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A Comparative Study of Manual Time Series Forecasting and AI Tools For Silver Price Prediction Using Agent AI

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***Abstract*—Predicting silver prices matters greatly - it affects decisions made by investors, policy makers, and finance experts because silver functions both in industry and as an asset. One reason this research exists? To weigh classic time-series approaches against modern artificial intelligence methods when estimating future values of silver. Past market figures form the backbone of several predictive systems tested here: LSTM networks take shape alongside Auto ARIMA setups, Seasonal Naive patterns emerge, while AutoGluon powers fully automatic machine learning versions. Another layer appears through inclusion of a third-party AI predictor brought in purely for contrast purposes.**

Despite its simplicity, time series prediction often relies on established methods such as the Wilder approach when estimating upcoming values. Performance gets measured through common indicators including MAE, RMSE, and MAPE - metrics widely accepted across evaluation practices. Instead of manual comparison, a system powered by Agent AI handles scoring and ordering of different models without human bias creeping in. Findings show Auto ARIMA achieving better accuracy than both deep learning setups and those built with AutoML tools on this particular data set. What stands out is how traditional statistical techniques still hold strong under real testing conditions, especially when matched against more complex alternatives.

I. INTRODUCTION

Silver is an exclusive, expensive metal, which is known for its high electrical conductivity of any elements, making it an essential technical powerhouse in modern electronics like solar panels, medical applications, and so on. While it is valued for its bright shine in jewelry and mirrors, its price depends on both industrial demand and how many people buy it for safe investment during inflation. So, it plays an important role in the global economy. Due to this dual role of silver, its prices are changing and impacted by a wide range of economic, industrial, and market forecasting factors. Predicting silver prices accurately is important for investors and analysts for knowledgeable decision-making and risk management. However, compared to gold, there is much less research on predicting silver prices.

Ancient methods for predicting time series, including ARIMA, remain common in finance because they rest on solid statistics and are easy to understand (Box et al., 2015). Built-in optimization tools such as Auto-ARIMA improved accuracy by selecting best-fit settings using the data itself (Hyndman & Khandakar, 2008). Even so, conventional approaches tend to miss curved relationships and intricate timing links found within market datasets.

As artificial intelligence advances, deep learning methods such as Long-Short-term Memory (LSTM) networks have emerged due to their efficiency in processing continuous data and preserving information over time (Hochreiter & Schmidhuber, 1997). In recent studies on commodity price forecasting, especially gold, LSTM models and hybrid strategies have shown remarkable results. The successful use of the LSTM framework to estimate the value of gold is an example (Adha, et al., 2024); at the same time, combinations of ARIMA and LSTM models achieve higher accuracy by combining linear patterns with complex nonlinear dynamics (Mun et al., 2025; Ye, 2025). Approaches that adapt to trends or use optimization also represent a continuous evolution in forecasting methodologies (Kazemdehbashi, 2026; Sha, 2024). However, despite these advances, comprehensive comparisons focused on silver price modeling are rare. Rather than relying on individual methods, recent forecasting research has tended to combine multiple models simultaneously—an approach that often improves the fit of predictions to actual outcomes (Zhang, 2003; Dietterich, 2000; Zhang et al., 2021). More advanced frameworks, such as DeepAR or Temporal Fusion Transformers, go a step further by using probabilistic outputs and attention algorithms to weight data during processing (Salinas et al., 2020; Lim et al., 2021). However, the large number of options makes it difficult to determine which method is best suited for a given historical data set. Evidence from extensive experiments, including the M5 competition, shows that one algorithm can perform well in one environment and significantly worse in another, depending on the data characteristics and evaluation criteria (Makridakis et al., 2022). To objectively assess performance under these conditions, strategies such as rolling window validation continue to play an important role (Bergmeir et al., 2018).

Facing tough choices in picking models, AutoML platforms step in by handling how forecasts are trained, adjusted, and checked without constant manual effort. Instead of testing each method one at a time, tools like AutoGluon mix deep learning with classic statistics under one roof (Erickson et al., 2020). Driven forward by these advances, neural networks designed for forecasting now shape how automated time series work gets done. Alongside them, systems including TimeGPT apply artificial intelligence to stretch what's possible across many data sequences quickly (Nixtla, 2023).

Building on recent advances, this paper presents a unique framework that combines conventional statistical methods with deep learning and artificial intelligence tools to predict silver prices. What makes this research unique is the use of an agent-based artificial intelligence system to evaluate model results. Rather than relying on conventional methods for model selection, this framework evaluates performance based on multiple metrics through a balanced comparative analysis. Combining the concepts of ensemble strategies (Dietterich, 2000; Zhang et al., 2021) with the structures found in large-scale forecasting competitions (Makridakis et al., 2020), a connection is made that is often missing in the research literature. Through this integration, a more intelligent and less biased method is developed to accurately determine which forecasting approach is most appropriate.

Although the current study is contextualized within silver price forecasting, its primary objective is to conduct a comparative analysis between conventional time series methods and emergent AI frameworks. This study does not focus solely on model building, but integrates LSTM, Auto-ARIMA, and AutoGluon under a unified computational framework to perform comparative analyses. By implementing agent AI to evaluate the performance of the models, the analysis shifts from isolated models to the interaction between statistics and AI. The algorithms are not analysed in isolation rather; their synergistic interactions are systematically accounted for. Since forecasts form the basis of actual trading decisions, these results directly impact on the way traders use and evaluate forecasts. Although these analyses are rooted in empirical evidence, they also reflect operational aspects of accuracy, adaptability, and processing.

Silver is a complicated thing because it has two jobs: it helps make things like solar panels and electronics, and people buy it to protect themselves. This makes it difficult to predict its price. What causes silver price changes? Can we use math or computers to predict prices? The study uses a specialized computer system that runs multiple models simultaneously, such as ARIMA, LSTM, AutoML, and TimeGPT. Each model demonstrates its potential, and together they help find the best way to predict silver prices.

This gives the method ability to adapt and real-world application.

A. Research Objectives

The main aim of the study is to build a smart forecasting system for silver prices by combining traditional statistical methods, deep learning models, and AutoML, guided by an Agent AI that helps choose and evaluate the best approach.

Objectives of the study are listed below.

- To develop and implement silver price forecasting models using traditional statistical and deep learning techniques.
- To establish basic AutoML goals for automated model learning, optimization of detailed detection parameters, and forecasting.
- To compare the forecasting performance of traditional statistical methods, deep learning methods, and AutoML-based methods using weighted estimation methods.
- To examine the effects of seasonality, constants, and uncertainties on the accuracy of forecasts.

- To develop an AI-based overfitting system based on an agent for recruitment, ranking, and selection.
- To evaluate the effectiveness of the integrated forecasting technique in detecting silver price movements.
- To provide practical forecasting advice for investment decisions, risk management, and regulation.
- To conduct a comprehensive analysis of the strengths, limitations, and applicability of various strategies and develop a strategic plan that can be identified and implemented in rapidly changing financial environments.
- This study contributes to existing research by proposing a predictive concept that incorporates statistical methods, deep learning, AutoML, and artificial intelligence for product pricing.

B. Contribution of the Study

The study gives practical solutions for the financial sector and AI users to estimate prices for silver using actual data.

Effective AI assistant: We set up an AI assistant that automatically picks out the best predictive tools. This makes predicted outcomes fair and unbiased. Combining widespread and new methods: We put together a simple system that blends traditional mathematical techniques with new tools such as AutoML and deep learning to produce improved forecasting. Sometimes little is more. For these data, the Auto-ARIMA approach performed better than the modern AI methods. This suggests higher-tech approaches are not necessarily superior.

The most effective method to forecast relies on the way silver prices change over time: We show that older methods outperform advanced neural networks because silver prices are fluctuating and occasionally follow simple patterns. Helping financial analysts, investors, and leaders: These tools will help consumers spot risks and better estimate prices of silver in the future. Easy to adapt: The methodologies we have created can be applied to predict other swiftly changing markets or assets.

II. LITERATURE REVIEW

A. Classical statistical forecasting models

Box, Jenkins, and Reinsel in their paper Time Series Analysis: Forecasting and Control. They discussed systematic modelling for time series data and the ideology used where statistical dependence can be modelled using ARIMA. They established the BOX-JENKINS forecasting framework. As their work result shows, ARIMA remains as the foundation for all forecasting methods. Hyndman and Khandakar in their work Automatic time series forecasting: The forecast packages for R. They work on automatic model selection for ARIMA and their basic ideology that statistical criteria can automate parameter selection. They use all basic steps used in Time series analysis like unit root tests and differencing and their work involves into step that deals with model selection based on AIC value. As a result, they developed the AutoARIMA procedure. As the conclusion of their work, forecasting efficiency is improved by automation.

B. Deep learning for financial time series

Hochreiter and Schmidhuber in their research work titled Long Short memory. They work on long-term dependency learning, which involves checking that memory cells can overcome vanishing gradients. For this, they used a recurrent neural network as input, forget, and output gates. As a result of their work, they proved that sequence learning capability has improved. Then they conclude that LSTM became a major deep learning forecasting model. Siami-Namini and Namin in their work Forecasting economic and financial time series.

They discussed the comparison between ARIMA and LSTM models, and they suggested that LSTM performs better than ARIMA while dealing with complex series.

A comparative forecasting experiment has been performed as the result of LSTM predictions with lower forecasting errors compared to ARIMA. The conclusion of their study is deep learning models have advantages in terms of nonlinear forecasting.

C. Hybrid forecasting models

Zhang (2021) – In their paper Ensemble learning for time series forecasting, he combines linear and nonlinear forecasting models. The ideology behind the study is that the ARIMA model is for linear patterns and neural networking models are for handling the residual nonlinearities. As a result of his work, the hybrid models' forecasting accuracy is improved compared to other independent models. Finally, there is one of the foundational hybrid frameworks for forecasting that has been founded.

D. Advanced deep learning and transformer-based forecasting

Lim et al. in their work Temporal fusion transformers for interpretable multi-horizon time series forecasting. This work develops a deep learning architecture to predict the upcoming values in multiple steps simultaneously.

The idea behind this is when we pay more attention to the more important data in a set of data and ignore all the rest, then we can improve forecasting for the long range. As a result, we get high accuracy and interpretable predictions. They conclude that TFT is suitable for complex forecasting.

Nixtla in his work TimeGPT: Foundation model for Time series forecasting. Where the foundational models can learn temporal patterns or not. As a result, this strong zero-shot forecasting performance has been achieved. And he concludes that foundational models can reduce manual feature engineering work.

E. Automated and intelligent forecasting systems

Erickson et al. in their work AutoGluon – Tabular: Robust and Accurate AutoML for structured data. They find that strong performance with minimal manual effort. And conclude that AutoML is practical tool for structured forecasting work also. Wooldridge In his book An Introduction to Multiagent Systems. He works on the problem Autonomous distribution decision-making.

The idea is to check that a specialized agent can improve complex tasks. It results that he established multi-agent architecture principles.

F. Research gap

The above-discussed work demonstrates the significance of advancements in AI forecasting but there is no work that exists as a unified framework using integrated statistical models, deep learning, and individual agents for silver or other price analysis. This study addresses the gap by using an agent AI-based framework designed to evaluate automatically, and then forecasting models are ranked based on their predictive performance and the best model for silver price prediction is suggested.

III. METHODOLOGY

A. Data Description

We are going to look at how the price of silver changes each day. To understand this, I will use old price records. What is the price of the silver is at the end of each day. To find out this, I have used the historical price of daily silver at the end of the day. Data for this study is taken from the GoodReturns database for the period of 1 January 2024 to 28 February 2026. This dataset contains almost 800 observations, and it is a univariate time series dataset.

For this study I like to use the Jupyter Notebook. As the first step of the study, import the dataset into the notebook and import some libraries that are used in the study, like NumPy, pandas, etc., then convert the data attribute into Datetime format because we are dealing with time series data. Then arrange all the observations in chronological order. After that, standardize the dataset structure by assigning the Timestamp and Target for the closing price of the silver. Then we come to the important step of preprocessing. This includes missing observations caused by weekends or any outliers found in the data, and the missing values are filled using the Last Observation Carried Forward (LOCF) method or linear interpolation, depending on the variable used and the patterns they follow in terms of missingness. After verifying the sequence integrity of the dataset and ensuring that they have a continuous daily frequency. These steps help our prediction more accurate and predictable of Silver in future.

As we are dealing with machine learning, we reached the important step of partitioning the dataset using a time-series split. Which includes splitting the data into training and testing data; mostly it holds 80 or 70 percent of the dataset for training and the remainder for testing for future predictions. In this case, training data ranges from January 2024 to January 2026, and the remaining 30 days of observation are from February 2026 for testing process.

B. Raining and Forecasting using Multiple Statistical and Deep Learning Models:

Then we reach the major part of this study: training the forecasting models independently, like LSTM, AutoGluon, Auto-ARIMA, and Seasonal Naïve then generating the forecasting using TimeGPT. Let's start with LSTM; it is a well-known machine learning model and it shows more accuracy than other models in general. This model was first trained by applying min-max normalization, and this is to scale the input features into the common range. Then it creates a sliding window to transform the time series data into supervised learning format. Then, finally, the model learned the temporal dependencies in the data using its memory cells and gating mechanism; now it can effectively capture long-term patterns and sequential relationships within the data. The AutoGluon it is AutoML framework it automatically preprocesses the dataset, which include handling missing values, encoding categorical variables, and scaling features if it needed. Then appropriate forecasting models are chosen and hyperparameter optimization is carried out and models are ranked based on their Mean Absolute Scaled Error (MASE). The Auto-ARIMA model is trained by calculating the optimal values of (p,d,q). These values are automatically chosen by itself using possible difference values and it select the model with lowest Akaike Information Criterion (AIC) to ensure the balance between model fit and complexity. Then forecast using the Seasonal Naive looking at the preceding seasonal cycle over and over again. This technique to strong baseline by expecting future values as like as prior observed seasonal patterns. The model does not require any further local model training and can conduct zero-scale forecasting directly on time series data and utilizing its pretraining on large-scale temporal datasets to get reliable forecasts. The forecast created using TimeGPT. After doing all those things we come end of the training process.

The testing process begins. It produces 30-day forecast values of the silver price for the period using the forecasting models used in this study. Then we evaluate the forecasting accuracy using error metrics like Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and Coefficient of Determination for the data, and they are comparing with each other in terms of performance for all forecasting models. Then we select the best model with the highest predictive accuracy and with lowest forecasting error.

C. Model Performance Evaluation

The performance of the forecasting models was evaluated in a systematic manner; first, we can obtain the actual silver prices from the testing dataset for 30 days. Next, the predicted values were collected from each and every forecasting model. Then for those predicted values compute the forecasting errors with the corresponding observed values.

Then calculate the error metrics one by one to calculate the difference aspects of the predicted values. The metrics are Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and Mean Absolute Scaled Error, whose characteristics are to measure the average magnitude of absolute forecasting errors, to highlight the larger forecasting deviations through computed squared error, to express forecasting error as a percentage of actual observation, and to compare the Seasonal Naïve benchmark with each model's forecasting accuracy, respectively.

MASE values are interpreted as if the value is less than 1, then the forecasting model performs better than the Seasonal Naïve Model. If it is greater than 1, then the seasonal naïve model performs better than all other forecasting performances. Next, compare all evaluations of metrics across all forecasting models under study. As the last step of this process, identify the forecasting model with the least amount of prediction error and with maximum forecasting accuracy as the best one.

D. Agent AI Framework

As the first step of this process collect the forecast results produced by all forecasting models. Then it removes raw and messy data for automated analysis or AI process for the prediction dataset by some important steps that include synchronizing of timetables, Time-series alignment, check the consistent price units, and to creating a unified evaluation dataset. Then Metric Computation Agent compare each and every model prediction with the original testing observations.

Then MAE, RMSE, and MAPE were computed for every forecasting models. After that all the models are ranked and sorted based the computed performance metrics. For this ranking process is done by apply weighted ranking method to identify the most consistent performer.

By this way the process is done and select the best forecasting model as the final recommendation for silver price prediction.

IV. RESULTS AND ANALYSIS

A. *Comparative interpretation of forecasting model performance*

Table 4.1: Model Comparison

S. No	Model	MAE	RMSE
1	AutoGluon	105309.45	109095.66
2	Seasonal Naïve	179653.67	180171.80
3	Auto ARIMA	14173.12	18832.82

Table 4.1 shows the comparison of forecasting models and shows a clear difference in their performances, and then the agent AI framework is used to evaluate the model objective based on the forecasting accuracy and stability. Under this, several models were used, such as AutoGluon, Seasonal Naïve, and Auto-ARIMA. Among those models, Auto-ARIMA achieved the lower forecasting errors, with the best values of MAE, RMSE, and MAPE; this makes it the most accurate model for forecasting the silver price for the period 2024-2026. This shows that the silver price series follows a linear trend and predictable patterns captured effectively by a statistical model. At the same time, LSTM and AutoGluon were performed, and they produced higher forecasting errors than I thought they would, even though they have advanced architectures. A likely reason is the limited dataset size of approximately 800 observations, which may have caused these complex models to learn random fluctuations rather than the underlying price trend. By comparing model performance using multiple error measures, the Agent AI framework identified Auto-ARIMA as the most accurate and stable model, making the model selection process transparent, objective, and reproducible.

B. *LSTM Model Performance and Interpretation*

The LSTM model was evaluated to check the ability to capture sequential and nonlinear patterns present in the silver prices, but it resulted in relatively high forecasting error with an RMSE value of 71,101.67 and an MAE of 68,779.63. This indicates lower forecasting accuracy than Auto-ARIMA. Where LSTM is designed for long-term relationships and for nonlinear patterns in the data, during the training of this, it was only able to capture short-term price movements, and during the testing period, it showed a decline for the 30-day prediction price of silver. Overall, the findings suggest that LSTM was not the most suitable model for this silver price dataset, whereas Auto-ARIMA provided better forecasting accuracy and greater stability.

These results show that the complex model does not always produce better forecasting accuracy. The findings show that advanced AI models are not necessarily superior for every forecasting problem. For univariate silver price forecasting with a minimal dataset, a simple statistical model such as Auto-ARIMA can provide more accurate and stable predictions. Therefore, before selecting forecasting model one should check the characteristics of the dataset, such as its linearity and size, other than on the complexity or popularity of the algorithm.

C. *Visualization*

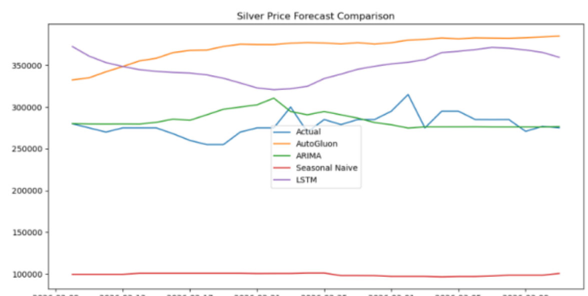

Figure 4.1: Visual comparison of actual and predicted silver prices

Figure 4.1 shows a comparison of the actual silver prices with forecasting values given by AutoGluon, Auto-ARIMA, Seasonal Naïve, and LSTM models over the 30-day test period. The ARIMA forecast remained closest to the actual price movements, indicating better monitoring of the underlying trend. AutoGluon consistently overestimated silver prices, while the LSTM model showed larger deviations from the actual values. The seasonal naïve model performed the poorest, with forecasts remaining nearly constant and far below the observed price levels. Overall, the figure visually demonstrates that the forecasting performance of Auto-ARIMA is far better compared with the other models.

D. *Predictive Evaluation*

To complement the statistical error metrics, a visual comparison was conducted between the forecasted silver prices and the actual prices over the 30-day evaluation period. The Auto-ARIMA model showed the closest alignment with the actual price movements, indicating better forecasting accuracy and stability. Its forecast curve followed the overall market trend closely, with relatively small deviations from the observed prices, demonstrating its ability to capture the underlying price pattern. In contrast, LSTM and AutoGluon showed larger differences from the actual trajectory, with LSTM displaying delayed responses to price changes and AutoGluon occasionally overestimating future prices. The Seasonal Naïve model performed the poorest, as its forecasts remained almost constant and failed to reflect the changing market behavior. The close agreement between the Auto-ARIMA forecasts and the actual price series supports the statistical results and confirms that, for a moderate-sized univariate silver price dataset, a simpler statistical model can provide more accurate and reliable forecasts than more complex AI-based models.

E. Agent AI-based model selection

The Agent AI framework was used to evaluate and compare the forecasting performance of Auto-ARIMA, LSTM, AutoGluon, Seasonal Naïve, and TimeGPT using multiple error measures. The evaluation process was fully automated and objective, allowing each model to be assessed consistently based on forecasting accuracy and stability. The framework compared model performance across different error metrics and identified the model that provided the most reliable predictions. The results showed that Auto-ARIMA was the best-performing model for forecasting silver prices during the 2024–2026 period, as it achieved the highest overall accuracy and the most stable performance across all evaluation measures. These findings demonstrate that an automated Agent AI framework can support transparent, objective, and reproducible forecasting model selection.

Table 4.2 Interpretation of Auto-ARIMA model

Metric	Value	Interpretation
MAE	14173.12	Low average deviation from actual prices (₹/kg)
RMSE	18832.82	Robustness against large outlier errors
MAPE	5.13%	High relative precision (94.87% accuracy rate)
Score	0.263	Leading score in the multi-agent ranking hierarchy

The Agent AI framework selected Auto-ARIMA as the best forecasting model based on its accuracy, stability, and consistency across multiple error measures. It achieved the lowest values for MAE, RMSE, and MAPE, with a MAPE of 5.13%, indicating strong forecasting performance. Compared with LSTM, AutoGluon, and TimeGPT, Auto-ARIMA produced more reliable and stable forecasts during the testing period. The automated evaluation process ensured objective, transparent, and reproducible model selection, demonstrating the effectiveness of Agent AI for evidence-based forecasting model evaluation.

V. CONCLUSION

As the result of this study, Auto-ARIMA is found to be the most effective model to predict the silver price for the period between 2024 and 2026. It achieved the lower forecasting error values, and it outperformed LSTM and TimeGPT. This finding shows that a well-specified statistical model can perform far better than well-known deep learning models known for their complex data prediction when it comes to forecasting a single-variable commodity series with a clear trend present in it. The Agent AI framework too demonstrated that model selection for forecasting is based on the objective performance evaluation other than assumptions about their model complexity. Contributions of this study:

It compares Auto-ARIMA, LSTM, and TimeGPT under an evaluation framework. Then pick the best model for predictive performance based on their empirical evidence other than the technological supremacy they have. Another contribution study is to introduce the agent AI-based evaluation framework; it is inspired by multi-agent systems that automatically select the model assessment and reduce the human bias and improve the reproducibility of forecasting decisions, etc.

The proposed work provides an effective approach for real-world experiments of forecasting modes and decisions about investments, market research, and policy analysis. It has been shown the simplified forecasting model can be successfully implemented effectively, very accurate and highly profitable forecast for silver and other costly metals, etc.

A. Limitation of the study

This study has many limitations. It's only based on the silver price only; it does not include any macroeconomic variables like exchange price, inflation, or any interest rates. And it only forecast for short period of 30 days only; its analysis is based on a silver price only. We cannot generalize this result for other commodities like gold and other metals or for any other financial markets.

B. Future works

Future work can extend this work by developing this framework for hybrid models like ARIMA-LSTM and trying to incorporate the macroeconomic and financial indicators. To explore unified framework for forecasting methods that combine more than three models through an adaptive weighting method. Then come to the Agent AI framework; this can be expanded to include transformer-based and foundation forecasting models and to create a more intelligent and adaptive system for forecasting financial and other commodities in the markets.

Overall, the research demonstrates that the accuracy of the forecasting models is based on selecting the right model for the data rather than choosing the most complex algorithm, and it highlights the efficiency of Agent AI for intelligent and objective forecasting model selection.

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