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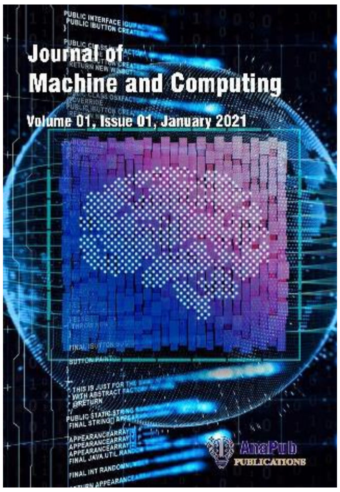

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Precious Metal Prices Forecasting Using Optimally Configured Hybrid Deep Learning Approach

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Abstract - Precious metals price forecasting represents an intricate task owing to their elevated volatility and delicacy to global economic variations. Conventional time series forecasting approaches frequently attempt to account for the non-linear and complex relationships that exist in commodity price movements, resulting in sub-optimal accuracy in price forecasting. Recently, the emergence of deep learning has provided outstanding modeling of such intricate patterns. This paper investigates the implementation of deep learning approaches, particularly One Dimensional Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), and the combination of 1D-CNN and LSTM, for precious metals prices forecasting. By drawing on the competitive unique capabilities of 1D-CNN in extracting essential features, LSTM in sequential data processing, and Hyperband optimization methodology in automatically optimizing hyper-parameters, the proposed hybrid approach endeavors to improve forecasting accuracy compared to individual approaches. Extensive experiments are conducted to assess the performance of implemented approaches using three datasets traded at the Multi Commodity Exchange (MCX), and the attained accuracy exhibits the hybrid approach's superiority over standalone architectures. Using the gold dataset as an example of a precious metal, the proposed hybrid approach results for the Absolute Error (MAE), Root Mean Squared Error (RMSE), and Rsquared were 0.0182, 0.1500, and 0.9616, respectively. The outcomes indicate that the proposed hybrid forecasting approach of 1D-CNN and LSTM can considerably enhance the capabilities of prediction in the precious metal price forecasting field, providing an encouraging architecture for analyzing the financial market.

Keywords - Precious Metal Prices, 1D-CNN, LSTM, Hyperband Optimization Methodology, Hybrid Forecasting Approach, Multi Commodity Exchange (MCX)

I. INTRODUCTION

Precious metals are gaining increasing attention owing to their elevated economic values. Precious metals prices represent a leading indicator of inflation, which can express the purpose of monetary policy for the economy as a whole. Precious metals serve as vital hedging instruments in the financial market, particularly as safe-haven assets to mitigate risks during financial crises. Additionally, precious metals are essential raw materials in contemporary advanced technologies, and the price fluctuation of precious metals profoundly influences the operations of relevant enterprises [1]. Accurate price forecasting is of great importance to stable corporate operations, financial risk management, and economic policy making. However, the price fluctuation of precious metals is influenced by various factors (such as global geopolitical landscape, economic policy, dollar exchange rates, and crude oil prices), and the price series exhibit the traits of instability, non-linearity, and extreme noise, hence accurately forecasting metal prices represent a difficult task [2] [3].

Forecasting precious metal prices has long been a key focus of the scholarly community, with models continuously developing as research progresses. In the past years, academics relied on econometric approaches (such as vector error correction, vector autoregressive, autoregressive integrated moving average, and generalized autoregressive conditional heteroscedasticity) for forecasting prices of precious metals (such as gold, silver, platinum, palladium, and rhodium) [2]. While these traditional econometric approaches perform well under linear assumptions, they struggle to capture more critical nonlinear traits of time series data [4]. With advancements in computing technology, machine learning approaches have become more and more distinguished in forecasting metal prices. Nevertheless, these models face many drawbacks such as limited generalization capabilities, constrained feature extraction, and sub-optimal forecasting accuracy [5] [6] [7].

Deep learning approaches have revealed considerable improvements in financial time series forecasting (especially, in metal price forecasting), exceeding both econometric and machine learning approaches [8]. Across various applications, deep learning approaches surpassed in extracting essential features utilizing various types of data [9] [10] [11], and recent progressions in the use of hybrid mechanisms have further improved forecasting accuracy beyond basic approaches. Regarding hybrid deep learning approaches, the main concept is to handle the deficiencies of individual approaches and create a synergistic impact in metals price forecasting, which has recently become the mainstream scheme [6].

Among the diverse deep learning approaches, one-dimensional convolutional neural networks (1D-CNN) and long short-term memory (LSTM) are the dominant approaches to financial time series forecasting, including metal price forecasting. 1D-CNN is superlative for sequential data (such as time series signals) because it deals with one-dimensional data. It uses convolution filters applied across the data to extract local patterns effectively. LSTM represents a kind of recurrent neural network constructed to deal with sequential data of long-term dependencies. It conquers the issue of vanishing gradient present in conventional recurrent networks by inserting effective gating mechanisms [12].

Accurate precious metals price forecasting would significantly support account managers, investors, and metal institutions in producing sound market decisions and evaluations, whereas further progress in accurately forecasting such metals prices is challenging owing to their oscillatory and non-linearity characteristics. This work provides the following essential contributions to forecasting the precious metal prices:

1. Developing an optimized hybrid deep learning approach by combining 1D-CNN and LSTM with Hyperband optimization methodology, using 1D-CNN to extract essential features, LSTM to capture temporal dependencies in time series data, and hyper-parameter optimization to improve approach performance. This approach is particularly proposed for precious metals price forecasting, which can outperform standalone approaches.
2. Providing a systematic comparison of the forecasting accuracy of the proposed hybrid approach with the individual approaches, and offering an in-depth analysis of the merits and restrictions of each approach in the metal price forecasting, particularly, precious gold and silver metals, and basic copper metal.
3. Utilizing the Multi Commodity Exchange (MCX), a real-world dataset, to highlight the applicability of deep learning approaches and their performance in forecasting precious metals prices. Since the MCX dataset has inherent volatility and market-driven patterns, it offers a suitable and challenging environment for approach testing.
4. Conducting extensive experiments based on several assessment metrics (like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Median Absolute Error (Median-AE), and Determination Coefficient (Rsquared)) to rigorously evaluate and compare the performance of the approaches.
5. The outcomes provide practical insights for financial analysts and investors, depicting that the proposed hybrid approach can improve forecasting accuracy and provide a competitive advantage in the financial market.

The remainder of the paper organization includes the following; an abbreviated description of the relevant systems is provided in the second section. The proposed system's general framework and construction are explained in detail in the third section. Experimental datasets, forecasting assessment metrics, experimental results, and comparison analysis with relevant systems are exhibited in the fourth section. Conclusions and some future directions are drawn in the final section.

II. RELATED WORKS

Precious metals, as unique commodities, have a distinguishing role in the global economy. In recent decades, increasing literature has concentrated on improving the accuracy of precious metal price forecasts relying on machine and deep learning approaches, providing valuable insights for monetary policy formulation, investment strategies, and mining production planning [13].

Alameer et al. [14] presented a hybrid system for gold price forecasting with several optimization algorithms for training a multilayer perceptron neural network. This system utilized a gold price dataset of 360 monthly observations, ranging from September 2013 to August 2017. The trained neural network with the Whale optimization technique surpassed other systems and revealed a significant reduction in MSE and RMSE and the highest generalization abilities, however, this hybrid system might need more computational resources in contrast to simpler systems.

Du et al. [15] presented a hybrid system for metal price forecasting. This system combined an Extreme Learning Machine (ELM) with a Marine Predator optimization technique to improve forecasting accuracy. Before the dataset time series is fed into this combination, it is decomposed into modes using filter-based empirical mode decomposition with time-varying to preserve the characteristics of time-varying. In this system, gold and copper price datasets (acquired from the Investing website) are utilized, ranging from the second of January, 2013 to the end of January, 2020. The incorporation of the optimized ELM with superior pre-processing improved the attained accuracies, however, this requires a significant effort of computation. Additionally, it concentrates on point forecasting, which led to a lack of uncertainty quantification for price fluctuations.

Elberawi and Belal [16] presented a hybrid deep learning system relying on the auto-encoder method and LSTM to predict daily gold and global other commodity prices. In this system, the recurrent variation auto-encoder was utilized for extracting higher-level and latent features from time series, and LSTM was utilized for capturing temporal dependencies throughout multiple past time steps for a dataset acquired from Quandl public repository (recorded since 1970). In addition, a Genetic Algorithm was incorporated to improve system hyper-parameters (like feature selection, learning and dropout rates, counts of layers, batch size, epochs, etc.). This system surpassed other baseline systems for next-day predictions. Although the error naturally increases with longer horizons, the system performed consistently over the two-, three-, and seven-day horizons, and showed inconsequential accuracy falls at specific points. However, genetic algorithm-based hyper-parameter search added more training time and complexity.

Huang et al. [17] presented a hybrid system for forecasting the price of various non-ferrous metals such as gold, copper, aluminium, and zinc. In this system, the initial forecasting for each metal was implemented using the Prophet approach, and the differences between forecasted and actual values (non-linear residual sequences) were also extracted. These residual sequences were then decomposed using an enhanced complementary ensemble empirical mode to be broken into intrinsic mode functions (multiple simpler sub-sequences) to decrease complexity and address aliasing and noise issues in the data. After that, every decomposed sub-sequence was forecasted by implementing multi-approaches like non-linear auto-regressive network, back propagation neural network, ELMAN neural network, LSTM, and ARIMA, and the optimal predictions resulted from all sub-sequences were combined to constitute the last residual forecasting. Eventually, this last forecasting was added to the initial forecasting to attain the final forecasted values for non-ferrous metal prices. In this system, daily closing prices for gold and copper (obtained from the Investing website) were used, ranging from 2013 to 2015, and daily closing prices for aluminium and zinc (obtained from the London Metal Exchange (LME) dataset), ranging from 2008 to 2015 and 2011, respectively. This hybrid system achieved the highest performance across all datasets used compared to the individual approaches, however, it could be computationally expensive.

Zhou and Xu [18] presented a multi-stage hybrid learning scheme for accurately forecasting the prices of platinum, palladium, and silver using data decomposition, optimized relevance vector machine, and error correction. In the first stage of this scheme, the input price series data is decomposed using complementary ensemble empirical mode, and these decomposed data are then passed to another decomposition and permutation entropy for minimizing noise and repetitive modelling. In the second stage, the resulting sub-sequences are fed into an optimized relevance vector machine predictor (utilizing African Vulture optimization technique) to attain the initial forecasting results and the error series. These error series are further decomposed and forecasted in the final stage to rectify the formerly forecasted prices of precious metals and attain the last forecasting outcomes. The hybrid learning scheme utilized the futures price datasets for platinum, palladium, and silver from the New York Mercantile Exchange (NYMEX), ranging from the first of January, 2018, to the end of December, 2021. This scheme provided high Rsquared and low error values across the three precious metals. However, it required more computational resources for optimization and multiple decomposition techniques.

Banerjee et al. [19] explored the responses of eight commodity futures (Gold, silver, copper, nickel, lead, zinc, natural gas, and crude oil) to propaganda indices during COVID-19, using several deep learning approaches. LSTM, Bidirectional LSTM, and Gated Recurrent Units (GRU) were implemented on the daily closing prices for eight commodities traded in the MCX and the National Commodity Exchange (from the first of January, 2020, to the end of May, 2021) and news sentiment indices from the RavenPack database. Among the implemented approaches, Bidirectional LSTM outperformed the others by achieving the lowest values for MAE and RMSE, especially in forecasting the precious gold and silver metal prices; however, it needs more computational resources in contrast to LSTM and GRU.

Li et al. [20] utilized the futures price of copper derived from the NYMEX, and this dataset is dependent on comprehensive market and historical data that might not apprehend unforeseen economic shifts. This dataset was first normalized and then analyzed to choose the ten most correlated factors with copper prices using the Pearson correlation coefficient method. After that, split into a training set (from April 1996 to November 2015) and a testing set (from December 2015 to July, 2022). Initially, the price of copper was forecasted by implementing deep extreme learning, extreme Gradient Boosting, and LSTM approaches with various factors. The Sparrow search optimization algorithm was utilized to choose the optimal hyper-parameters for these approaches. The deep extreme learning exceeded the other approaches with an Rsquared value of 0.956. Moreover, these approaches were combined using a CNN with the ten correlated factors to present an ensemble approach to forecasting the price of copper. The presented ensemble approach significantly enhanced the forecasting accuracy and exceeded the other individual approaches with an Rsquared value of 0.959. However, this combination of approaches increased the computational complexity. Regardless of high achieved accuracy, the ensemble approach, like CNN, lacks transparency in decision-making operations.

Yang et al. [21] presented an ensemble deep learning-based prediction system incorporating LSTM, GRU, recurrent, and multilayer perceptron neural networks, improved via temporal fusion transformers and attention mechanisms to acquire ultimate interval-valued metal prices and enhance prediction performance. In this system, futures prices of silver (from the first of January, 2006, to the end of April, 2024) and copper (from the first of June, 2012, to the end of November, 2023) were obtained from the LME dataset. The proposed system achieved IRMSE values of 0.17496 and 62.51197 for silver and copper prices, respectively, demonstrating error reduction and hence strong predictive accuracy. However, this system necessitates high-quality data and large training periods, and according to its complexity, it may require more computational costs.

The most notable shortcomings determined in the previously mentioned related works are the limited ability of traditional approaches to extract essential features, dependency on intensive preprocessing stages that work on making modelling complicated, and the insufficiency of processing spatial and sequential data synchronously. Also, many of these works have relied on decomposition or autonomous optimization techniques to address the inherent restrictions of the underlying neural networks, resulting in hybrid approaches that are expensive and computationally complex. In addition, many approaches, like multilayer perceptron neural networks and ELM, lacked strength in finding temporal dependencies and even local patterns inherent in metal price data. Moreover, most previously related works depend on manual tuning, which is ineffective and time-consuming. In our proposed architecture, the combination of 1D-CNN and LSTM addresses these shortcomings by effectively capturing local price fluctuations and the characteristics of long-term sequential dependencies, and utilizing the hyperband optimization methodology avoids manual tuning and prevents overfitting and underfitting through finding the best hyper-parameters. As a result, this simplifies the model structure, reduces computational complexity, improves interpretability, and enhances prediction accuracy, accordingly overcoming the major shortcomings mentioned in previous works. **Table 1** summarizes the main techniques and datasets used, target metals, and the highest obtained results of the related works.

Table 1. Comparison of deep learning-based metal price prediction approaches

Author(s), Ref. (Year)	Deep Learning and Techniques Used	Dataset Used	Target Metals	Obtained Results
Alameer et al., [14] (2019)	Multilayer perceptron neural network and Whale optimization technique	Monthly gold price data	Gold	Optimized the accuracy of prediction (the results specifics were not detailed)
Du et al., [15] (2021)	ELM with a Marine predator optimization technique	Gold and copper price datasets (acquired from the Investing website)	Gold and Copper	Optimized the accuracy of prediction (exact metrics were not demonstrated)
Elberawi and Belal, [16] (2021)	Recurrent variation auto-encoder method and LSTM with Genetic algorithm	Global commodity prices (acquired from Quandl public repository)	Gold, silver, iridium, and gas	Achieved MAE of 15[illegible] and RMSE of 20.8 for the next day prediction of gold prices
Huang et al., [17] (2022)	Hybrid system of Prophet model, improved complementary ensemble empirical mode, and multi-model optimization error correction utilizing ARIMA, LSTM, etc.	Metal prices (obtained from LME dataset)	Gold, copper, aluminum, and zinc	The highest results obtained were for copper (RMSE [illegible]1.63, MAE [illegible]91, using the hybrid system
Zhou and Xu, [18] (2023)	A multi-stage hybrid scheme of complementary ensemble empirical mode, another decomposition with permutation entropy, and optimized predictor of relevance vector machine	Precious metals price data (acquired from NYMEX)	Platinum, palladium, and silver	MAE of 3.79[illegible], 21.1615, and 0.0714; RMSE of 4.6599, 24.8232, and 0.0884 for platinum, palladium, and silver prices, respectively.
Banerjee et al., [19] (2024)	LSTM, Bidirectional LSTM, and GRU	Eight commodities traded in the MCX and the National Commodity Exchange	Gold, silver, copper, nickel, lead, zinc, natural gas and crude oil	Bidirectional LSTM outperformed alternatives with MAE of 0.0057 and RMSE of 0.0072 for gold metal prices
Li et al., [20] (2024)	Optimized deep extreme learning, extreme Gradient Boosting, and LSTM	Copper futures price (acquired from NYMEX)	Copper	Ensemble approach outperformed single approaches with MAE of 253.033 and RMSE of 385.005
Yang et al. [21] (2025)	Two-stage ensemble learning system	Metal prices (obtained from LME dataset)	Silver and copper	Achieved IRMSE of 0.17496 for silver prices, and IRMSE of 62.51197 for copper prices

III. PROPOSED ARCHITECTURE

In this section, the precious and basic metal prices datasets with the main preprocessing steps and several deep learning approaches (1D-CNN, LSTM, hybrid 1D-CNN and LSTM, and the overall proposed optimal hybrid framework using hyper-parameter optimization methodology) will be described in detail. **Fig 1** depicts a detailed description of each stage in the proposed architecture. In this architecture, the closing prices of the input metal datasets are first preprocessed over many steps, and time-series data are then formed (using sliding windows) to be passed to the deep learning approaches. Eventually, the optimally configured standalone and hybrid approaches were implemented, and their forecasting performance was compared.

Datasets

Datasets were returned from the first of January, 2014, to the end of August, 2024, for two precious metal prices of Gold, Silver, and one basic metal price of copper traded at MCX India, and downloaded through the Kaggle data science platform (https://www.kaggle.com/). Each dataset includes closing, opening, high, and low prices. The implemented baseline and hybrid forecasting approaches utilized the closing daily prices (which reflect the final traded price of each day). According to the correlation matrices depicted in **Fig 2**, the closing price feature is chosen since it demonstrates a high correlation with other significant features. The shapes of the closing prices for the metals datasets are demonstrated in **Fig 3**, and the descriptive statistics for the selected price features are depicted in **Table 2**. It's worth noting that these closing prices have fluctuated irregularly, particularly since 2020, and lack an obvious pattern, making it difficult for any single forecasting approach to extract complicated features.

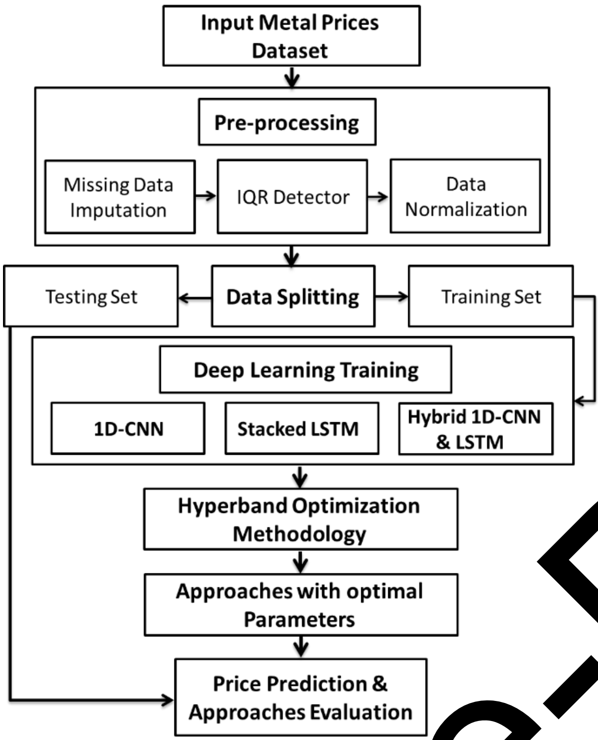
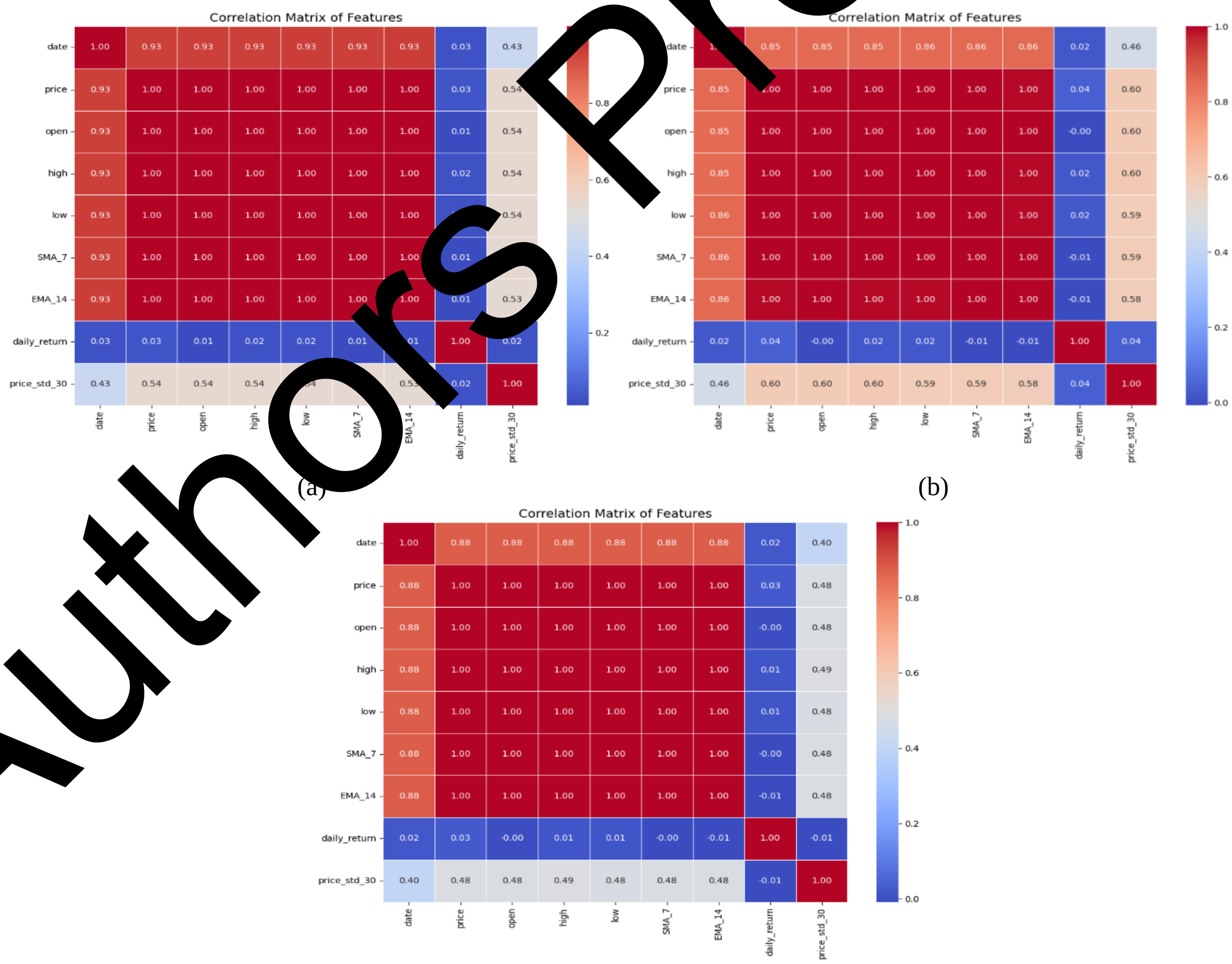


Fig 1. Workflow of proposed architecture



(a)

(b)

(c)

Fig 2. Correlation matrices for (a) Gold, (b) Silver, and (c) Copper metal prices in the MCX datasets

Fig 3. A series of original closing prices for gold, silver, and copper closing prices

Table 2. Outline of descriptive statistics for gold, silver, and copper closing prices

Precious and Basic Metals	Count	Mean	Std.	Min	25%	50%	75%	Max
Gold Prices	2760	40133.79	13227.64	24597	28959	32314.5	50379.5	74367
Silver Prices	2759	51137.16	14921.93	33170	38689.5	44281	64875	96162
Copper Prices	2758	521.61	165.51	291.9	402.46	445	709.53	936.5

Regarding the gold dataset, closing prices include 2,760 data points, averaging approximately 40,134, which is very close to the average opening price, signifying price stability at market opening. The range (from low to high) is between 24,451 and 74,731, and the standard deviation is greater than 13,200, signifying high price fluctuations. And in the silver dataset, the closing prices include 2,759 data points and average around 51,137, which is very close to the average opening price, indicating that the markets open at the previous closing price. The range (from low to high) is between 32,600 and 96,000, and the standard deviation is larger than 14,900, signifying high price fluctuations. While the copper dataset includes 2,758 records, averaging approximately 521.6 points, which is too close to the opening prices. Prices fluctuate significantly, with a standard deviation of approximately 165, indicating moderate volatility.

Missing Data Imputation

Handling missing values is a key part of data preprocessing for these metal price datasets. Because the datasets are relatively well-behaved (i.e., they do not contain extreme or highly skewed values), calculating the arithmetic mean represents the optimal and most efficient process for processing these datasets. The mean imputation replaces the missing values with the mean of the closing price column. This preprocessing stage helps enhance the quality of the dataset and prepare it for the approach training.

Interquartile Range (IQR) Detector

It is common to notice extreme values when dealing with closing prices. These are caused by data entry errors, abrupt market fluctuations (especially during wars), or abnormal trading circumstances. These extreme values significantly impact descriptive statistics and the accuracy of predictive modeling. Therefore, implementing an outlier detector on closing prices will guarantee that the metal datasets remain representative and accurate.

The interquartile range (IQR) represents the most accurate and typical outlier detector for financial data. In this detector, the quartiles (Q1 and Q3, which denote 25% and 75%) of closing prices are first computed, and the value of IQR is then obtained by subtracting these quartiles (IQR=Q3-Q1). After that, the upper and lower outlier boundaries (U_{band} and L_{band}) are established using the following formulas:

$$U_{band} = Q_3 - h \times IQR \tag{1}$$

$$L_{band} = Q_1 - h \times IQR \tag{2}$$

Where h denotes a practical threshold selected empirically (equal to 1.5) to discriminate between typical variation and extreme anomaly. The closing prices above U_{band} and below L_{band} are detected as outliers, and replaced with the median value, which is a central value of the sorted metal closing prices and is favored owing to its strength against outliers.

Data Normalization

Closing metal prices have been observed to be highly variable, and without normalization, the deep learning approach applied can assign disproportionate significance to higher values due to the influence of large differences in price magnitudes, which may lead to biased or inaccurate predictions. Therefore, another preprocessing technique (called data normalization) is applied, which is accomplished using Min-Max scaling to transform the closing prices data into a regulated range (between one and zero), ensuring data points are within the same scale to be comparable. This scaling technique can improve the approach's performance and achieve more stable and faster convergence throughout training. The scaled closing prices P_{scaled} can be calculated as follows:

$$P_{scaled} = \frac{P - P_{minimum}}{P_{maximum} - P_{minimum}} \tag{3}$$

Where P denotes the original closing price data, $P_{maximum}$ and $P_{minimum}$ denote the maximum and minimum values in the closing prices, respectively.

Data Partitioning

Each dataset is eventually partitioned into 90% training and 10% testing sets and reformed to a compatible shape for input into the baseline and hybrid deep learning approaches. The incipient analysis involves a window of 30-day periods (each 30 reads) that are selected as inputs.

1D-CNN Approach

1D-CNN can be utilized for handling sequential or time-series data by passing a convolutional filter over it to obtain local patterns. Its typical architecture encompasses various layers.

- The first is an input layer, which consists of a series of data points arranged as a one-dimensional vector for each time step.
- The second is a convolution layer which works on applying learnable filters or weight matrices $\mathcal{L}$ over the input series for producing essential local feature maps $\mathcal{F}$. This operation can be given as follows:

$$\mathcal{F}(i) = \sum_{j=1}^{N} s_{i+j-1} \cdot \mathcal{L}_j \tag{4}$$

- Where $\mathcal{F}(i)$ denotes the produced feature map at ith position, s_{i+j-1} denotes the elements of input sequence, and $\mathcal{L}_j$ denotes the weigh at jth position in the filter.
- The third is a layer of activation called Rectified Linear Unit (ReLU), which provides nonlinearity.

- The maximum pooling layer, which decreases dimensionality and reserve the most appropriate features.

For metal prices forecasting, 1D-CNN approach works on extracting local patterns over a specified window (30 days) of closing price sequence data, which is advantageous in perceiving irregularities and short-term trends.

LSTM Approach

LSTM approach represents a variation of Recurrent Neural Networks (RNNs) formed for time-series data modeling. Its units can learn and recall (long-term) dependencies, solving the vanishing gradient issue that plagues conventional RNNs [22] [23]. The unit of LSTM can be formed from: a forget gate, which is responsible for determining which information should be ignored from the cell state; an input gate, which is responsible for updating the cell state with the newest information; and an output gate, which specifies the subsequent hidden state. Every unit accepts the former hidden state d_{n-1}, the former cell state ℓ_{n-1}, and the present input x_n, and calculates the subsequent hidden state d_n and the subsequent cell state ℓ_n. Generally, for each step of time n, the LSTM can carry out the succeeding activities:

- The first activity involves determining information to throw out from the cell state using the forget gate. This gate exploits a sigmoid layer to produce an output f_n, ranging between one and zero for every number in the cell state ℓ_{n-1}.

$$f_n = sigmoid(M_f \cdot [d_{n-1}, x_n] + B_f) \tag{5}$$

Where M_f and B_f denote the matrix of weights and bias for the forget gate, respectively.

- In the second activity, the input gate works on updating the cell state with the newest information, including two layers: a sigmoid layer to determine which values should be updated, and a hyperbolic tangent layer ($tanh$) to create the latest candidate values to potentially be included in the cell state $\check{\ell}_n$. The main goal of the sigmoid function is to make the model differentiable, while the tanh function aims to distribute the gradients due to its central zero (range from negative one to one), which alleviates the issue of vanishing gradients and allows cell information to flow for a longer period.

$$i_n = sigmoid(M_i \cdot [d_{n-1}, x_n] + B_i) \tag{6}$$

$$\check{\ell}_n = tanh(M_\ell \cdot [d_{n-1}, x_n] + B_\ell) \tag{7}$$

Where i_n denotes the output of this gate, and M_i, M_ℓ and B_i, B_ℓ denote the matrices of weights and biases for the input gate, respectively.

- The third activity involves updating the cell state ℓ_n via incorporating forget and input gates.

$$\ell_n = f_n \cdot \ell_{n-1} + i_n \cdot \check{\ell}_n \tag{8}$$

- In the last activity, the hidden state d_n is controlled using the output gate, and it is given to the subsequent unit of LSTM and the output layer. Ultimately, the output depends on the output of this gate o_n and the updated cell state ℓ_n.

$$o_n = sigmoid(M_o \cdot [d_{n-1}, x_n] + B_o) \tag{9}$$

$$d_n = o_n \cdot tanh(\ell_n) \tag{10}$$

Where M_o and B_o denote the matrix of weights and bias for the output gate, respectively.

A Stacked LSTM approach represents an expansion of the original LSTM approach [24], which comprises multiple hidden layers of LSTM stacked on each other. Owing to its higher depth and complexity contrasted with the single approach, this sophisticated approach allows us to capture higher-level temporal patterns within the input data, providing higher efficiency in modeling complicated sequential data and achieving more accurate predictions. In this stacked approach, the output of one LSTM layer is used as the input for the succeeding LSTM layer. Considering the mth layer (here we use, m=1, 2, 3), the input to the mth LSTM layer is d_{n-1}^{m-1} from the former layer (or input sequence for the 1st layer), and the output of the mth LSTM layer is d_n^m, which will be approved as input to the subsequent layer.

Hybrid Forecasting Approach

The proposed hybrid approach incorporates 1D-CNN and LSTM layers. In this approach, the 1D-CNN layer assist in extracting essential features from input metal prices, and the LSTM layer seize temporal dependencies in time series data. Then, there are two dense layers that reduce the dimensions of the extracted features and produce the final prediction.

- The first 1D-convolution layer encompasses (32, 64, or 128) filters (of size 3) applied over the input data to learn or obtain (32, 64, or 128) various feature maps. And to make the network learn more complicated patterns, the activation function ReLU is applied.
- Maximum Pooling is added to decrease the data dimensionality via downsampling, decreasing the cost of computations and complexity of the approach. This process preserves the principal features via choosing the maximum value within the window (of size 2).
- The Batch Normalization layer is utilized for speeding up and stabilizing training via normalizing activations in the previous layer throughout the batch.
- LSTM layer is utilized to model long-term sequential data dependencies. This layer is capable of learning from previous information and maintaining a memory of previous states, which is beneficial for time series prediction. It contains (64, 128, 192, or 256) neurons (units) and produces the entire sequence of outputs.
- A dropout layer is utilized after the LSTM layer with a dropping (between 0.3 and 0.5) to decrease overfitting by randomly selecting between 3% and 5% of the layer's output units to be zero throughout training without changing the data shape and having any parameters, making the approach more generalizable and robust.
- Dense Layers (fully connected layers) conduct the last output transformation, relying on the underlying features extracted via the previous 1D-convolutions and LSTM layers. The first dense layer with (32, 64, 96, or 128) neurons is utilized to decrease the data dimensionality gradually and ReLU is then utilized to present non-linearity, succeeded by a dropout layer with a dropping (between 0.1 and 0.4) to attain further regularization. The last dense layer is utilized to output a single value for time series forecasting.

Hyperband Optimization Methodology

The presence of multiple hyper-parameters can significantly impact an approach's predictive performance, so determining the approach's parameters is a critical process in its training. There are several fundamental methodologies for deciding hyper-parameters, such as grid search, random search, optimization algorithms, and so on. In particular, the Hyperband optimization methodology is more efficient for tuning deep learning approaches in which the training process is expensive and the hyper-parameter space is vast. This methodology integrates a random search through configuring hyper-parameters and a strategy of early-stopping to assign more resources for promising approaches (called successive halving).

- The hyperband optimization methodology attempts to use multiple combinations to reach the optimal hyper-parameter configuration ($f(\mathcal{H}) \rightarrow Minimum$), where $\mathcal{H}$ denotes a hyper-parameter configuration, by trying to use (32, 64, 128) filters in the 1D-CNN layer, (64, 128, 192, 256) units in the LSTM layer, (32, 64, 96, 128) units in dense layer, (between 0.3 and 0.5, and between 0.1 and 0.4) rates of dropouts, and (0.0001, 0.001, 0.01) rate of learning, and $f(\mathcal{H})$ denotes a validation loss after training within a budget.
- The maximum brackets "B_{max}" and reduction factor "$\mathcal{R}$" should be specified, and the total budget "$\mathcal{B}$" should also be computed, which depends on B_{max} and maximum resources "R_{max}", (here we utilize maximum 30 epochs), and the formulas are as follows:

$$B_{max} = \lfloor \log_{\mathcal{R}}(R_{max}) \rfloor \tag{11}$$

$$\mathcal{B} = (B_{max} + 1) \cdot R_{max} \tag{12}$$

- Hyperband assigns a few initial epochs (resources) to a substantial count of configurations. Then, it discards underachieving approaches and reassigns resources to the superior configurations. The early stopping guarantees that epochs are not wasted on underachieving configurations. When no improvement in validation loss is achieved over several epochs, training will be stopped early. In each bracket i, Hyperband activates successive halving, as follows:

$$C = \left\lceil \frac{\mathcal{B}}{R_{max}} \cdot \frac{\mathcal{R}^b}{b+1} \right\rceil \tag{13}$$

$$R_{min} = \frac{R_{max}}{\mathcal{R}^b} \tag{14}$$

  Where C denotes initial count of configurations, and R_{min} denotes minimum resource assigned per configuration, $\mathcal{R}$ is assigned to 3. For $i = 0, 1, \ldots, b$, every round trains $C_i = \lfloor C \cdot \mathcal{R}^{-i} \rfloor$ configurations, each for $R_{min}i = R_{min} \cdot \mathcal{R}^i$ resources.
- Once the optimization process is complete, the optimal approach (based on the minimal validation loss) is chosen and can be utilized for future forecasts.

The Hyperband methodology was utilized to optimize the accuracy of forecasting metal prices using standalone and hybrid approaches. This optimization methodology effectively searches the hyper-parameter space to obtain the optimal configuration for these approaches, improving performance with lower computational cost.

IV. EXPERIMENTAL ANALYSIS

In order to depict the efficiency of the proposed optimized forecasting architecture, several approaches were applied. These approaches involve standalone 1D-CNN, stacked LSTM, and a hybrid 1D-CNN and LSTM.

Evaluation Measures

The evaluation measures like MAE, $RMSE$, $Median - AE$, and $R_{squared}$ are employed in this proposed architecture to determine the most appropriate approach. Lower values for these metrics (except $R_{squared}$), denote better approach performance [25].

MAE is used as a regression measure to find the average absolute errors (differences) between actual 'A' and forecasted 'F' price values of precious metals. The formula for this metric is given as follows:

$$MAE = \frac{1}{l}\sum_{i=1}^{l}|A_i - F_i| \qquad (15)$$

Where l denotes the series length.

$RMSE$ is more interpretable than MAE in penalizing larger errors, in other words, it is beneficial when required to minimize large errors. The formula of this metric is given as follows:

$$RMSE = \sqrt{\frac{1}{l}\sum_{i=1}^{l}(A_i - F_i)^2} \qquad (16)$$

$Median - AE$ is also used as a regression measure to find the median of all absolute errors (differences) between the actual and forecasted price values. The formula for this metric is given as follows:

$$Median - AE = median(|A_i - F_i|) \qquad (17)$$

$R_{squared}$ is used to measure how well forecasts agree with actual data. The formula for this metric is given as follows:

$$R_{squared} = 1 - \frac{\sum(A_i - F_i)^2}{\sum(A_i - \bar{A})^2} \qquad (18)$$

Where $\bar{A}$ denotes the mean of actual price values of precious metals.

Results and Comparison

To evaluate the proposed architecture, an extensive comparison between optimally configured deep learning approaches is conducted to verify the forecasting performance of these approaches.

In this proposed architecture, various hyper-parameters are considered for optimization utilizing the hyperband methodology (such as Filters, LSTM Units, Dense Units, Dropouts, Learning Rate, and Epochs). **Table 3** demonstrates the optimal combination of hyper-parameters for the optimized approaches attained using the hyperband methodology.

Table 3. Optimal hyper-parameters for the approaches by hyperband methodology

Approaches	Filters	LSTM Units	Dense Units	1st Dropout	2nd Dropout	Learning Rate	No. of Epochs
1D-CNN	128	-	-	0.3	-	0.001	30
Stacked LSTM	-	128, 64, and 32	-	0.4	0.4	0.001	30
Hybrid Approach	64	256	128	0.3	0.2	0.001	30

The choice of the above hyper-parameters directly influences the capability of approaches to learn and fit the data, which in turn affects the accuracy of the forecasting results, as depicted in **Tables 4**, **5**, and **6**.

Table 4. Forecasting results of the optimally configured approaches for gold prices

Approaches	MAE	RMSE	$\boldsymbol{Median - AE}$	$\boldsymbol{R_{squared}}$
1D-CNN	0.0456	0.1547	0.0414	0.7821
Stacked LSTM	0.0244	0.14207	0.0169	0.9144
Hybrid Approach	0.0182	0.1500	0.0164	0.9616

Table 5. Forecasting results of the optimally configured approaches for silver prices

Approaches	MAE	RMSE	$\boldsymbol{Median - AE}$	$\boldsymbol{R_{squared}}$
1D-CNN	0.0388	0.1410	0.0253	0.7874
Stacked LSTM	0.0194	0.1579	0.0124	0.9427
Hybrid Approach	0.0159	0.1719	0.0121	0.9682

Table 6. Forecasting results of the optimally configured approaches for copper prices

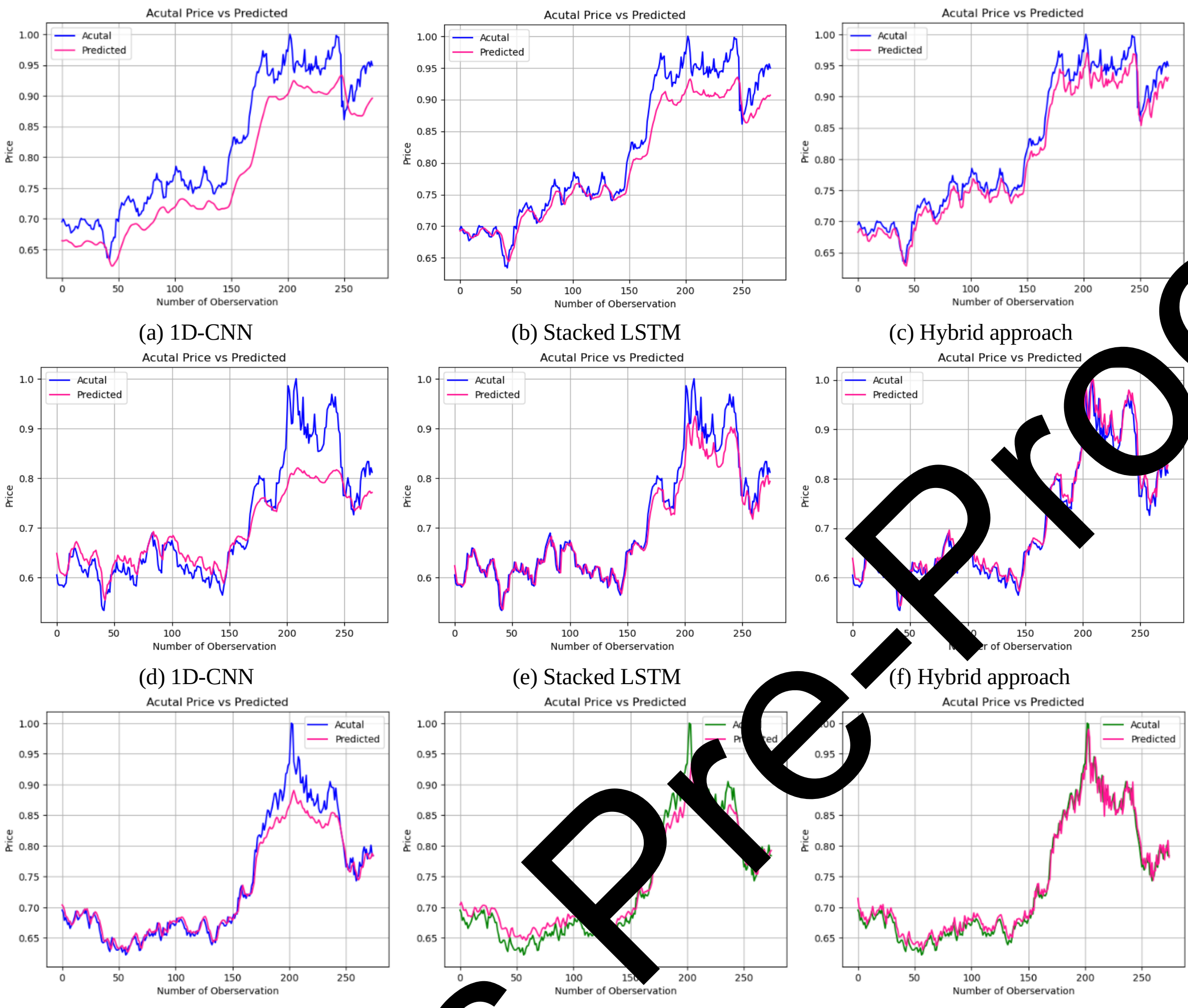
Approaches	MAE	RMSE	$\boldsymbol{Median - AE}$	$\boldsymbol{R_{squared}}$
1D-CNN	0.0158	0.1268	0.0093	0.9375
Stacked LSTM	0.0186	0.1257	0.0162	0.9436
Hybrid Approach	0.0107	0.1358	0.0096	0.9816

As depicted in previous Tables, the optimally configured hybrid approach provides superior results among all the approaches with the highest $R_{squared}$ values, reaching 0.9616, 0.9682, and 0.9816, accompanied by minimal MAE values, reaching 0.0182, 0.0159, and 0.0107, RMSE values, reaching 0.1500, 0.1719, and 0.1358, and $Median - AE$ values, reaching 0.0164, 0.0121, and 0.0096 for gold, silver, and copper price data, respectively. This indicates that the variability of data is effectively captured by the optimized hybrid approach, which is well-generalized and likely to perform similarly with other precious metal prices.

For the optimized single approaches, the stacked LSTM results outperformed the 1D-CNN approach by a large margin. Additionally, stacked LSTM results were somewhat close to those of the optimized hybrid approach, with $R_{squared}$ values, reaching 0.9144, 0.9427, and 0.9436, MAE values, reaching 0.0244, 0.0194, and 0.0186, RMSE values, reaching 0.14207, 0.1579, and 0.1257, and $Median - AE$ values, reaching 0.0169, 0.0124, and 0.0162 for gold, silver, and copper price data, respectively. However, the standalone 1D-CNN approach provided reasonable performance by exploiting its ability to capture short-term features in the metal price data.

Fig 4 depicts the actual and predicted values for each optimized approach on the testing data. It is noticeable that the curves in this figure, which represent price predictions using the optimized hybrid approach, are very close to reality.

Furthermore, for a more visual comparison of actual and predicted values for the metal prices data, scatter plots are depicted in **Fig 5**. It is noticeable from these plots, especially for the optimized hybrid approach, that the points are almost closely spaced around the diagonal, indicating that the predicted values are very close to the actual values. In the other approaches, the dispersion is minimal, indicating that the hybrid model is capable of providing accurate and consistent predictions.

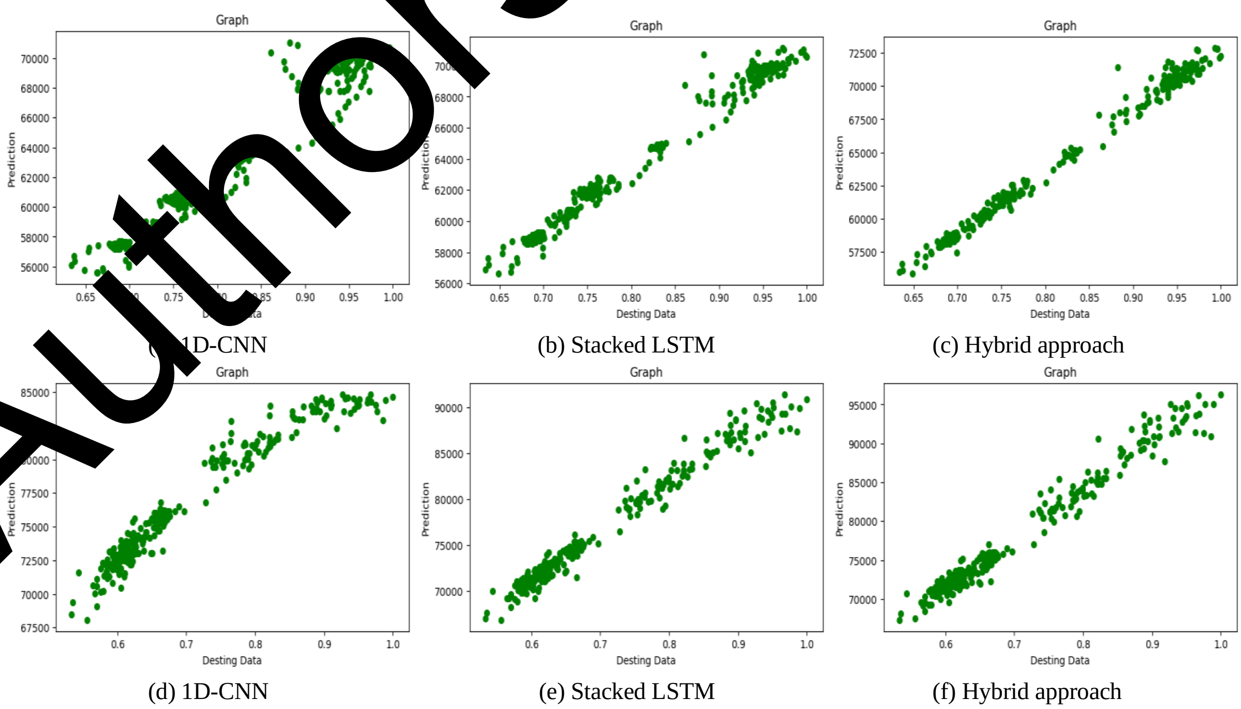


(a) 1D-CNN (b) Stacked LSTM (c) Hybrid approach

(d) 1D-CNN (e) Stacked LSTM (f) Hybrid approach

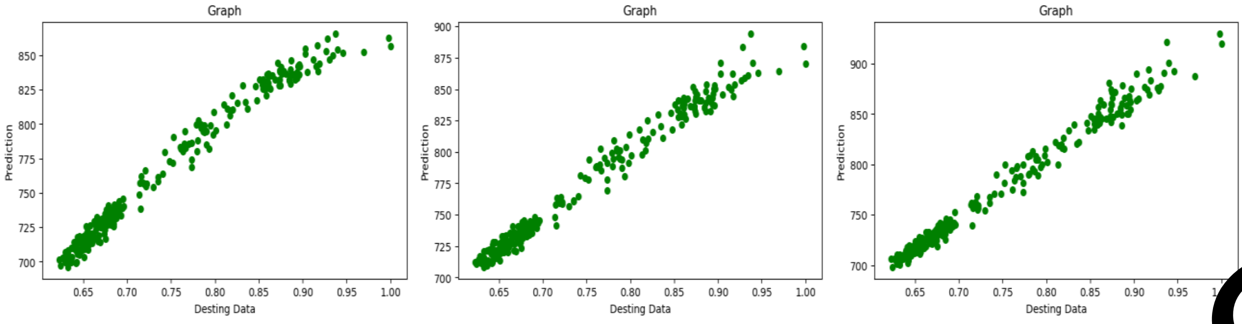
(g) 1D-CNN (h) Stacked LSTM (i) Hybrid approach

Fig 4. Approaches Performance over the testing set for (a-c) Gold, (d-f) Silver, and (g-i) Copper price data



(a) 1D-CNN (b) Stacked LSTM (c) Hybrid approach

(d) 1D-CNN (e) Stacked LSTM (f) Hybrid approach



(g) 1D-CNN (h) Stacked LSTM (i) Hybrid approach

Fig 5. Scatter plots of the actual and predicted (a-c) Gold, (d-f) Silver, and (g-i) Copper price data

To visualize how well the optimized hybrid approach's predictions match the actual data, all prediction results are depicted in **Fig 6**. This comparison confirmed that the optimized hybrid approach has minimal prediction error, robust prediction stability, and high curve-fitting accuracy.

Fig 7 and **Fig 8** depict the performance assessment results of all optimized approaches for metal price forecasting.

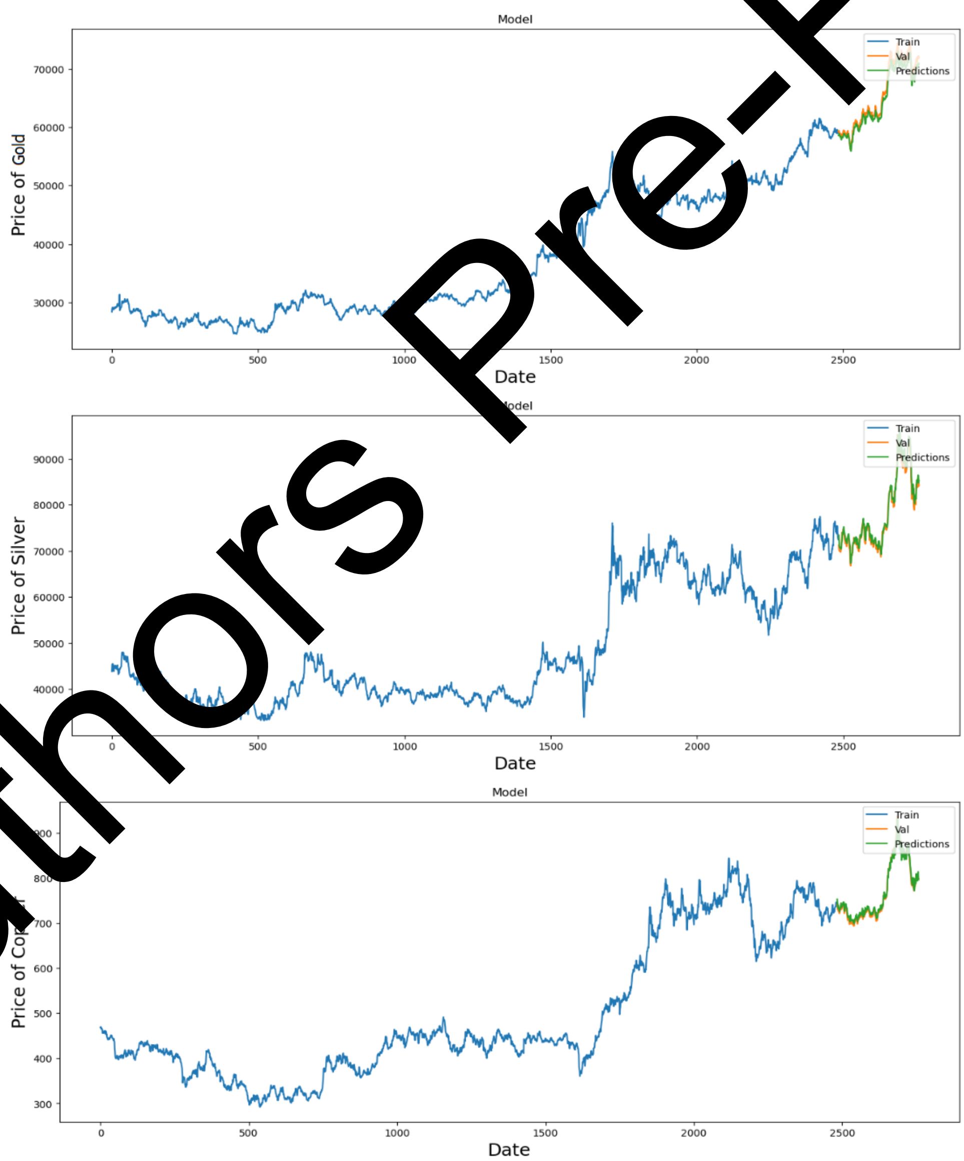


Fig 6. Visualization comparison of the predicted values against the actual prices using the optimal hybrid approach

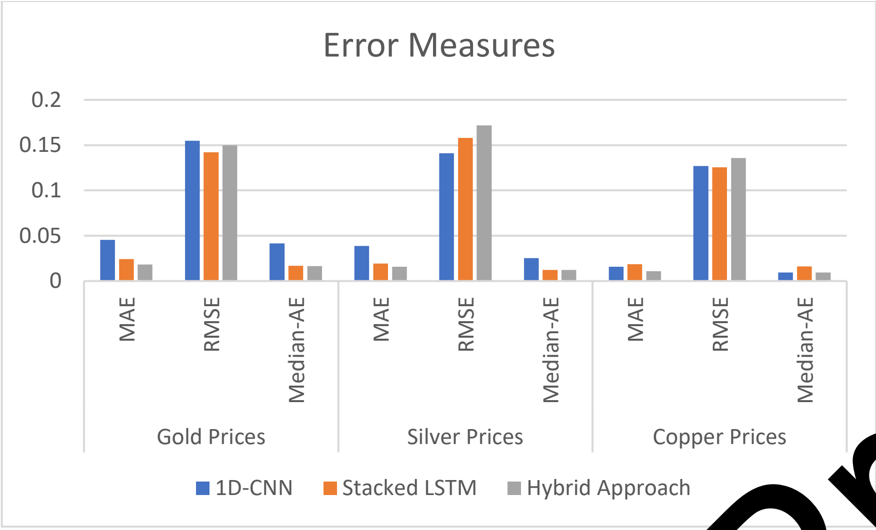


Fig 7. Comparison of error measures results for all optimized approaches

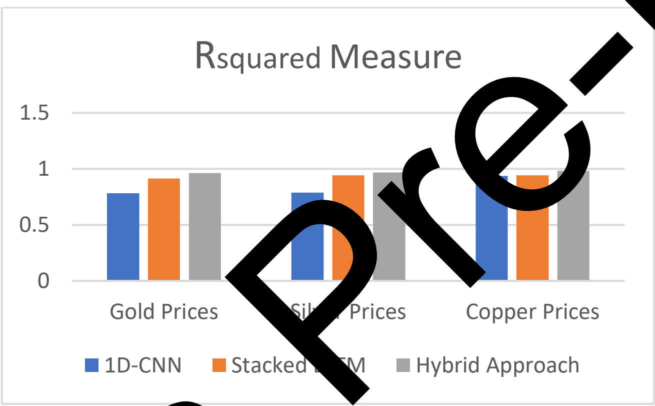


Fig 8. Comparison of accuracy measure results for all optimized approaches

Based on the previous comparison, we conclude that the single-prediction approaches exhibit a notable weakness in making accurate predictions for highly complex sequences. On the contrary, the hybrid approach could mutually compensate for the weaknesses of the single-prediction approach. Furthermore, the utilization of the Hyperband methodology proved to be highly efficient for tuning hyper-parameters in all approaches.

V. Conclusion

Accurate forecasting of time series, like precious metal prices, represents a significant challenge due to the fluctuating and dynamic nature of the price data. Conventional approaches often face numerous obstacles in effectively obtaining long-term dependencies and short-term fluctuations. Therefore, the proposed architecture works on optimizing and comparing the performance of various deep learning approaches for price metal forecasting, utilizing an effective optimization methodology to fine-tune hyper-parameters and enhance the performance of these approaches. Applying the hyperband optimization methodology to 1D-CNN, stacked LSTM, and hybrid 1D CNN and LSTM approaches showed that the hybrid approach attained superior results in loss reduction and validation accuracy. Since the standalone 1D-CNN was capable of effectively capturing short-term features, and the stacked LSTM was adept at modeling long-term dependencies, combining the two approaches in a hybrid architecture exploited their abilities, making it more suitable for forecasting metal prices. Moreover, the hyper-parameter methodology enabled effective exploration of the hyper-parameter space, resulting in optimal performance.

In future work, the architecture could be expanded to handle further features such as sentiment data and external incidents, enabling approaches to obtain additional factors affecting the time series and enhancing the accuracy of their predictions. Additionally, we will concentrate on real-time forecasts rather than batch forecasts, so that the approaches can continuously update their predictions as new data appears. It is particularly beneficial for applying to the global commodities markets, where prices change rapidly.

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