NIET Journal of Engineering & Technology (NIETJET)
Volume 11, Issue Winter 2022 ISSN: 2229-5828 (Print)

Artificial Intelligence-driven model for Gold Price Prediction

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Abstract: *This study introduces an innovative approach to forecasting gold prices by employing Artificial Intelligence (AI)--driven models. By applying the sophisticated machine learning methods, such as the Random Forest, Decision Tree, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 Error, the study assesses the predictive power of these models by means of thorough evaluations. A particular focus is placed on ensemble learning, exemplified by the Random Forest model, which demonstrates superior accuracy in capturing intricate patterns within gold price data. These findings contribute valuable insights to the field of financial forecasting, emphasizing the potential of AI-driven models to inform stakeholders in gold investment and financial markets. The study concludes by advocating for ongoing research and continuous model refinement to adapt to dynamic market conditions and enhance the precision of gold price predictions.*
Keywords *gold price prediction artificial intelligence, MSE.*

1. INTRODUCTION

In recent times, the incorporation of artificial intelligence (AI) into financial markets has transformed the decision-making processes of analysts and investors [1]. An especially interesting application of AI in the financial sector is its role in predicting gold prices [2]. Gold, renowned as a safe-haven asset and an indicator of economic uncertainty, undergoes dynamic price fluctuations influenced by factors like Geopolitical Indicator events, inflation, and global economic conditions [3]. Traditional methods of forecasting gold prices often struggle to grasp the intricacies of these dynamic factors [4].

The emergence of AI, with its capacity to handle vast datasets, identify patterns, and adapt to evolving market conditions, has introduced new avenues for more precise and insightful gold price predictions [5]. Machine learning algorithms, neural networks, and other AI techniques empower analysts to analyze historical data, monitor market sentiment, and assess macroeconomic indicators in real-time, offering a comprehensive understanding of the factors impacting gold prices [6].

The integration of AI into gold price prediction not only improves forecast accuracy but also empowers investors to make more informed decisions in the face of an increasingly volatile market [7]. With ongoing technological advancements, the synergy between artificial intelligence and the complexities of gold market dynamics holds the promise of a more sophisticated and efficient approach to forecasting gold prices, potentially reshaping investment strategies in the precious metals market [8]. This paper delves into the methodologies and advancements in AI-driven gold price prediction, shedding light on the potential benefits and challenges associated with this innovative approach [9].

2. LITERATURE REVIEW

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The paper [10] presents a compelling contribution to the field of gold price prediction through the introduction of an innovative deep-learning forecasting model. The combination of convolutional and LSTM layers demonstrates promising results, showcasing the potential for improved forecasting accuracy. As the research progresses, addressing some minor limitations and expanding the comparative analysis could further solidify the paper's impact within the domain of financial forecasting. In paper [11] stands out as a valuable contribution to the domain of gold rate prediction. Leveraging LSTM networks and grounded in both robust theory and empirical evidence, the proposed methodology holds promise for enhancing financial forecasting accuracy. Addressing the aforementioned suggestions, particularly providing additional details on the dataset and delving into comparative analyses and limitations, would undoubtedly bolster the overall impact and scholarly significance of the paper. this article [12] offers a valuable contribution to the understanding of gold price dynamics by exploring the multifaceted relationship between gold prices and influencing factors. The application of machine learning algorithms, coupled with thoughtful temporal segmentation, provides nuanced insights into the varying predictive accuracies of these models across distinct market conditions. This research holds significance for both academics and practitioners seeking a comprehensive understanding of the intricate interplay between gold prices and diverse economic factors. the paper [13] presents an innovative approach by integrating agent-based simulation and machine learning, particularly simulated annealing, for financial time series approximation. This literature review aims to contextualize the proposed methodology by exploring existing research in agent-based modelling, machine learning, and their integration in financial contexts. Additionally, it will discuss the originality of the paper's approach and its potential implications for advancing the field of financial modeling and analysis. In the article [14] highlights the growing importance of accurately predicting gold prices in the realms of investment and economic decision-making. The comparative analysis of ARIMA and SVM models demonstrates the superior predictive accuracy of SVM, suggesting its applicability in forecasting commodity prices. As uncertainty continues to shape global markets, the study advocates for the adoption of advanced machine learning techniques, with SVM emerging as a preferred choice for enhancing the accuracy of gold price predictions.

3. PROPOSED METHODOLOGY:

For the purpose of our gold price prediction study, we utilized a dataset for training and testing our models. Specifically, In order to help our models discover patterns and relationships in the data, 80% of the dataset was set aside for training. 20% of the dataset was set aside for testing, which gave us the opportunity to check how well the models performed on omitted data and gauge their predictive power.

i) DATASET

The dataset utilized in this study was sourced from the Kaggle repository. The dataset consists of the following attributes:

a) Date: Represents the date associated with each data entry.
b) SPX: Refers to the stock market index, specifically the S&P 500.
c) GLD: Denotes the price of gold.
d) USO: Represents he US Oil Fund, an exchange-traded fund (ETF) that follows changes in the price of crude oil.
e) SLV: Indicates the price of silver.
f) EUR/USD: Represents the exchange rate between the Euro (EUR) and the United States Dollar (USD).

These attributes collectively provide a comprehensive view of financial and economic indicators, facilitating the exploration and analysis conducted in this research. Fig 1 shows the co-relation heat map of the Gold Price dataset.

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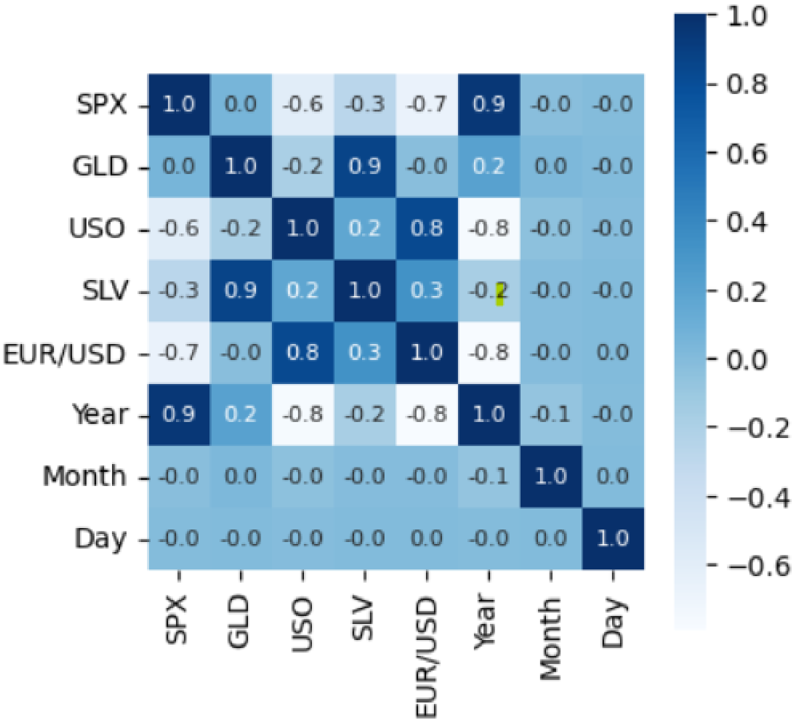

Fig 1: Heat map of the dataset

ii) MODEL IMPLEMENTED

In our research paper, we explore the applicability of various machine learning algorithms to predict gold prices.

- **logistic regression is** one of the popular statistical technique for binary classification problems. Logistic Regression models the probability of an event occurrence and is particularly suitable for scenarios where the outcome is binary. In the context of gold price prediction, Logistic Regression offers insights into the likelihood of specific price movements, aiding in forecasting whether the gold price will increase or decrease.

- **Decision Trees**, which are non-linear models capable of capturing complex relationships within datasets. Decision Trees recursively split data based on feature values, enabling them to identify critical decision points within historical gold price data. By leveraging these

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decision points, the model becomes adept at predicting future gold price movements with the high degree accuracy.

- **Support Vector Machines (SVM),** are powerful classifiers that aim to find the optimal hyperplane to separate data points into distinct classes. SVM excels in delineating boundaries between various gold price trends, leveraging its capability to handle non-linear relationships to discern intricate patterns in the data. This makes SVM particularly effective for gold price prediction tasks, where the relationships between features may be non-linear and complex.

- **Random Forest**, an ensemble learning method is that constructs multiple decision trees and merge the all outputs to improve predictive generalization and accuracy. Random Forest is well-suited for capturing intricate relationships within gold price data. By amalgamating insights from diverse decision trees, the model provides a robust prediction mechanism for gold price movements, offering reliable forecasts that account for various factors influencing gold prices.

4. RESULT

In our research paper, we present the results of our gold price prediction models, each evaluated based on the main performance metrics including the Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R2 Error (Table 1).

Model	**MSE**	**RMSE**	**R2 Error**
Logistic regression	0.0961	0.3100	0.6157
Random forest	0.0306	0.1748	0.8777
Decision Tree	0.0393	0.1982	0.8428
SVM	0.0961	0.3100	0.6157

Table 1 performance metrics

The Logistic Regression model yielded an MSE of 0.0961, RMSE of 0.3100, and an R2 Error of 0.6157. The Random Forest model demonstrated superior performance with the lowest MSE of 0.0306, RMSE of 0.1748, and the highest R2 Error of 0.8777. The Decision Tree model exhibited an MSE of 0.0393, RMSE of 0.1982, and an R2 Error of 0.8428. Notably, the Support Vector Machine (SVM) model mirrored the results of the Logistic Regression, sharing an MSE of 0.0961, RMSE of 0.3100, and an R2 Error of 0.6157. Fig 2 shows the ROC curve.

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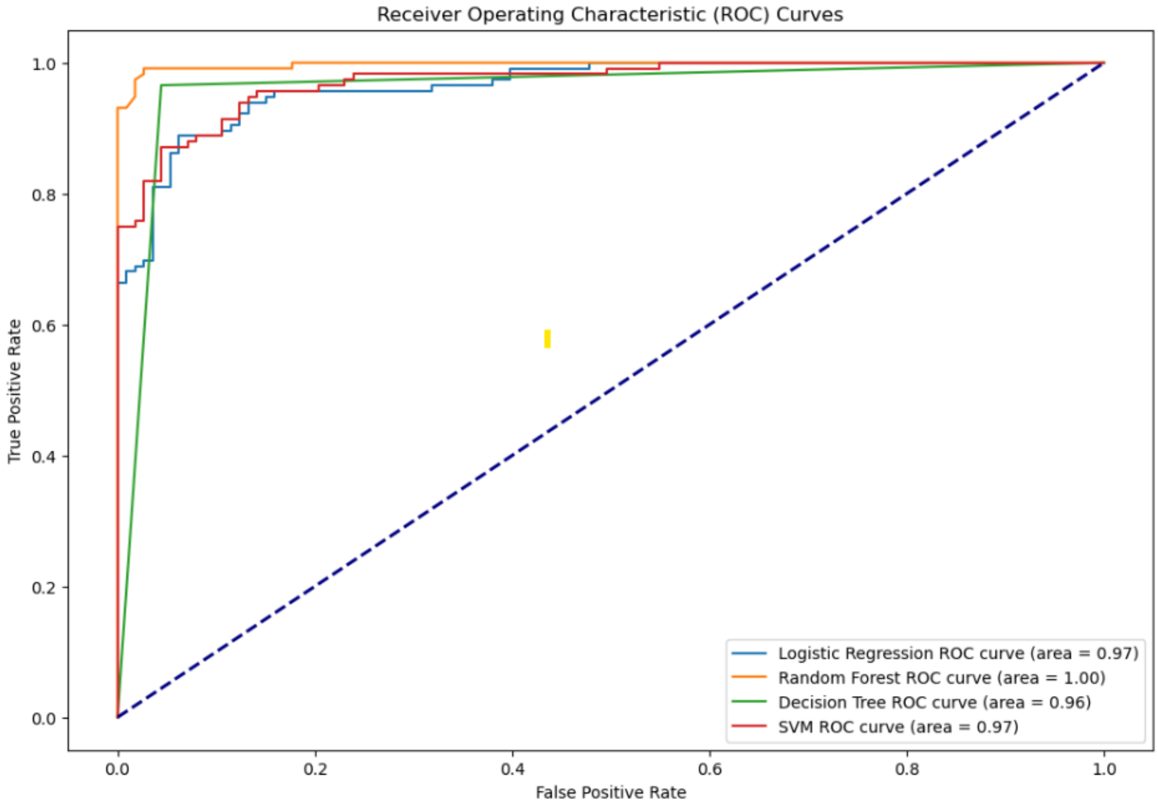

Fig 2 ROC Curve

5. CONCLUSION

In conclusion, our investigation into gold price prediction models reveals that the Random Forest model consistently outperforms its counterparts, showcasing superior accuracy and demonstrating its potential efficacy in predicting gold prices. The meticulous evaluation of the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 Error metrics substantiate Random Forest model's robust performance, with the lowest MSE and RMSE values and the highest R2 Error among the models considered. These results underscore the significance of ensemble learning and the amalgamation of multiple decision trees in capturing intricate relationships within gold price data. The Random Forest model's ability to navigate complex patterns positions it as a promising tool for accurate and reliable gold price predictions, offering valuable insights for stakeholders in financial markets and investment decision-making. However, ongoing research and refinement of predictive models are recommended to adapt to evolving market dynamics and enhance the precision of gold price forecasts.

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