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Forecasting Silver Price Using Monte Carlo Simulations and Prophet Models

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Abstract: **Precious metals have long been considered safe havens for investors due to their anti-inflationary nature and ability to store value. In 2025, silver was put under the spotlight due to its dramatic price change, hitting new historical records and increasing investors' attention to the commodity. This study is conducted to provide a comparative analysis between Monte Carlo simulation and the Prophet model using historical data from January 2019 to October 2025, to generate two-year silver price forecasts. Monte Carlo simulation generated results for different seniors showing uncertainty and price fluctuation under various market circumstances, while the hybrid model provided more accurate and reliable results. The key discoveries included the significance of combining multiple techniques to generate better predictions and to estimate trends and market directions. This study also contributes to the evolving discussions on forecasting silver prices by providing the groundwork for further studies in this area.**

Keywords: *Silver Price Prediction, Monte Carlo Simulation, Prophet, Random Forest, Time Series Forecasting, Machine Learning.*

I. INTRODUCTION

In the world`s economy, silver has played a significant role due to its many applications in technology, production, and investment, besides its value as a precious metal. The prices of silver tend to fluctuate frequently in response to the investor's behavior, economic growth, and inflation, which makes it a reliable measure for general marketplace conditions. Forecasting silver price has been crucial for investors, policymakers, and traders. Predicting the prices will assist them to make better decisions.

Considering all the recent advancements in machine learning and data science, reliability and accuracy have increased in forecasting. The prophet model and monte Carlo simulation are two effective techniques that are applied in this paper. Facebook has created the prophet model, it is created to deal with time series data, it examines past data, identify trends and patterns. Prophet model typically preforms well even with outliers and irregular data, and that's what makes it a useful tool to forecast.

Monte Carlo simulation was invented by Jhon von Neumann and Stanislaw Ulam. It is a model of probability. It examines historical prices, and it predicates a range of probable values. Combining the two models all together will provide us with an extensive understanding of the silver marketplace. By using both forecasting models, this paper aims to provide a comprehensive study of how silver prices may change in the near future, allowing investors, policymakers, and traders to make better financial decisions and foresee any potential change in the market.

II. LITERATURE REVIEW

Key factors affecting the silver price are global and geopolitical conditions, USD value, industrial demand, investment demand, financial market dynamics, central bank policies and actions, market sentiment and investors' risk appetite, and demand and supply factors. However, many other variables can influence the price of silver, especially in periods of crises and pandemics, such as the global financial crisis in 2008 or the COVID-19 pandemic in 2020 [17].

One of the major concerns regarding silver is the emerging risk of supply shortage, which could lead to a significant increase in silver prices. Although silver is not among the materials at great risk, estimations suggest that there will be a shortage of silver supply in the long run. The world average demand per capita for silver is expected to increase around the year 2030 for the following sectors: jewelry, manufacturing and the PV industry [9]. However, due to the expanding gap between demand and supply, only around 62-70% of silver total demand is expected to be met by the 203rd decade "in press"[2].

A. Silver Price Prediction Using Monte Carlo Simulation:

Monte Carlo simulation is a fundamental quantitative method for forecasting the dynamics of precious metal prices, as it models stochastic processes and the inherent randomness of financial markets. Recent empirical studies integrate Monte Carlo techniques with Geometric Brownian Motion (GBM) to simulate thousands of potential silver price trajectories, thus generating probabilistic pricing distributions. This methodological framework was demonstrated by researchers to provide an exhaustive risk assessment by incorporating price volatility, exogenous market shocks, and macroeconomic variables [1].

Similarly, another study found that Monte Carlo simulations are beneficial during times of increased instability in commodity markets, as they provide realistic ranges of possible price movements rather than single-point predictions [7]. Monte Carlo-based models are argued to outperform traditional linear forecasting methods when predicting price reactions to geopolitical crises, currency fluctuations, and shifts in industrial demand [11]. Overall, the literature suggests that Monte Carlo simulation is effective for assessing uncertainty and stress-testing future silver prices.

B. Silver Price Prediction Using FB Prophet and Random Forest Hybrid Model:

Hybrid forecasting models that combine time-series analysis with machine learning techniques have recently been used to forecast precious metals. For example, one framework first applies FB Prophet to identify trends and seasonality, then uses Random Forests to model nonlinear relationships. It was found that this hybrid approach enhances silver price prediction accuracy by merging statistical decomposition with machine learning [18].

Similar hybrid method was used to predict precious metal prices. And it was found that combining Prophet with Random Forests reduced forecasting errors compared to traditional models such as ARIMA [10]. Combining machine learning with advanced time-series techniques yields more stable, resilient predictions during market disruptions, making hybrid modeling a promising approach for forecasting silver prices amid rapid economic shifts [3].

C. Comparative Analysis and Insights:

The literature shows that Monte Carlo simulation and hybrid Prophet–Random Forest models have distinct yet complementary strengths for analyzing silver price patterns. Monte Carlo simulation is particularly effective at quantifying risk, allowing researchers and investors to explore a wide range of future price scenarios and assess the likelihood of extreme market events. This makes it especially useful for long-term planning and for evaluating uncertainty.

In contrast, the hybrid Prophet–Random Forest model tends to achieve higher predictive accuracy by combining the strengths of time-series analysis with nonlinear machine learning. While Monte Carlo focuses on uncertainty and probabilistic ranges, the hybrid model aims to provide more accurate directional forecasts. When used together, these methods offer a more comprehensive analytical view, supporting better decision-making in commodity trading, investments, and policy development.

TABLE I. LITERATURE MATRIX:

Author(s) & Year	***Title***	***Key Findings***
[20]	The Dichotomous Nature of Silver in the 21st Century	Investment use of silver may increase due to its anti-inflationary properties.
[5]	Assessing the Effectiveness of Machine Learning Techniques for Silver Price Prediction: A Comparative Study	Price predictions using linear regression, SMOReg, K-nearest neighbors, and random forest.
[14]	Predicting Gold and Silver Price Direction Using Tree-Based Classifiers	Comparison of the price direction prediction accuracy of multiple tree-based classifiers for gold and silver.
[6]	Silver Price Forecasting Using Extreme Gradient Boosting (XGBoost) Method	Application of gradient boosting method with hyperparameter tuning to forecast silver prices.
[15]	Gold or Silver: An Alternative to Investing	Investing in gold is better than investing in silver.
[13]	Precious Metals Market Forecasting in the Current Environment	Analysis of precious metals market dynamics and forecasts using graphical methods.
[12]	Advanced Machine Learning Techniques for Predicting Gold and Silver Futures	Effectiveness of Gaussian Processes, Quantile Regression Forests, Extreme Learning Machines, and Support Vector Regression with an RBF kernel for silver and gold price predictions.
[8]	The role of precious metals in extreme market conditions: evidence from stock markets	Long and intensive market shocks increase the number of safe haven precious metals, especially gold silver and palladium.
[16]	How good are different machine and deep learning models in forecasting the future price of metals? Full sample versus sub-sample	The outcome of machine learning and deep learning model is different according to the type of metal being forecasted, time period, and variables.
[4]	Algorithmic Strategies for Precious Metals Price Forecasting	Analysis of five precious metals, discovering the most accurate forecasting strategy for each. The linear regression is the most effective technique in predicting both silver and gold prices.

D. Summary of Literature Review Matrix:

The literature highlights that a broad range of economic and financial factors, including inflation pressures, global uncertainty, currency fluctuations, and changes in industrial consumption, influence silver prices. Silver is consistently viewed as both an industrial material and a safe-haven asset, becoming increasingly important during periods of market stress. Forecasting studies indicate a notable shift toward advanced analytical models, with machine learning techniques and boosting algorithms demonstrating greater accuracy in predicting silver price movements. Research on price direction modeling and market-trend analysis emphasizes the importance of understanding both the magnitude and direction of future price changes [19]. While gold is often regarded as the more stable investment, silver still offers significant potential due to its widespread industrial applications. Overall, literature underscores the value of modern predictive tools in capturing the complex dynamics of the silver market and aiding better investment and decision-making strategies.

III. METHODOLOGY

This study adopts a quantitative research methodology to predict future silver price movements using two advanced analytical techniques: Monte Carlo simulation and a hybrid Prophet–Random Forest model. The process involves data collection, preprocessing, stationarity testing, model implementation, and comparative forecasting analysis.

A. Data Collection and Preprocessing

Historical daily silver price data were sourced from Yahoo Finance through the Python yfinance library. The dataset contains observations of opening, high, low, and closing prices, as well as trading volume, over the selected study period.

Before analysis, the dataset was examined for missing values and inconsistencies. Any anomalies identified were addressed to ensure data integrity. The closing price of silver was selected as the target variable for forecasting owing to its significance in reflecting market valuation. The time variable was converted into a proper datetime format and designated as the index to preserve the correct chronological structure required for time-series modeling.

These preprocessing measures ensured that the dataset was accurate, clean, and statistically appropriate for forecasting utilizing both econometric and machine learning methodologies.

B. Stationarity Testing Using the Augmented Dickey–Fuller Test

To verify the time series' statistical properties, the Augmented Dickey–Fuller (ADF) test was used to assess the stationarity of silver prices. Stationarity is a fundamental assumption in many forecasting and simulation models, as non-stationary data may produce spurious results.

The application of the ADF test to the original price series revealed the presence of a unit root, thus confirming that the series was non-stationary at its level. To rectify this, first-order differencing was conducted. After this transformation, the ADF test confirmed that the series became stationary, thereby fulfilling the prerequisites for reliable forecasting and simulation. This adjustment ensured that the models were constructed on a stable statistical basis.

C. Monte Carlo Simulation

In order to accurately account for market uncertainty and price volatility, a Monte Carlo simulation framework was applied. This methodology relies on random sampling and probabilistic modeling of asset price fluctuations.

Initially, logarithmic daily returns were derived from historical silver prices to estimate return volatility. The mean and standard deviation of these returns served as parameters to generate numerous simulated price trajectories over a one-year forecasting horizon (approximately 250 trading days). Each simulation represents a potential future scenario of silver price development under stochastic market conditions.

The outcomes of these simulations were consolidated to produce a probability distribution of future silver prices, from which the expected future price and confidence intervals were subsequently derived. This approach offers a risk-oriented perspective that complements the deterministic forecasts produced by Prophet.

D. Hybrid Prophet–Random Forest Model

To enhance forecasting precision, a hybrid modeling framework combining Prophet and Random Forest techniques was devised. Initially, the Prophet model was used to extract the trend and seasonal components inherent in the silver price series. The residuals remaining after this decomposition were then modeled utilizing the Random Forest algorithm, which adeptly captures nonlinear relationships and complex interactions among variables such as market sentiment and trading volume.

The fusion of statistical decomposition with machine learning techniques enriches the model's capacity to represent both structured patterns and irregular fluctuations in silver prices. This hybrid methodology is particularly effective during periods characterized by economic and financial instability.

E. Comparative Forecasting Framework

The forecasting efficacy of the Prophet model, Monte Carlo simulation, and the hybrid Prophet–Random Forest model was evaluated through a comprehensive comparative analysis. Prophet offers structured, trend-based forecasts; Monte Carlo simulation quantifies uncertainty and risk via probabilistic methods; and the hybrid model enhances directional prediction accuracy through nonlinear learning.

Integrating these three methodologies, the study establishes a robust and integrated forecasting framework that balances predictive accuracy with uncertainty quantification, thereby facilitating informed investment decisions and policy formulation within the silver market.

IV. RESULTS

This section presents the findings from the Augmented Dickey-Fuller test (ADF test) on the silver time series data, along with a visualization of the test results. It also includes price forecasting results using Monte Carlo, hybrid prophet and random forest models. The ADF test was performed to check the stationarity. After that, machine learning models were used to generate the silver price forecasts for 2026 and 2027. Each of these models provides distinct perspective on future price movements, with varying levels of uncertainty and confidence intervals.

TABLE II. UNIT ROOT TEST

ADF Test for "Differencing 0 times"
Test Statistic: 0.46376736588824546
p-value: 0.9837292193552682
Lags Used: 1
Observations: 1699
Critical Value 1%: -3.4342047424645092
Critical Value 5% : -2.8632426521042587
Critical Value 10%: -2.5676764469249473
The series is NOT stationary.
ADF Test for "Differencing 1 times"
Test Statistic: -43.02683082243784
p-value: 0.0
Lags Used : 0
Observations: 1699
Critical Value 1%: -3.4342047424645092
Critical Value 5%: -2.8632426521042587
Critical Value 10%: -2.5676764469249473
The series is stationary.
Series became stationary after 1 differencing(s).

The ADF test is a common statistical method to detect unit roots in time series data. This test was applied to the silver time series data in order to ensure its stationarity before conducting the machine learning analysis. Applying the ADF test was crucial before the analysis process because stationarity is a fundamental assumption for statistical models.

The results of the original data series before differencing were 0.463 for the test statistic, 0.983 for the p-value, -3.434 for the critical value at 1%, -2.863 for the critical value at 5%, and -2.567 for the critical value at 10%. Since the test statistic is much higher than all critical values, and the p-value is greater than 0.05, the null hypothesis of a unit root cannot be rejected, meaning that the time series data is not stationary. The silver demand is likely to show trends and seasonality due to the fluctuations caused by various factors creating a permanent pattern rather than temporary effects.

Moreover, the results after differencing for 1 time were significantly different, as the new test statistic value was -43.026, which is far below the critical values, and the p-value was 0.0, which is less than 0.05. This means that the null hypothesis is rejected, and the series data is stationary after detrending.

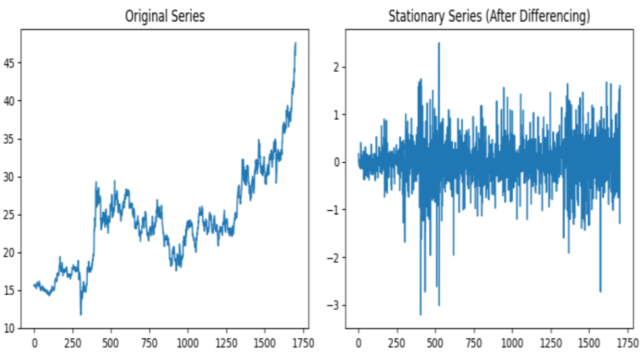

Fig. 1. UNIT ROOT TEST PLOT

Visualizing the unit root testing results was essential to provide a better understanding of the series data stationarity before and after differencing.

The plot on the left shows the results of the data before detrending, where there is a clear upward trend over time and the values start at 15 and climb past 45, indicating growth in silver demand. There are also visible long-term fluctuations such as periods of rise and fall. These fluctuations get larger as values increase which means that the variance is increasing over time. These results reconfirm the non-stationarity of the series data.

However, the second plot shows the test results after the first differencing, where values oscillate around 0 with no visible trends. The mean and variance are roughly consistent over time, and the fluctuations are random and short term, showing no systematic drift. This plot confirms that the series became stationary after differencing and the series fluctuates around a stable mean without a visible long-term trend.

In summary, the raw silver demand reflects long term economic or market influences but after differencing once, the data became suitable for modeling and forecasting.

TABLE III. SILVER PRICE FORECASTING FOR 2026

	ds	*yhat_lower*	*yhat_upper*	Expected Stock Price after 1 year: $54.41 95% Confidence Interval: (np.float64 (32.745696 9514983), np.float64(76.079449 46853709))
2061	2026-09-29	41.283332	53.662843	
2062	2026-09-30	41.409499	53.231695	
2063	2026-10-01	41.350222	53.364259	
2064	2026-10-02	41.355547	53.611864	
2065	2026-10-03	41.117260	53.31401	

This table highlights the silver price forecast produced by the prophet model for the period September 29, 2026 to October 3, 2026. The result of the model predicts a relatively steady change in prices. The model's outcome contains a confidence interval, with lower and upper forecast values, spanning from about $41.12 to $53.66 per ounce. This range indicates where real prices are expected to go downward and upward, and it shows the uncertainty of the model. In general, the silver prices predicted by the prophet model will stay steady around this period, with no significant raise or falls predicted. With this very narrow confidence interval, the prophet model forecast appears to be reliable to some extent. In contrast, the Monto Carlo model predicts average simulated price of $54.41 after one year, which is in alignment with the prediction in the first model. Both models forecast shows a steady increase in silver prices.

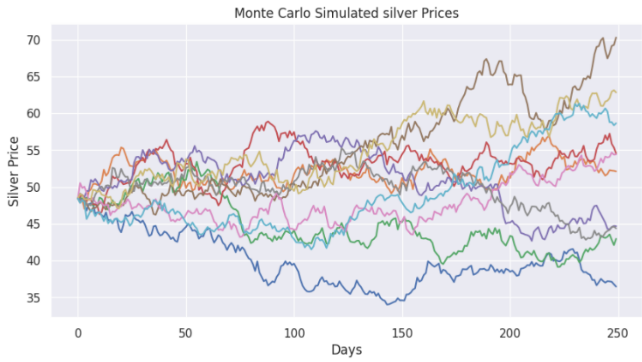

Fig. 2. MONTE CARLO PREDICTION

The graph shows the results of a Monte Carlo simulation that predicts possible silver price changes over a one-year period, which is about 250 trading days. Each colored line indicates a different simulated price path, showing how silver prices might fluctuate under various market conditions. The simulation starts with an initial price of around $50, and as time progresses, the lines spread apart, demonstrating the impact of randomness and uncertainty in price movement. This widening towards the end of the period indicates that the longer the forecast, the more potential variation there is in the outcomes.

Some simulated paths show upward trends, signaling periods of strong market performance driven by positive economic or investment influences. Others show declines or fluctuations, indicating potential market drops or instability. This visualization highlights the unpredictable nature of silver prices, where both gains and losses can occur due to factors like demand shifts, inflation, or currency changes. The graph clearly demonstrates how randomness and volatility shape potential future prices, emphasizing the inherent uncertainty of financial markets. As a result, forecasts should account for a variety of possible outcomes rather than a single prediction.

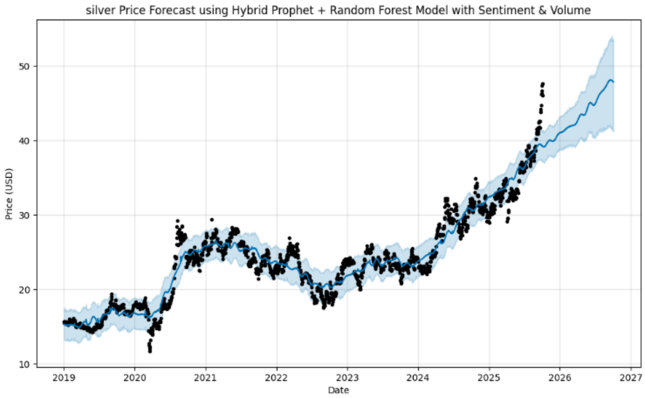

Fig. 3. Prophet & random forest model prediction

This graph demonstrates the silver price predictions using hybrid prophet and random forest model, that include sentiment and trade volume as explanatory factors. The x-axis shows the time frame from 2019 to 2027, while the y-axis represents the prices of silver in US dollars per ounce. The blue line represents the model forecast for the prices, while the black dots are the real prices, and the uncertainty is presented by the region in the light blue shade, corresponding to the confidence interval.

The model uses historical data from 2019 to 2025, a significant change in silver prices was taken into consideration, including the sudden increase of prices around 2020-2021 followed by the stability of prices in 2022-2023. The forecast section in the graph, which covers the end of 2025 to 2027 shows an upward increase in prices, the expected prices are ranging between$45 and $50 per ounce. After the year 2025 the confidence interval widens which indicates a level of uncertainty. Overall, the hybrid model shows how combining time series forecast and machine learning algorithm can increase the accuracy of the prediction, this model provides a significant insight for investors, the hybrid framework offers relatively reliable predictions.

V. Conclusion

In conclusion, this paper aimed to gain a better understanding of how silver price would fluctuate in the near future, through the use of two forecasting techniques: the hybrid Prophet & random forest model, and Monte Carlo simulation. Both approaches contributed to a better understanding of how silver reacts to market volatility, economic condition, and investors' behaviors. The Monte Carlo simulation demonstrates a wide range of potential silver prices, based on historical data, it highlights how uncertain the market can be. On the other hand, the hybrid model`s results show a more stable outcomes, it reflects how silver prices fluctuate focusing on patterns and trends that appear over time.

Prior to developing the model, a unit test was applied to determine whether the data is stationary or not, and after applying the differencing one time, the data has become stationary.

One of the key conclusions of this study is that silver prices show specific trends through time, especially when looking at long-term data. The hybrid model was able to identify the trends and patterns, it provided insight about the general direction of prices. The Monte Carlo simulation, in contrast, shows the uncertainty, in addition to how the market is not entirely predictable. Prices might get affected by the change in economy, shift in investors behavior, or supply issues.

The research outcome shows how using both techniques is an advantage to better understand the market for investors, policymakers, and traders. Monte Carlo simulation highlights the risk by predicting several potential future scenarios, it predicted the price to reach $54.41 in 2026. The hybrid model offers more stable outcome showing the estimated direction of the prices with upper and lower ranges. This combination provides investors both the direction and cation, where the hybrid model shows the long-term planning, and the Monte Carlo shows the uncertainty.

Nevertheless, these approaches have limitations, same as any other forecasting approach. When presented with unexpected economic trends, change in industrial demand for silver, or political crisis. Both models might be less reliable because of their reliability of historical data. To improve the predictive ability, researchers can conduct to investigate how the unexpected factors affect the prediction ability.

In addition, the study provided a relatively reliable prediction on the general direction on the prices. This study will assist investors, policymakers, and analysts in their decision-making process by offering them with a better understanding of the market.

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