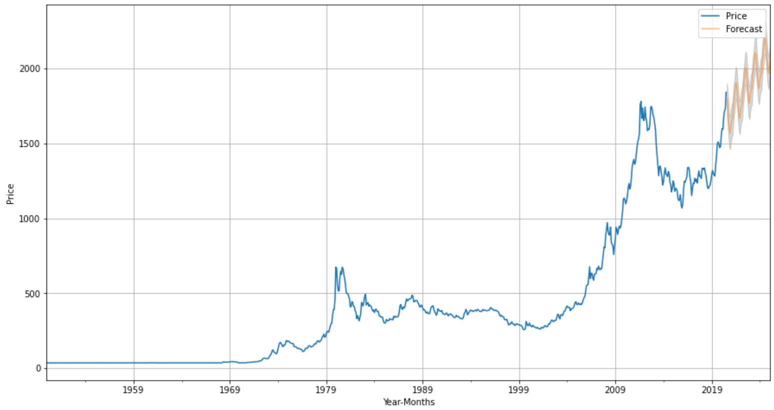


Figure 7. Exponential smoothing on the gold price dataset.

3) The analysis results are compared with historical gold price data to evaluate the accuracy of the predictions by comparing the predicted results with the actual gold prices for the same period.
4) The evaluation results are translated into recommendations useful for market participants, such as investors or gold traders.
5) The evaluation results are published in the form of a report or academic publication to be shared with experts in the field and serve as a reference for further research.

4. Result and Discussion

Gold price is considered a significant indicator in the financial market. Gold is viewed as a safe haven for investors due to its perceived stability and resistance to economic fluctuations. Therefore, gold prices are often used as a reference for investment decision-making. From the data, it can be observed that gold prices tend to remain stable in the long term.

The increase in gold prices (per month) over a 70-year range is shown in Figure 2. The average gold price over the last 70 years is approximately $416.56. There have been no significant long-term changes in gold prices. However, in the short term, gold prices can experience relatively high fluctuations. Gold prices above $447.07 occurred only about 25% of the time, indicating that most of the time, gold prices were below $447.07. This does not mean that gold prices never exceeded that level, as the highest gold price ever reached was $1840.81. This demonstrates that gold prices can experience significant short-term increases. Overall, gold prices tend to remain stable in the long term, but they can exhibit considerable short-term fluctuations, which investors should consider in their investment decisions.

A more detailed visualization of the average and gold price increases can be seen in Figure 3, which includes (a) a candle chart of gold price increases from 1950, (b) the average gold price increase per year, and (c) the average gold price increase per decade. The Train-Test split is a method used to divide data into two parts: training data and testing data. The data partitioning in the time-series prediction process is illustrated in Figure 4. Figure 5 displays (a) the results of linear regression testing, (b) the results of naive bayes testing, and (c) the results of simple average forecast testing.

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By splitting the data in this manner, we can assess the accuracy of models built using different data for training and testing.

An 80:20 data split is an ideal division in the computational process. In this case, 80% of the data will be used as training data, while the remaining 20% will be used as testing data. This ensures that we have enough data to train the model effectively and also enough data to test the model's accuracy. Time series forecasting is a method used to predict changes in time-series data. In this context, the constructed model will be used to predict future data changes. Therefore, splitting the data in this way allows us to test the model with data relevant to future situations.

Using data from before the year 2015 as test data also enables us to evaluate the model's ability to handle previously unseen situations. This is essential because, in the real world, we often have to deal with unprecedented situations. Testing the model with data that has not been used before allows us to evaluate the model's ability to handle unforeseen circumstances. Table 1 shows the results of the overall Mean Absolute Percentage Error (MAPE) values for each algorithm in this study.

Table 1. MAPE Test Values

	Test MAPE (%)
Linear Regression	18.33
Naïve Bayes	25.31
Simple Average Model	21.86
Moving Average	14.92
Exponential Smoothing	7.12

Exponential Smoothing is a method used in forecasting gold price data. In performing forecasting, Exponential Smoothing provides the most ideal accuracy and precision. This can be seen from the obtained MAPE (Mean Absolute Percentage Error) value, which is 7.12. The MAPE value obtained from Exponential Smoothing indicates that the error in forecasting the gold price is only 7.12%. This is a very good value, considering the randomness and unpredictability of gold prices over a 70-year period.

Exponential Smoothing utilizes a method that takes into account the average values of historical gold price data, thereby providing more accurate results compared to other methods. Additionally, Exponential Smoothing also considers the impact of price changes over a relatively long period, resulting in more precise outcomes.

The research results demonstrate that by using a 70-year dataset of gold prices, it is possible to generate a forecast graph of gold prices for the next 10 years. The testing of the smoothing algorithm is shown in Figure 6. The algorithm used in this research is Exponential Smoothing, known for its superior performance compared to other algorithms.

Figure 7 depicts Exponential Smoothing on the gold price dataset, and the graph produced by this research indicates that gold prices will continue to rise in the next 10 years. This is quite reasonable since gold prices are considered a stable investment instrument that tends to increase over the long term. Additionally, gold is also regarded as a safe haven asset used as protection against inflation and economic crises.

However, in the graph forecasting gold prices for the next 10 years, there is a unique aspect to consider. This is because gold prices are not always stable and tend to fluctuate in the short term. Factors such as changes in monetary policy, global politics, and economics can influence gold prices in the short term.

Overall, the research results show that the Exponential Smoothing algorithm can be used to generate a forecast graph of gold prices for the next 10 years. However, it is important to remember that gold prices are not always stable and are still influenced by external factors. Therefore, routine and in-depth analysis is necessary to predict gold price movements in the long term.

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5. Conclusion

In conclusion, the findings of this research present a compelling case for the use of Exponential Smoothing in predicting gold prices over the next decade based on a comprehensive dataset spanning 70 years. The algorithm's superior performance underscores its efficacy in forecasting, providing a basis for a forecast graph that suggests a continued upward trajectory in gold prices. This prognosis aligns with the well-established perception of gold as a stable asset and a safe haven, particularly during times of economic uncertainty.

A key contribution of this research lies in its recognition of the multifaceted influences on gold prices. External factors, notably developments in global politics and economics, emerge as significant determinants. The observed stability or slight decrease in gold prices during periods of global political and economic stability contrasts with the notable uptick during times of instability. This nuanced understanding emphasizes the importance of considering broader contextual factors when predicting gold prices.

The implications of this study extend beyond the realm of forecasting, offering valuable insights for investors. The indication of a continued rise in gold prices over the next decade aligns with its role as a hedge against inflation and a refuge during economic turbulence. As such, this research serves as a reference point for informed investment decisions in the realm of gold, acknowledging the interconnectedness of economic conditions and geopolitical developments with the trajectory of gold prices. The impact of this research is not only in its predictive capabilities but also in its potential to guide strategic investment decisions that account for the dynamic interplay of factors influencing gold markets.

6. Declarations

6.1. Author Contributions

Conceptualization: I.M. and C.; Methodology: C.; Software: I.M.; Validation: I.M. and C.; Formal Analysis: I.M. and C.; Investigation: A.S.P.; Resources: A.S.P.; Data Curation: A.S.P.; Writing Original Draft Preparation: I.M. and A.S.P.; Writing Review and Editing: I.M. and A.S.P.; Visualization: A.S.P.; All authors, I.M., C., and A.S.P., have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

References

[1] I. E. Livieris, E. Pintelas, and P. Pintelas, “A CNN–LSTM model for gold price time-series forecasting,” *Neural Comput. Appl.*, vol. 32, no. 23, pp. 17351–17360, 2020.

[2] L. Chen and X. Zhang, “Gold price forecasting based on projection pursuit and neural network,” in *Journal of Physics: Conference Series*, 2019, vol. 1168, no. 6, p. 62009.

[3] J. Fajou and A. McCarren, "Forecasting gold prices using temporal convolutional networks," in *29th Irish Conference on Artificial Intelligence and Cognitive Science 2021*, 2021, vol. 3105, pp. 248–259.

[4] F.-C. Yuan, C.-H. Lee, and C. Chiu, "Using market sentiment analysis and genetic algorithm-based least squares support vector regression to predict gold prices," *Int. J. Comput. Intell. Syst.*, vol. 13, no. 1, pp. 234–246, 2020.

[5] S. Garg, "Forecasting of gold prices using Bayesian regularization neural network," in *Nanoelectronics, circuits and communication systems, Springer,* 2021, pp. 147–153.

[6] T. B. Qasim, G. Z. Iqbal, M. U. Hassan, and H. Ali, "Application of Markov Regime Switching Autoregressive Model to Gold Prices in Pakistan," *Rev. Econ. Dev. Stud.*, vol. 7, no. 3, pp. 309–323, 2021.

[7] X. Yang, "The prediction of gold price using ARIMA model," in *2nd International Conference on Social Science, Public Health and Education (SSPHE 2018),* 2019, pp. 273–276.

[8] D. Makala and Z. Li, "Prediction of gold price with ARIMA and SVM," in *Journal of Physics: Conference Series,* 2021, vol. 1767, no. 1, p. 1, 2022.

[9] M. Mohtasham Khani, S. Vahidnia, and A. Abbasi, "A deep learning-based method for forecasting gold price with respect to pandemics," *SN Comput. Sci.*, vol. 2, no. 4, pp. 1–12, 2021.

[10] X. Li, D. Li, X. Zhang, G. Wei, L. Bai, and Y. Wei, "Forecasting regular and extreme gold price volatility: The roles of asymmetry, extreme event, and jump," *J. Forecast.*, vol. 40, no. 8, pp. 1501–1523, 2021.

[11] S. Verma, G. T. Thampi, and M. Rao, "ANN based method for improving gold price forecasting accuracy through modified gradient descent methods," *IAES Int. J. Artif. Intell.*, vol. 9, no. 1, p. 46, 2020.

[12] E. Jianwei, J. Ye, and H. Jin, "A novel hybrid model on the prediction of time series and its application for the gold price analysis and forecasting," *Phys. A Stat. Mech. its Appl.*, vol. 527, p. 121454, 2019.

[13] A. K. Anima Estetikha, D. H. Gutama, M. G. Pradana, and D. P. Wijaya, "Comparison of k-means clustering & logistic regression on university data to differentiate between public and private university," *IJIIS: International Journal of Informatics and Information Systems,* vol. 4, no. 1, pp. 21–29, 2021. doi:10.47738/ijiis.v4i1.74

[14] R. Chen and J. Xu, "Forecasting volatility and correlation between oil and gold prices using a novel multivariate GAS model," *Energy Econ.*, vol. 78, pp. 379–391, 2019.

[15] C. Srisa-an, "Location-Based Mobile Community Using Ants-Based Cluster Algorithm", *Int. J. Appl. Inf. Manag.*, vol. 1, no. 1, pp. 36–41, Apr. 2021.

[16] F. Weng, Y. Chen, Z. Wang, M. Hou, J. Luo, and Z. Tian, "Gold price forecasting research based on an improved online extreme learning machine algorithm," *J. Ambient Intell. Humaniz. Comput.*, vol. 11, no. 10, pp. 4101–4111, 2020.

[17] P. Zhang and B. Ci, "Deep belief network for gold price forecasting," *Resour. Policy,* vol. 69, p. 101806, 2020.

[18] S. Ben Jabeur, N. Stef, and P. Carmona, "Bankruptcy prediction using the XGBoost algorithm and variable importance feature engineering," *Comput. Econ.*, pp. 1–27, 2022.

[19] Z. Alameer, M. Abd Elaziz, A. A. Ewees, H. Ye, and Z. Jianhua, "Forecasting gold price fluctuations using improved multilayer perceptron neural network and whale optimization algorithm," *Resour. Policy,* vol. 61, pp. 250–260, 2019.

[20] Y. Liang, Y. Lin, and Q. Lu, "Forecasting gold price using a novel hybrid model with ICEEMDAN and LSTM-CNN-CBAM," *Expert Syst. Appl.*, vol. 206, p. 117847, 2022.