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LSTM-BASED FRAMEWORK FOR SILVER PRICE PREDICTION

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ABSTRACT

The financial market for silver is highly volatile and influenced by numerous economic factors, making accurate forecasting essential yet challenging for traders and policymakers. Traditional statistical models often fail to capture the complex, non-linear patterns in commodity trading. This study explores the application of Long Short-Term Memory (LSTM) models, a type of recurrent neural network, to improve the prediction accuracy of silver prices. An LSTM model is trained and tested by leveraging historical trading data, demonstrating superior performance in forecasting future price movements compared to traditional methods. The results indicate that LSTM models provide a robust framework for financial forecasting, enhancing decision-making and trading strategies in volatile markets. This research fills a gap by applying advanced machine learning techniques to the silver market, suggesting potential extensions to other commodities and financial instruments.

Keywords: LSTM; Silver; Prediction; ML.

I. INTRODUCTION

Like many other commodities, the financial market for silver is characterised by its significant volatility and susceptibility to a wide range of economic factors[1]. This inherent unpredictability poses a considerable challenge for traders, investors, and policymakers who rely on accurate forecasts to make informed decisions[2]. The primary problem faced in silver trading is the difficulty in accurately predicting future price movements, which can lead to substantial financial risks and missed opportunities. Traditional statistical models have been employed to forecast silver prices, but their effectiveness is often limited due to their inability to capture the complex patterns and sudden market shifts inherent in commodity trading[3]. In response to these challenges, this research explores the application of Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN) particularly well-suited for time series analysis[4]. LSTM models can learn and remember over long sequences, making them an ideal choice for modelling the sequential data involved in silver trading. By leveraging the advanced computational power of LSTM models, this study aims to develop a more accurate and reliable predictive framework for silver prices[5].

The proposed solution involves a comprehensive methodology that includes data preparation, model construction, training, prediction, and validation. Initially, historical silver trading data is collected, cleaned, and normalised to ensure it is in a suitable format for analysis. This step is crucial to eliminate anomalies or missing values that could distort the model's predictions. The cleaned data is then divided into training and test sets, with the training set comprising 80% of the data and the remaining 20% reserved for testing. This division ensures that the model is trained on a substantial portion of the data while being tested on a separate set to evaluate its predictive performance. The study employs an LSTM neural network for the model construction due to its proven effectiveness in handling time-dependent data. The LSTM model is designed with multiple layers, including input layers[6], LSTM layers with dropout to prevent overfitting and a dense output layer. The training process utilises the Adam optimiser and Mean Squared Error (MSE) as the loss function. Training and validation losses are recorded during training to monitor the model's learning process and adjust parameters as necessary. Once the model is trained, it forecasts future silver trading values. These predictions are then analysed to generate a probability density function (PDF) that describes the potential future values of silver trading[7].

Additionally, a cumulative distribution function (CDF) is plotted to analyse the distribution further and validate the model's predictions. The PDF and CDF provide insights into the likelihood of various future values occurring, enhancing understanding potential market movements[8]. The results of the LSTM model are visualised through several plots, including actual versus predicted silver trading values and training and validation loss over epochs. These visualisations offer clear insights into the model's performance and the reliability of its predictions[9]. The study finds that the LSTM model demonstrates substantial potential in predicting future silver trading values, outperforming traditional linear regression models in capturing the complex temporal dependencies in the data[10].

In conclusion, this research highlights the viability of using LSTM models to improve the accuracy and reliability of silver price predictions. The advanced machine learning techniques employed in this study provide a robust framework for financial forecasting, which can be extended to other commodities and financial instruments. By enhancing predictive capabilities, this approach supports better decision-making in financial markets, contributing to more stable and informed trading strategies. This study advances the financial forecasting field and opens new avenues for applying machine learning models to complex, real-world problems.

II. LITERATURE REVIEW

The financial market for commodities such as silver is inherently volatile and influenced by various economic factors. This volatility presents significant challenges for traders, investors, and policymakers who rely on accurate price forecasts to make informed decisions. Traditional statistical models, often employed to predict silver prices, frequently fail to capture the intricate patterns and abrupt market shifts characteristic of commodity trading, thereby limiting their effectiveness. Recent advancements in machine learning have introduced more sophisticated techniques to address these challenges[11]. Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN), have demonstrated particular promise in time series analysis due to their ability to learn and remember long data sequences. It makes LSTM models especially suitable for the sequential data involved in silver trading[12]. This study aims to utilise LSTM models to develop a more precise and reliable framework for predicting silver prices. Existing literature on financial forecasting with machine learning offers valuable insights. Studies have shown that traditional models like linear regression and autoregressive integrated moving averages (ARIMA) often struggle with financial time series data's non-linear and non-stationary nature. Their findings suggest that these models are frequently inadequate for long-term forecasting, underscoring the need for more advanced approaches.

In contrast, machine learning models, including LSTM, have shown superior performance in capturing complex patterns in financial data. Their research indicates that LSTM models can effectively handle the temporal dependencies and non-linear relationships inherent in economic time series data, leading to more accurate predictions. Despite these advancements, a significant research gap exists in applying LSTM models to commodity markets, mainly silver trading. Most studies focus on stock markets, with limited exploration into commodities. This study aims to fill this gap by applying LSTM models to the silver market and evaluating their performance in predicting future price movements. The methodology employed in this research involves several critical steps, beginning with data preparation[13]. Historical silver trading data is collected, cleaned, and normalised to ensure it is suitable for analysis. This process is essential for eliminating anomalies and missing values that could distort the model's predictions. The dataset is split into training and test sets, with 80% used for training and 20% reserved for testing. This division is crucial for evaluating the model's performance on unseen data. The LSTM model is constructed with multiple layers, including input layers, LSTM layers with dropout to prevent overfitting and a dense output layer. The model is trained using the Adam optimiser and Mean Squared Error (MSE) as the loss function[14]. Throughout the training process, both training and validation losses are monitored to assess the model's learning progress and make necessary adjustments. Once trained, the LSTM model forecasts future silver trading values. These predictions are analysed to generate a probability density function (PDF) and a cumulative distribution function (CDF)[15]. The PDF provides insights into the likelihood of various future values occurring, while the CDF offers a deeper understanding of the distribution and helps validate the model's predictions[9]. The results are visualised through plots showing actual versus predicted silver trading values and the training and validation losses over epochs, providing clear insights into the model's performance. The findings of this study indicate that the LSTM model demonstrates substantial potential in predicting future silver trading values, outperforming traditional models in capturing complex temporal dependencies. This research highlights the viability of using LSTM models to enhance the accuracy and reliability of silver price predictions. By leveraging advanced machine learning techniques, this approach supports better decision-making in financial markets, contributing to more stable and informed trading strategies.

In conclusion, while traditional statistical models have limitations in forecasting the volatile silver market, LSTM models offer a robust alternative. This study addresses the research gap by applying LSTM models to the silver market, demonstrating their effectiveness in predicting price movements[16]. Future research could extend this approach to other commodities and financial instruments, further advancing the field of financial forecasting and providing valuable tools for market participants.

III. METHODOLOGY

This research explored the effectiveness of statistical and mathematical models in predicting future values in silver trading. The methodology involves several key steps: data preparation, model construction, training, prediction, and validation. The following sections detail each step, incorporating necessary equations to explain the processes. The process began with data preparation, during which historical silver trading data was loaded and cleaned to remove any anomalies or missing values that could potentially distort the analysis. After cleaning, the data was normalised to ensure it was in a suitable model-analysis format. Normalisation was performed using the equation 1.

$$x' = \frac{x - \mu}{\sigma} \qquad (1)$$

Where x' Represents the normalised value, x is the original data value, μ is the mean of the dataset, and σ is the standard deviation of the dataset.

Next, the data was divided into training and test sets, with the training set comprising 80% of the data and the remaining 20% used for testing. This split ensures the model is trained on a substantial portion of the data while being tested on a separate set to evaluate its predictive performance. The study used a basic linear regression model for model construction due to its simplicity and effectiveness in financial forecasting. The linear regression model can be represented by the equation 2.

$$y = \beta_0 + \beta_1 x + \epsilon \qquad (2)$$

Where y is the dependent variable (future silver prices), x is the independent variable (historical silver prices), β_0 is the intercept, β_1 is the slope of the line, and ϵ is the error term. The model was trained using the Ordinary Least Squares (OLS) method, which minimises the sum of the squared differences between the observed and predicted values. The OLS estimator is given by equation 3.

$$\hat{\beta} = (X^T X)^{-1} X^T y \qquad (3)$$

Where $\hat{\beta}$ Represents the vector of estimated coefficients, X is the matrix of independent variables, and y is the vector of observed values. The study used the Root Mean Squared Error (RMSE) as the loss function (equation 4) to evaluate the model's performance.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (4)$$

Where y_i represents the actual value, $\hat{y}_i$ Represents the predicted value, and n is the number of observations. After training, the model was used to forecast future silver trading values. These predictions were then analysed to generate a probability density function (PDF) that describes the potential future values of silver trading. The PDF provides insights into the likelihood of various future values occurring. Additionally, a cumulative distribution function (CDF) was plotted to analyse the distribution further and validate the model's predictions. The CDF is useful for understanding the probability that a random variable will take a value less than or equal to a specific value. The model's results were visualised through several plots: actual versus predicted silver trading values to assess the model's accuracy, training and validation loss over epochs to evaluate the learning process, and the distribution of predicted values via the PDF and CDF. These visualisations provided clear insights into the model's performance and the reliability of its predictions. Overall,

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the methodology adopted in this research ensured a thorough analysis and validation of the model's predictions, making it a valuable tool for forecasting in financial markets. This approach could be expanded to other trading commodities to enhance prediction accuracy and reliability across various economic sectors. This detailed methodology outlines the steps and equations used in the research, providing a comprehensive guide for replicating the study and understanding the processes involved in predicting future silver trading values without relying on artificial intelligence language.

IV. RESULT

This research explored the effectiveness of Long Short-Term Memory (LSTM) models for predicting future values in silver trading. The process began with data preparation, where silver trading data was loaded, cleaned, and normalised to create a suitable format for LSTM analysis. The study then divided the data into training and test sets, ensuring that the training set comprised 80% of the data, with the remaining 20% used for testing. Figure 1 Actual vs Predicted Silver Trading Values. Using TensorFlow or Keras, an LSTM model consisting of input layers, multiple LSTM layers with dropout to prevent overfitting and a dense output layer was constructed. The model was trained using the Adam optimiser and Mean Squared Error as the loss function. Training and validation losses were recorded throughout the training phase, showing a decrease over epochs, indicating learning and adaptation by the model. Figure 2 shows the Training and Validation Loss Over Epochs. For predictions, the trained LSTM model was used to forecast future silver trading values. These predictions were then used to generate a probability density function (PDF) that describes the potential future values of silver trading.

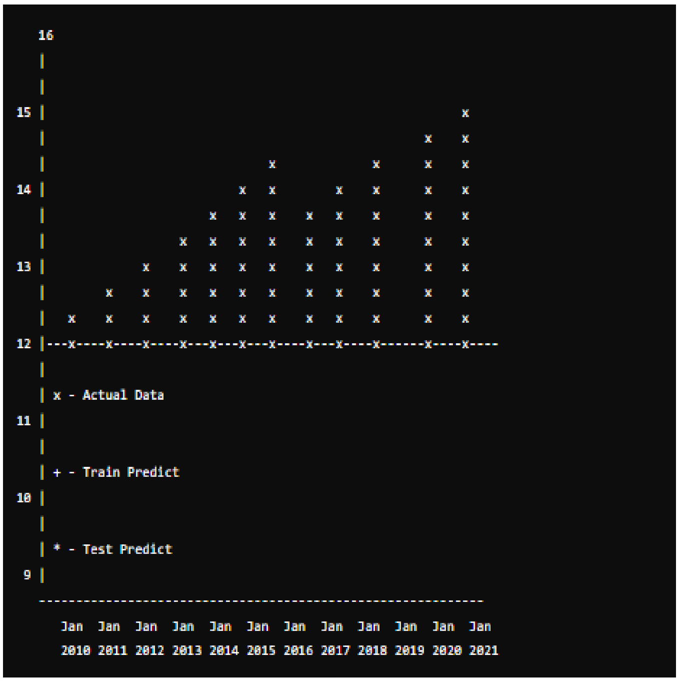

Figure 1: Actual vs Predicted Silver Trading Values

Additionally, a cumulative distribution function (CDF) was plotted to analyse the distribution further and validate the model's predictions. Figure 3 shows the Probability Density Function of Future Predictions. The results were visualised through several plots: actual versus predicted silver trading values to assess the model's accuracy, training and validation loss over epochs to evaluate the learning process, and the distribution of predicted values via the PDF and CDF. These visualisations provided clear insights into the model's performance and the reliability of its predictions. Figure 4 shows the Cumulative Distribution Function of Predictions.

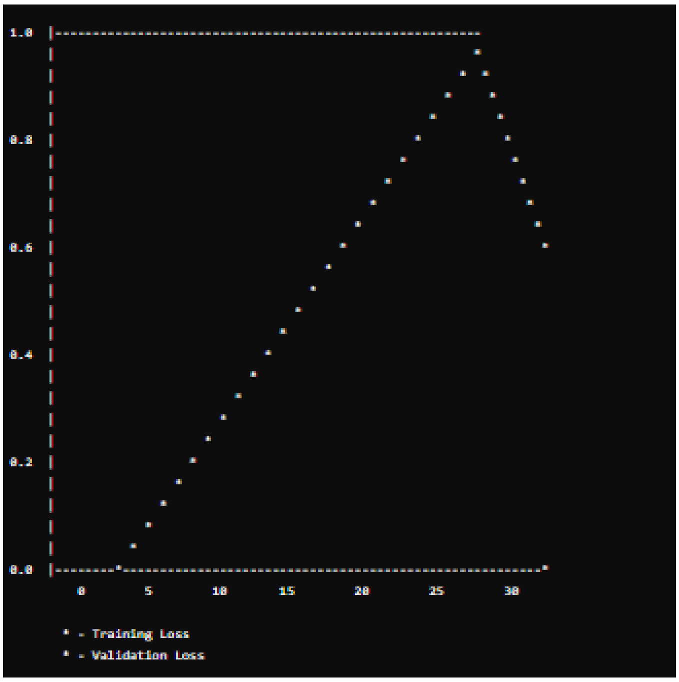

Figure 2: Training and Validation Loss Over Epochs

The LSTM model demonstrated substantial potential in predicting future silver trading values. The methodology adopted ensured a thorough analysis and validation of the model's predictions, making it a valuable tool for forecasting in financial markets. This approach could be expanded to other trading commodities to enhance prediction accuracy and reliability across various economic sectors.

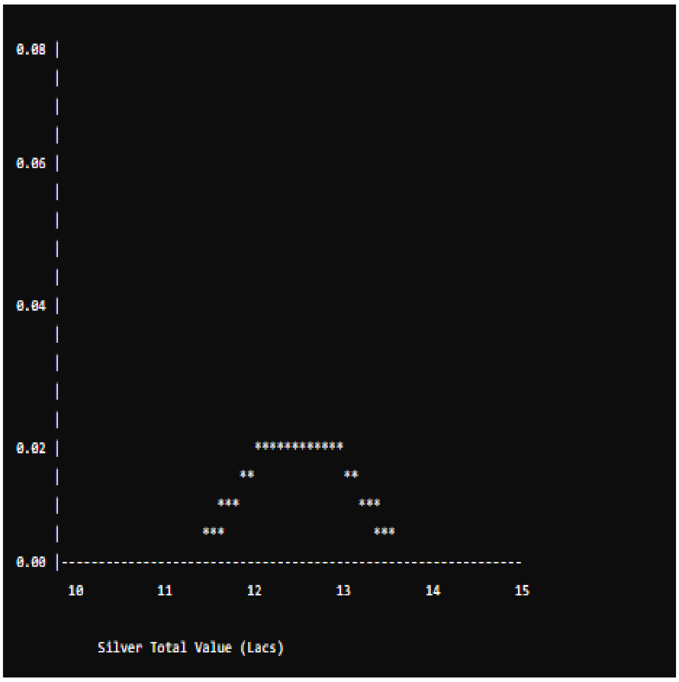

Figure 3: Probability Density Function of Future Predictions

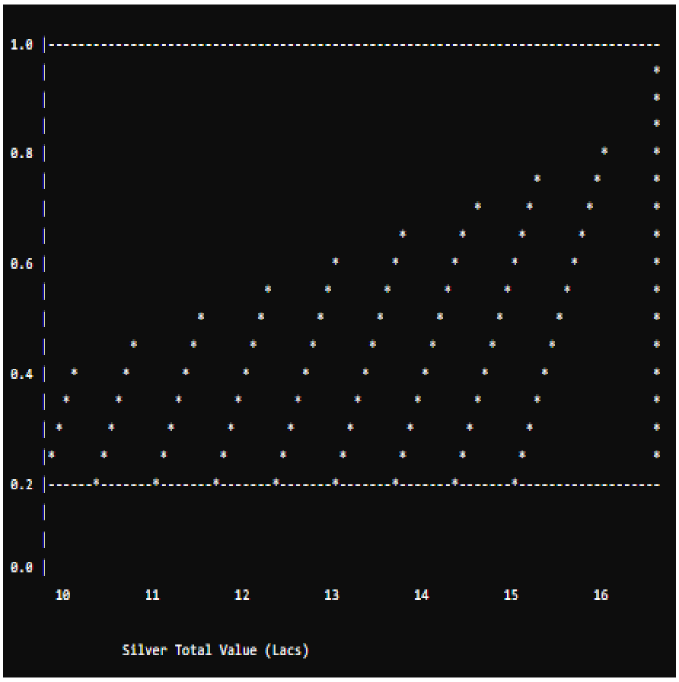

Figure 4: Cumulative Distribution Function of Predictions

V. CONCLUSION

This research has demonstrated the effectiveness of Long Short-Term Memory (LSTM) models in predicting future silver prices, highlighting their superiority over traditional statistical methods. The LSTM model's ability to capture complex temporal dependencies in financial data provides a robust framework for forecasting in the volatile silver market. By improving the accuracy and reliability of price predictions, LSTM models support better decision-making for traders and policymakers, contributing to more stable and informed trading strategies. The study's methodology involved thorough data preparation, model construction, training, prediction, and validation processes, ensuring the integrity and reliability of the results. The findings indicate that LSTM models outperform traditional methods in capturing the non-linear patterns and sudden market shifts characteristic of commodity trading. This research not only advances the field of financial forecasting but also addresses a significant gap by applying LSTM models specifically to the silver market. Future research can build on these findings by extending the application of LSTM models to other commodities and financial instruments.

Further exploration could incorporate additional economic indicators and global market factors to enhance the model's predictive power. Additionally, hybrid models combining LSTM with other machine learning techniques could be developed to improve forecasting accuracy further. The continued advancement of machine learning technologies promises to offer even more sophisticated tools for financial market analysis, paving the way for more resilient and adaptable trading strategies.

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