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To Determine the Futures pricing of Metal Commodities using Deep Learning

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Abstract. Manufacturing industries have been growing in terms of their market size and their revenue generated in the past decade. With rapidly evolving technologies, accurate forecasting and predictions act as a strong pillar in strategic planning. Predicting the prices of commodities helps in reducing the financial losses incurred while procurement of the inventory. In this paper, we used the deep learning methods to develop some models for predicting the prices. Deep learning is basically a part of the bigger sphere of machine learning and artificial intelligence. It is based on artificial neural networks with representation learning. The models based on deep learning are superior to any machine learning models in predicting the prices, hence our methodology consists of such techniques. This paper is a preliminary attempt to predict the future prices by using hybrid LSTM-Attention-CNN model with the help of the past 10 years data. The proposed model performed significantly better than traditional ARIMA model which has been a benchmark in time-series for a long time.

Keywords: Metal Commodities, Deep learning, CNN, LSTM, Attention, Time series models.

1. Introduction

Commodities are the common materials used in industries and businesses which can be traded for or exchanged with the materials of the same type. Trading of these commodities and establishing commodity exchanges are very important as they establish worldwide standard prices, and are essential for both producers and consumers[1)]. These commodities are traded through future contracts. A future contract is basically a contract between the two parties where an agreement of buying and selling a specific amount of any commodity is signed. This agreement is done at a predetermined price and at a specified date in the future. A commodity exchange is the legal body or an entity which is responsible for the rules and regulations for trade of commodities. It may also refer to an actual physical space where this trading takes place. The interested buyers use future contracts to fix prices of certain commodities, which reduces the risk of price hike. The commodity centric industries, manufacturers and service providers often participate actively in these exchanges and markets to reduce the risks of financial losses due to changing prices[2)]. The rise of the industrial economy has fuelled the rise of the commodities market over the last few decades[3)]. Many traders have switched to commodity markets in search of new trading options, as capital markets have become more available. The commodities market is notorious for its high uncertainty, which can influence a trader's trading strategy. The extreme volatility of the commodities market can be attributed to a number of reasons, including commodity supply and demand, currency fluctuations, geopolitical conditions, government policies, and economic development[4-5)].

Over the past years, the economies of the world have been evolving and the trade of basic commodities have seen a diminishing trend. Taking the developing nations into perspective, the primary commodities are an important export earning source and the fluctuations and movements in prices of these commodities affect their economic conditions[6)].

The pricing of metals in the markets directly affects the mineral industry and hence the forecasting of the metal markets have been receiving a lot of light in the past decade. The prediction of these markets starts with the analysis of past accumulated data which help in selecting an accurate machine learning model to perform accurate predictions[6)]. To forecast these prices, methods such as econometric, time series models, qualitative, have been used[7-8)].

Copper is one of the most important industrial commodities and has a strong impact on the global economy. It is a widely used alloy with strong resistance to corrosion and acts as a very strong conductor for heat and electricity. Hence being of extreme importance for the electrical power industry and manufactures of electronic products. Given the industrial importance of this metal, its consumption and rising prices reflect upon a good economic health. India is currently ranked 30th in copper producers and given the industrialization the demand of this metal is growing per year. Gold has since long been present in our heritage as one of the most precious metals. And due to its limited supply and the inability to dilute it enables the retention of its value. Hence is very useful in hedging against inflation. India being the world's most ardent gold buyer, is also one of the world's most important Gold markets today. However, due to limited domestic gold supply, imports are the primary source of supply. Our gold market is mainly dominated by the gems and jewellery industry which contributes to 7% of our GDP. Silver is the most ideal metal for electrical applications, and its non toxic composition makes it useful in the medical and consumer product industry. India is one of the largest consumers of silver and hence our demand impacts the global markets. The industrial demand of silver is more than 50% of the worldwide demand. Solar energy is also a major consumer of silver as it is used in fabrication of photovoltaic cells.

In this research, we aim to forecast metal prices for the commodities using a hybrid LSTM - Attention - CNN model. The metals we are considering for our research are Gold, Copper, and Silver. The paper will begin with a Review of the past research, followed by the Research Methodology and Results[9)].

2. Literature Review

Forecasting the future prices plays an important role in trading of goods and services in today's world. A challenging area in the field of prediction is selecting or designing the appropriate and accurate model for the prediction. Various methods were implemented in the past decade for accurate prediction of the price in the market of the specific commodity.

There is a considerable amount of literature on the prediction of prices using different models. The models are categorised into two main segments; (i) econometric models such as time series, regression analysis, ARIMA, GARCH, and SARIMA and (ii) computing techniques such as ANN, CNN, and LSTM driven models. Now, the models based on traditional econometrics pose a strong challenge as they fail to detect the hidden non linear patterns in the price series[10)]. When compared to the models utilising soft computing techniques, they tend to perform better as they are more robust and have the ability to forecast the volatility[11)].

Deep learning is a subset of machine learning and is widely applied in today's day and age. The effectiveness of deep learning and its models are so remarkable, that many organizations are pouring capital and resources into developing this architecture. In recent years, highly efficient deep learning based models are being used for predictive applications. The Long Short Term Memory (LSTM) based models have proven their high degree of accuracy and have been successfully applied for various price forecasting related objectives[12)]. Recent studies have also indicated the better performance of the models based on machine learning and neural networks than stochastic methods in prediction of commodity prices[6) 13)].

For instance, a study based on Korean stock exchange through two models (autoregressive & deep learning) was performed and upon comparison of results, deep learning models outperformed the linear autoregressive models [14)]. Artificial Neural Network based models were tested on the New York Stock exchange and its efficiency was compared with ARIMA linear model, it was found that the Convolutional neural network (CNN) was more accurate than the other neural networks used and the CNN networks were capable of capturing the changes in trends [15-16)]. An experiment was conducted with LSTM prediction models, and these neural network based models were getting upwards of 55% accuracy while predicting the movement of a stock price[17)]. Efficient models based on support vector machines and artificial neural networks were tested on the Istanbul Stock Exchange National 100 Index and the results showed the accuracy of the predictions to be in the range of 70% to 75%[18)].

On the other hand, he stated that computational complexities and constant error flow through CECs have been some of the limitations of that model. In 2021, LSTM is in third place in the Large Text Compression Bench.[19-20)]

Squared regression models usually impose an uncompromising requirement on the real-world data, whereas the time series and Econometric models depend on the trend and seasonality for forecasting with higher accuracy and prediction. The randomness exhibited by the time series models drastically decreases the accuracy of the existing models[21)].

3. Approach

To have a high level of accuracy, we propose a hybrid LSTM (Long-and-Short-Term-Memory) - Attention - CNN (Convolutional Neural Network) model. This section talks about our approach towards building a forecasting model for metal commodities. In this study, we have used the LSTM (GRU) - attention-CNN model to forecast using 10 years data respectively for three metals Gold, Copper and Silver. The LSTM GRU model uses CNN to memorize short- and long-term patterns. Due to gradient vanishing and training instability, LSTM or GRU models cannot memorize very long-term independencies. LSTM along with the attention model is used to smoothen out the data[22)]. In alignment, we identified the parts of the input sequence that are relevant to each word in the output, whereas in translation we used relevant information to select the appropriate output. Here after, we used CNN to compile all the layers and produce the desired forecasted output[23)]. At last we have concluded our results by detecting the RMSE (Root mean squared error), RMAE(Root Mean Absolute Error) and MAPE (Mean

Absolute Percentage Error).[24-25]

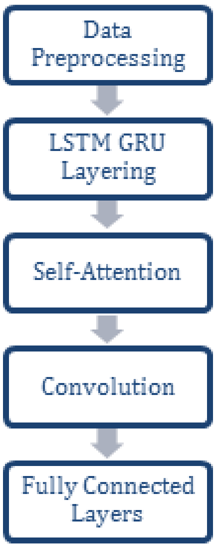

Fig. 1: Flowchart of model

3.1 Data Extraction

We have extracted the 10 years historical pricing data of three of the most commonly traded metals which are Gold, Silver and Copper from Yahoo Finance. All of these metals are widely used in industries as well as retained by individuals as a mode of investment[26].

3.2 Data Preparation

During data extraction, to remove the null values we have used interpolation. As we were dealing with prices of the metal commodities which turns out to have somewhat of a polynomial growth, for this reason we have used polynomial interpolation in this study to fill in the missing values in the series. Polynomial interpolation uses the minimum polynomial that passes the resulting graph and predicts the values of the missing points from the same. The degree of the polynomial interpolation that we have considered here is quadratic.

3.3 Long Short-Term Memory (LSTM) - Gated recurrent units (GRU)

LSTM is a part of a family of Recurrent Neural Networks (RNNs). These layers have a special property of retaining the information extracted from the previous state. This fundamental property makes them particularly useful in time series analysis, as they can account for the historic trend in the time series.

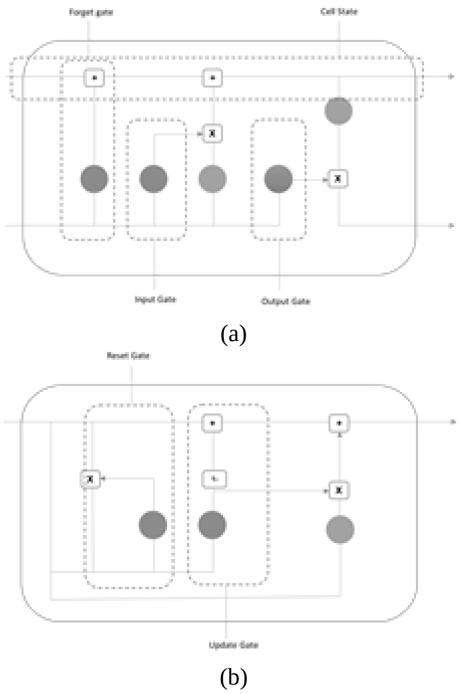

Fig. 2: Gate system of (a)LSTM and (b)GRU.

3.4 Attention Model

Attention models are relatively new in deep learning and are finding their extensive use in Natural Language Processing and Machine Translations. They can be used to assign different weights to different time-steps, and this determines how much weight-age should be given to each point to forecast the time-series[27-29].

In this research, we have created three vectors namely, Query, Key and Value vector from the encoder's input vector. Using the dot product of the Query and Key vector we have calculated the score which helps us to determine how the focus on the different inputs needs to be distributed. Here after, for a stable gradient we divided the scores by 8 which is a default value for the same and the result has been passed to the softmax operation which normalizes the score i.e scores turn to be positive and add up to 1. We multiplied values of the vector by the normalized scores and added the weighted value error[30-33].

To form the self-attention matrix, we packed the resulting vectors in the form of matrix and condensed them into a layer using the formula:

$$\text{Softmax } \left(\frac{QxK^T}{\sqrt{d_K}}\right) V = Z \qquad (1)$$

In the following model we have used 8 similar layers for the data prediction.

3.5 Convolutional Neural Network (CNN)

A typical CNN has a sequence of layers stacked together. Mainly, a convolutional layer, a ReLU Layer, a pooling layer and a fully connected layer. In the First layer, the convolutional procedure is followed wherein the exact features are extracted. Then an activation function is used to give the final result. The pooling layer has the purpose of reducing the spatial size of the map of features and gives the most feasible learning results for the data that is provided as input. The output is then passed through the next layer where the entire process is repeated. This ensures that the most optimal solutions are received at every stage. Finally, the classification and regression are obtained through the fully connected layer.

Fig. 5: Structure of a typical Convolutional Neural Network

3.6 Error Measurement

To evaluate the performance of our model we use different error metrics namely, Root Mean Square Error, Root Mean Absolute Error and Mean Absolute Percentage Error.

Root Mean Square Error is calculated by the formula:

$$\text{RMSE} = \sqrt{\frac{\Sigma(Pi - Oi)2}{n}} \qquad (2)$$

Root Mean Absolute Error is calculated by the formula:

$$\text{RMAE} = \sqrt{\frac{\Sigma_{i=0}^{n}(Pi - Oi)}{n}} \qquad (3)$$

Root Mean Square Error is more sensitive to the outliners than RMAE hence mostly RMSE is used for the error prediction.

$$\text{MAPE} = \frac{1}{n}\Sigma_{t=1}^{n}\left|\frac{At - Ft}{At}\right| \qquad (4)$$

4. Results & Discussions

A Keras environment was used to implement the model. We trained and tested our model on three different commodities, namely Gold, Copper and Silver. This was done to make sure that the model was generic in nature rather than being specific to a single commodity. Initial data pre-processing was done and the missing data points were calculated using spline interpolation. We then divided the data into training and testing sets and trained the model. Different window sizes were tried for the CNN and ultimately we worked with a window of size 7 as it was found to give the optimum look back window. Ultimately, the three error metrics namely Root Mean Square Error, Root Mean Absolute Error and Mean Absolute Percentage.

5. Conclusion and Future Scope of Work

Precious metal price forecasting can be a much significant and challenging task. Precious metals find their usage in industry and households and are an important financial holding all over the world.

This study proposed a new deep learning-based model featuring CNN, LSTM and Attention mechanism for price forecasting. This method is different from traditional statistical and data-based techniques and takes into account both the historical trend and the signal of the time series.

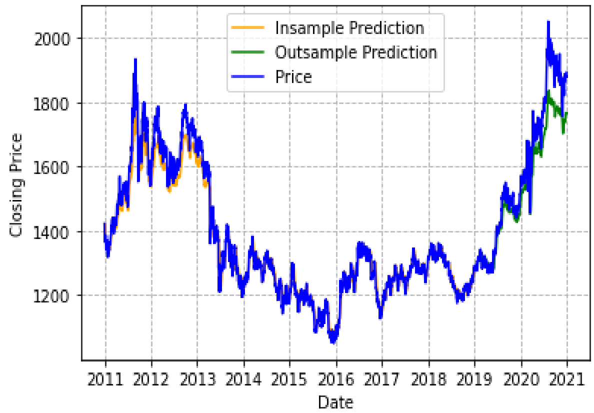

Fig. 3 (a)

Fig. 3 (b)

Fig. 3 (c)

Fig. 3: Predicted price vs Actual Price for (a) Gold, (b) Silver, (c) Copper

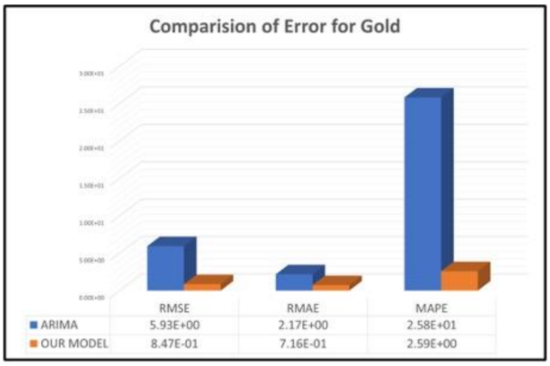

Fig. 4 (a)

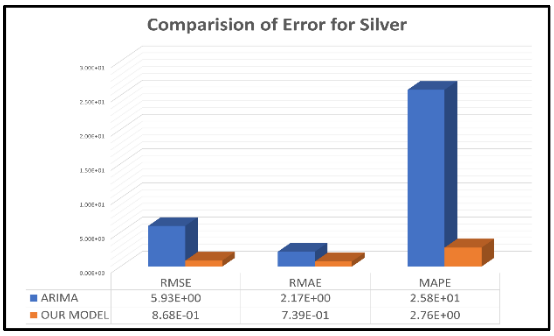

Fig. 4 (b)

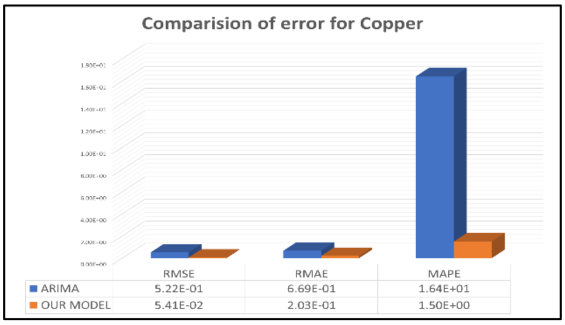

Fig. 4 (c)

Fig. 4: Comparison between the error of Arima model and proposed model prediction for (a) Gold, (b) Silver and (c) Copper.

In our empirical results we found out that the proposed model performed significantly better than traditional ARIMA model which has been a benchmark in time-series for a long time. This work may be further improved by accounting for the correlation between different commodities and using signal processing techniques like Fourier analysis.

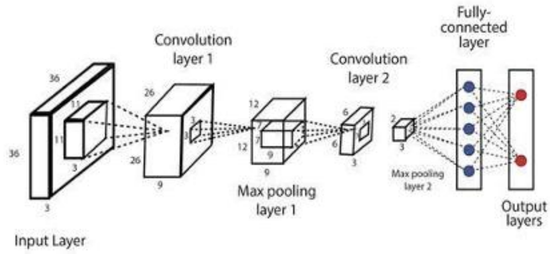

Fig. 5: Structure of a typical Convolutional Neural Network 3`21`21`

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Nomenclature

CNN	Convolutional Neural Network
LSTM	Long-Short Term Memory
ARIMA	Auto-Regressive Integrated Moving Average
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
ReLU	Rectified Linear Unit
GRU	Gated Recurrent Unit
RMSE	Root Mean Squared Error
RMAE	Root Mean Absolute Error
MAPE	Mean Absolute Percentage Error

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