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Comparative Modeling of Naïve Bayes and LSTM with Monte Carlo Forecasting for Silver Prices

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***Abstract*— Silver price volatility has increased markedly in recent years, particularly since 2023, driven by growing demand from the renewable energy sector. This study compared two conceptually distinct forecasting approaches: Naïve Bayes (NB), which relies on conditional independence assumptions, and Long Short-Term Memory (LSTM), which models temporal dependencies in time-series data. Daily silver price data (USD/troy ounce) from January 1989 to October 2025 were analyzed. NB was implemented using a single lagged price feature (t−1), while LSTM employed a two-layer architecture with 50 units, 0.2 dropout, and a 60-day sequential window. Empirical results showed that NB achieved R^2 of 0.9818, reproducing dominant price dynamics but exhibiting slight lagging during sharp price movements. In contrast, LSTM achieved lower RMSE and MAE, with an R^2 of 0.9939, effectively capturing nonlinear dependencies and volatility patterns. When extended with Monte Carlo simulation, LSTM enabled uncertainty-aware short-term forecasting, providing median price trajectories and prediction intervals, making it a more robust framework for silver price prediction under extreme volatility.**

***Index Terms*— silver price; Naïve Bayes; LSTM; Monte Carlo.**

I. INTRODUCTION

Silver is one of the key precious metal commodities in the global economic system, functioning both as an investment asset and an industrial raw material. Its price dynamics often move in tandem with gold and serve as an alternative investment during periods of economic uncertainty [1]. However, silver prices are well known for their sharp fluctuations, driven by macroeconomic factors such as inflation, interest rates, exchange rates, and rapidly changing industrial demand [2]. These characteristics make accurate silver price forecasting particularly important for investors, financial institutions, and policymakers in formulating investment strategies and managing economic risk [3].

In line with the increasing volatility of commodity markets, various analytical approaches have been developed to understand and forecast silver prices. Conventional statistical methods such as ARIMA and Exponential Smoothing have been widely applied, but their reliance on linearity and stationarity assumptions often limits their effectiveness when applied to highly volatile and nonlinear commodity price data [4]. As a result, machine learning-based approaches have gained attention due to their ability to capture complex patterns and nonlinear relationships without requiring strict parametric assumptions [5].

Among machine learning methods, Naïve Bayes and Long Short-Term Memory (LSTM) represent two fundamentally different modeling philosophies. Naïve Bayes is a probabilistic classifier grounded in Bayes' Theorem and is valued for its simplicity and computational efficiency [6]. LSTM is a development of Recurrent Neural Network (RNN) designed to recognize patterns and long-term dependencies in sequential data, thus making it highly effective for analyzing time series data such as silver prices [7]. Despite these differences, both methods continue to be used in empirical studies, often motivated by trade-offs between model complexity, interpretability, and computational cost.

The Long Short-Term Memory (LSTM) method has been widely applied across various domains, including stock market analysis and prediction, cryptocurrency price forecasting such as Dogecoin, indoor air quality modeling, and railway transportation operations environments [8, 9, 10, 11]. Meanwhile, Naïve Bayes has also been applied in weather forecasting studies, where temperature, humidity, and wind speed are commonly used as predictor features, demonstrating its practicality as a probabilistic baseline despite the strong independence assumptions [12]. These studies illustrated the broader applicability and contrasting strengths of probabilistic and machine learning-based models, particularly in terms of accuracy, robustness, and computational efficiency.

Many studies emphasize performance improvement without explicitly examining whether complex deep learning models provide meaningful advantages over simpler probabilistic baselines when applied to long-horizon commodity data, while comparative analyses rarely consider extended historical periods encompassing multiple volatility regimes, including recent episodes of extreme price fluctuations. In addition, limited attention has been given to the practical implications of model behavior during trend reversals and high-volatility phases, which are critical for real-world decision-making. Addressing these gaps, this study goes beyond a simple comparison of predictive accuracy by evaluating how Naïve Bayes and LSTM differ in capturing temporal dynamics, responsiveness to trend changes, and predictive stability when applied to long-horizon silver price data. Using daily world silver prices over an extended period, this research assesses the practical suitability of probabilistic versus deep learning approaches for forecasting silver prices under nonlinear and volatile market conditions, thereby contributing to a more nuanced understanding of model selection in commodity price forecasting.

II. METHOD

To address the research question regarding the comparative performance of Naïve Bayes and LSTM in predicting silver prices, this study adopts a comparative experimental design, where both models are trained and evaluated in parallel on an identical dataset, ensuring a controlled and fair comparison. The workflow includes: collection and validation of historical data, temporal preprocessing, construction of two distinct model architectures, training, objective evaluation using regression metrics, and interpretation of performance in the context of the temporal characteristics of silver price series. An overview of the research workflow is presented in Fig. 1.

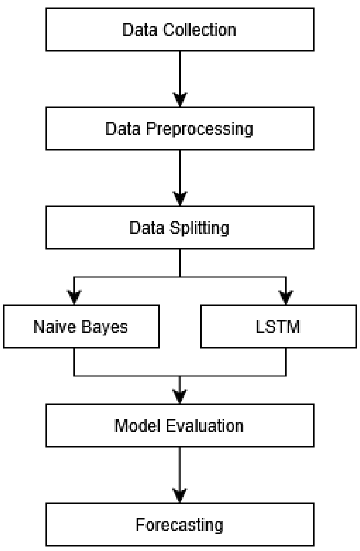

Fig. 1. Research Design

A. Data Collection

Historical silver price data (USD per troy ounce) were obtained from Investing.com, covering daily observations from January 3, 1989 to October 30, 2025, resulting in 9,384 observations. This data source was selected because market holidays are handled consistently through forward-filling, ensuring a continuous time series and preventing temporal bias [1]. The dataset contains two main columns: *Date* and *Price*, exported to CSV format and loaded into the Python environment using pandas with parameters *parse_dates=['Date']* and *index_col='Date'* to ensure chronological ordering and compatibility with time series analysis tools (e.g., *statsmodels* and *scikit-learn*).

B. Data Preprocessing

Data preprocessing was conducted to transform the raw silver price series into a suitable representation for machine learning–based regression models. Since Investing.com applies forward-filling to account for non-trading days, no missing values were expected; nevertheless, explicit checks were performed using *df.isnull().sum()* to confirm data completeness, along with data type inspection *(df.dtypes)* to ensure numerical consistency. The dataset was chronologically ordered to preserve the temporal structure required for time-series modeling.

Prior to feature construction, an autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis was conducted exclusively on the training dataset to avoid information leakage. The ACF results indicate statistically significant short-term autocorrelation, while the PACF exhibits a clear cutoff after the first lag, suggesting that short-term temporal dependence dominates the silver price dynamics. Based on this empirical evidence, a lagged price feature ($Price_{t-1}$) was constructed to represent short-term memory in the Naïve Bayes model. Rows containing missing values introduced by the shift operation were removed, yielding a clean and temporally aligned dataset suitable for supervised learning.

The dataset was divided using an 80:20 temporal split without shuffling to prevent look-ahead bias. The training set consists of 7,505 observations spanning January 3, 1989 to December 31, 2023, while the testing set contains 1,877 observations from January 2, 2024 to October 30, 2025, a period characterized by heightened price volatility. In contrast to the Naïve Bayes model, the LSTM model does not rely on explicitly defined lag variables. Instead, temporal dependence is captured implicitly through fixed-length input sequences. In this study, the data were reshaped into 60-day sequences (n_steps = 60) using a sliding-window approach, where each input sequence consists of silver prices from the previous 60 trading days to predict the subsequent day's price. This sequence-based representation enables the LSTM to learn nonlinear temporal patterns and medium-term dependencies directly from historical price trajectories without requiring manual lag selection.

C. Naïve Bayes Model

Naïve Bayes was employed in this study as a computationally efficient probabilistic baseline for modeling silver price dynamics. Although Naïve Bayes is conventionally designed for classification tasks, it has been previously adapted for regression-oriented problems through discretization or probabilistic approximation, particularly in exploratory or comparative modeling contexts [13]. The silver price distribution exhibits moderate positive skewness (skewness = 0.8549), indicating asymmetry and deviations from strict normality. While this level of skewness does not represent an extreme heavy-tailed distribution, it suggests that Gaussian assumptions may not be fully satisfied across the entire price range, thereby motivating the exploration of a probabilistic modeling framework that is less sensitive to distributional symmetry.

To accommodate the continuous nature of silver prices, the target variable was discretized into a finite number of intervals prior to model training. Discretization enables the Naïve Bayes classifier to approximate regression behavior by estimating the posterior probability of future price intervals conditional on historical observations [14]. In this study, historical price information from the preceding three trading days was used as input features, and conditional independence among lagged variables was assumed. While this assumption is strong and may not fully hold in financial time series, it allows the model to remain analytically tractable and computationally efficient, serving its intended role as a baseline comparator rather than a primary predictive model.

The Naïve Bayes model estimates the posterior probability of a price interval C given observed historical prices X as Equation (1).

$$P(C \mid X) = \frac{P(X \mid C) \cdot P(C)}{P(X)} \quad (1)$$

with:

$P(C \mid X)$: posterior probability of class C given evidence X

$P(X \mid C)$: probability that evidence X is assigned class C

$P(C)$: prior probability of class C

$P(X)$: probability of evidence X

For numerical data, likelihood calculations can use the Gaussian distribution [15].

D. LSTM Model

The Long Short-Term Memory (LSTM) network is an advanced recurrent neural network architecture introduced by Hochreiter and Schmidhuber to address the vanishing gradient problem commonly encountered in standard Recurrent Neural Networks (RNNs) when modeling long sequential data [16]. Conventional RNNs process time-ordered data recursively but often fail to retain long-term dependencies due to exponentially diminishing gradients during backpropagation [17]. LSTM mitigates this limitation by incorporating a memory cell regulated by three gating mechanisms such as input, forget, and output gates, which collectively control the storage, update, and release of information over time, enabling more stable learning of temporal dependencies in volatile financial time series such as silver prices [18].

The internal operations of the LSTM unit are governed by gating equations that regulate information flow within the memory cell. These mechanisms are mathematically expressed through the input gate, forget gate, cell state update, and output gate formulations, which are summarized in Equations (2)–(7). Through these equations, the LSTM learns to selectively preserve relevant historical information while discarding noise, enabling robust modeling of nonlinear temporal dependencies in long-horizon silver price forecasting.

$$i_t = \sigma(W_i x_t + W_{hi} h_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_f x_t + W_{hf} h_{t-1} + b_f) \quad (3)$$

$$\bar{C}_t = \tanh(W_c x_t + W_{hc} h_{t-1} + b_c) \quad (4)$$

$$C_t = f_t \times C_{t-1} + i_t \times \bar{C}_t \quad (5)$$

$$o_t = \sigma(W_o x_t + W_{ho} h_{t-1} + b_o) \quad (6)$$

$$h_t = o_t \times \tanh(C_t) \quad (7)$$

with:

i_t : input gate,

f_t : forget gate,

o_t : output gate,

C_t : cell state,

h_t : hidden state,

x_t : input at time-t,

W : network weight, and

b : bias

In this study, the LSTM was implemented using a sequence-based forecasting framework, with the silver price series reshaped into fixed-length input sequences of 60 trading days (n_steps = 60), where each sequence predicted the subsequent day's price. The model architecture consisted of two stacked LSTM layers with a tunable number of hidden units (50 or 100) and dropout layers (rate = 0.2) to reduce overfitting, followed by a fully connected layer to transform the LSTM features into predicted prices. A grid search was performed over the number of units per layer, learning rate (0.001, 0.0005), batch size (64), and epochs (200, with early stopping), and the optimal model was selected based on the lowest root mean squared error (RMSE) on the validation set. Training employed the Adam optimizer with the selected learning rate, mean squared error (MSE) as the loss function, and mean absolute error (MAE) as an auxiliary metric, while early stopping ensured generalization and prevented overfitting. The resulting model was then used for both test set prediction and short-term Monte Carlo forecasting.

E. Model Evaluation

To assess the predictive performance of Naïve Bayes and LSTM, given the silver price series characteristics such as volatility clustering, regime-switching, and heavy-tailed distribution evaluation was conducted using three complementary regression metrics: MAE, RMSE, and R^2 [19]. These metrics jointly capture different aspects of prediction error: absolute accuracy (MAE), sensitivity to large deviations (RMSE), and the proportion of variance explained by the model (R^2).

1. MAE (Mean Absolute Error)

MAE computes the average absolute deviation between predictions and observed values, treating small and large errors equally [20]. Unlike RMSE, which squares errors and thus penalizes large deviations more heavily, MAE is more robust in the presence of outliers such as silver price spikes due to geopolitical turmoil or supply shocks [21]. In practice, models with lower MAE generally yield more consistently accurate predictions on average, though they may not excel at capturing extremes. The MAE formula using Equation (8).

$$MAE = \frac{1}{n} \times \sum |y_i - \hat{y}_i| \qquad (8)$$

with:
n : amount of data,
y_i : true value,
$\hat{y}_i$: model prediction value.

2. RMSE (Root Mean Squared Error)

RMSE is a standard performance indicator in numerical prediction evaluation, especially in financial time series studies, due to its sensitivity to large errors making it an informative early signal of potential underfitting or over-smoothing. RMSE quantifies the magnitude of the difference between model predictions and actual observations [22]. As a widely used technique, RMSE helps assess the level of error in numerical prediction models. It is derived from the square root of the mean squared prediction errors. A decreasing RMSE generally reflects improved prediction accuracy particularly for trend direction changes though interpretation should consider residual patterns, as an extremely low RMSE may indicate overfitting or data leakage. Prediction accuracy is determined by the smallest error value across evaluation methods [23]. The RMSE formula using Equatiaon (9).

$$RMSE = \sqrt{\frac{1}{n} \times \sum (y_i - \hat{y}_i)^2} \qquad (9)$$

3. R^2 (The coefficient of determination)

R^2 indicates the proportion of actual data variance explained by the model, ranging from 0 (no explanatory power) to 1 (perfect explanation) [16]. Although a high in sample R^2 is often considered a success marker, in out-of-sample evaluation, an R^2 close to 1 does not necessarily guarantee generalization abilityespecially if residuals still exhibit autocorrelation or systematic patterns [20]. The R^2 formula using Equation (10).

$$R^2 = 1 - \left(\frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \hat{y}_i)^2} \right) \qquad (10)$$

.

III. Result and Discussions

A. Naïve Bayes Model Prediction Results

The autocorrelation function (ACF) and partial autocorrelation function (PACF) analyses were conducted exclusively on the training dataset to determine the optimal lag structure while avoiding information leakage. As illustrated in Fig. 2 and Fig. 3, the silver price series exhibited a clear AR(1)-type behavior. The PACF plot showed a single statistically significant spike at Lag 1 followed by an immediate cutoff into the insignificance region, indicating that only the most recent past observation has a direct and meaningful influence on the current price level. This pattern provideed strong empirical justification for selecting Lag 1 as the primary explanatory feature in the Naïve Bayes model.

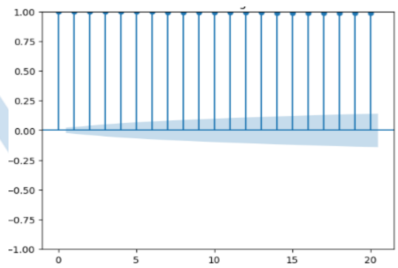

Fig. 2. ACF for training data

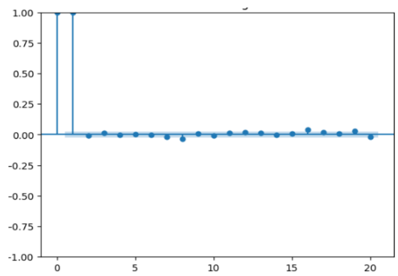

Fig. 3. PACF for training data

The ACF plot exhibited a slow and gradual decay across multiple lags, indicating strong persistence and a potentially non-stationary structure in silver prices, while the PACF showed a clear cutoff after Lag 1, justifying the selection of a single lag as the most parsimonious feature for Naïve Bayes modeling.

Although such non-stationarity might have violated classical linear time-series assumptions, it did not invalidate lag-based features in supervised learning, and differencing was intentionally not applied to preserve the original price scale and ensure a fair comparison with the LSTM model, which could learn non-stationary patterns implicitly. Based on this empirical evidence, a Lag-1 Naïve Bayes specification was adopted and yielded strong predictive performance, as summarized in Table 1, with RMSE = 0.9180, MAE = 0.7042, and R^2 = 0.9818, indicating that short-term price dependence alone captures a substantial proportion of the variability in silver prices under long-horizon and volatile market conditions.

TABLE 1. NAÏVE BAYES MODEL EVALUATION

Model	RMSE	MAE	R^2
Naïve Bayes	0.9180	0.7042	0.9818

Fig. 4 further supported this conclusion by comparing the actual silver prices with the Lag-1 Naïve Bayes predictions over the test period. The predicted series closely followed the overall trajectory of the observed prices, demonstrating that immediate past information is sufficient to reproduce the dominant price dynamics. Minor deviations appeared during episodes of sharp price acceleration and extreme volatility, particularly toward the end of the sample, where the model exhibits slight lagging behavior. This smoothing effect reflected the inherent limitation of a probabilistic baseline model relying on conditional independence assumptions.

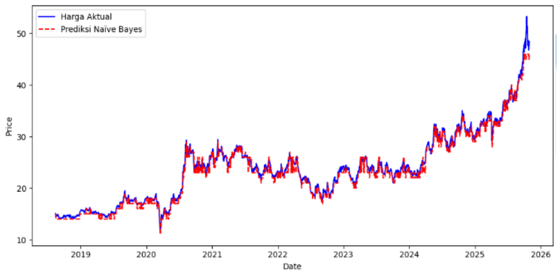

Fig. 4. Actual vs. predicted silver prices by Naïve Bayes model (Lag-1)

B. *LSTM Model Prediction Results*

The LSTM model was constructed using a two-layer architecture with 50 units per layer, a dropout rate of 0.2, and two dense layers (25 and 1 unit). The silver price data were normalized using a Min-Max Scaler and reshaped into 60-day input sequences (n_steps = 60) to predict the subsequent day's price. Hyperparameter optimization was conducted via grid search over the number of units, learning rate (0.001, 0.0005), batch size (64), and epochs (200), with early stopping applied based on validation loss, and the best model was selected using the lowest RMSE. The optimal configuration consisted of 2 LSTM layers, 50 units, dropout 0.2, batch size 64, learning rate 0.0005, and 200 epochs. Evaluation on the test data demonstrated strong predictive performance with RMSE = 0.5277, MAE = 0.3493, and R^2 = 0.9939, indicating that the model explains 99.39% of the variance in actual prices, as summarized in Table 2.

TABLE 2. LSTM MODEL EVALUATION

Model	RMSE	MAE	R^2
LSTM	0.5277	0.3493	0.9939

Visualization in Fig. 5 showed that the LSTM predictions closely track the actual silver price series, even during periods of high volatility. This demonstrated that the model effectively captures nonlinear trends and short- to medium-term temporal dependencies in the data, indicating strong predictive performance and the ability to follow rapid price movements in the market.

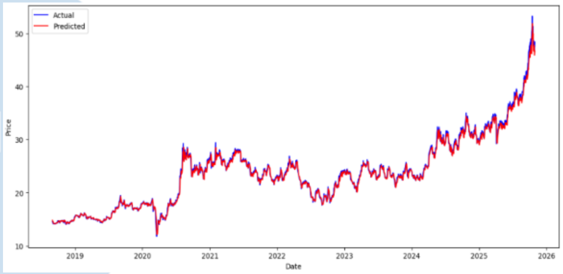

Fig. 5. Actual vs. predicted silver prices by LSTM model

C. *Performance Comparison: Naïve Bayes vs. LSTM*

Based on Table 3, LSTM was the most superior model overall. This conclusion was drawn from the fact that its prediction errors were lower and it explained a higher proportion of the variance in the data, with an R^2 of 0.9939, compared to Naïve Bayes. Using only MAE would not have capture the impact of extreme prediction errors, while using only RMSE could have overemphasize outliers. Therefore, considering both metrics together, along with the high R^2, provided a more balanced and informative assessment, confirming LSTM's better predictive performance.

TABLE 3. EVALUATION OF BOTH MODELS ON THE SAME TEST SET

Model	RMSE	MAE	R^2
Naïve Bayes	0.9180	0.7042	0.9818
LSTM	0.5277	0.3493	0.9939

D. *Short-Term Forecasting Using Monte Carlo LSTM*

The short-term forecasting results using Monte Carlo LSTM for the next 90 days (Figure 6) showed historical silver prices in blue, while the red line represented the model's median predictions. The transparent red area depicted the 10%-90% prediction interval (PI), indicating the range of price uncertainty with an 80% probability. The visualization suggested that silver prices were expected to moderately decline from 48.44 USD to a median of 43.84 USD by day 90, although price volatility remained high.

The purple and green dashed lines marked the train/test split and the start of the forecast period, making it easier to distinguish historical data from predictions. The prediction interval on day 90 ranged from 40.94–47.46 USD, indicating that actual prices could deviate from the median forecast. Overall, Monte Carlo LSTM effectively captured historical trends while providing useful uncertainty information for short-term risk planning.

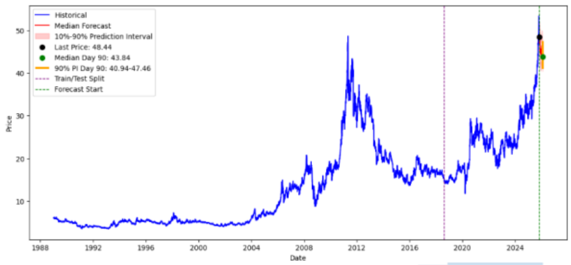

Fig. 6. Forecasting Results

IV. CONCLUSIONS

This study evaluated the efficacy of Naïve Bayes and LSTM models in forecasting silver prices. The Lag-1 Naïve Bayes model captured short-term price dependence and reproduced the dominant price dynamics, yielding strong predictive performance (R^2 = 0.9818), although it exhibited slight lagging behavior during episodes of rapid price acceleration and extreme volatility. In contrast, the LSTM model effectively tracked nonlinear trends and short- to medium-term temporal dependencies, achieving lower prediction errors and superior accuracy with an R^2 of 0.9939. The integration of Monte Carlo simulations extended the LSTM framework into uncertainty-aware short-term forecasting, providing both median price trajectories and 10%-90% prediction intervals that quantified forecast uncertainty. Overall, while Naïve Bayes provided a computationally efficient baseline, LSTM significantly outperformed it, particularly under volatile market conditions, confirming its robustness and suitability for capturing complex silver price dynamics and supporting strategic financial risk planning.

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