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INTEGRATING FIBONACCI RETRACEMENT TO IMPROVE ACCURACY OF TIME SERIES PREDICTION OF GOLD PRICES

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ABSTRACT
The prediction of gold prices is crucial for investors and policymakers due to its significant impact on global financial markets. Machine learning and deep learning have been used for predicting gold prices on time series data. This study employs MLR, SVM and CNN LSTM with Fibonacci retracement levels to forecast gold prices based on time series data. The experiment results demonstrate that combining Fibonacci retracement with model prediction significantly enhances predictive performance compared to prediction without Fibonacci. The use of Fibonacci levels has resulted in a higher R^2 score and lower RMSE score showing that Fibonacci levels influence the accuracy of gold price predictions and strengthen the overall reliability of gold price forecasts. The findings underscore the potential of combining machine learning models with technical analysis tools in financial forecasting. Integrating the Fibonacci retracement level offers valuable insights for market participants, enabling more informed investment decisions and effective risk management strategies.
Keywords: *Predict Gold Price, Multiple Linear Regression, Fibonacci, SVM, CNN-LSTM*

1. Introduction

Investment involves allocating funds with the expectation of generating future profits. Generally, the greater the potential return, the higher the associated risk. Various investment options, including property, stocks, and gold, have gained widespread popularity across different economic classes, serving as a means of supplementing income (Ruth Elizabeth & Sitorus, 2021). Gold, as a commodity, is regarded as one of the foremost investment instruments for companies engaging globally and for any nation(Kilimci, 2022). The importance of predicting gold prices spans multiple domains, including investment strategy, economic stability, and industrial applications. Accurate gold price forecasts enable investors to make informed decisions, help central banks manage reserves, and allow industries to plan efficiently(Bulut & Rizvanoghlu, 2020). Given its multifaceted role in the global economy, ongoing research and advancements in predictive models for gold prices remain crucial for financial stability and economic planning. Continuous exploration of factors influencing gold prices ensures that stakeholders can better navigate the complexities of the financial markets. Considering external factors, it becomes nearly impossible to control the future level of gold prices and their market. This unpredictability makes gold price forecasting an increasingly attractive and active area of research (Kilimci, 2022). Several studies have predicted the time series of gold price data. There are two main approaches for predicting gold, first predict gold prices using multivariate approach and second is predicting gold prices using time series approach. Some studies predict gold prices using a multivariate approach (Manoj & Suresh, 2019; Yanto et al., 2021), this approach models the relationship of economic indicators for predicting gold prices. The second approach is predicting gold prices using the time series approach (Makala & Li, 2021) (S. K. Singh et al., 2021)(Dubey, 2016), this approach models the relationship between gold prices and time for predicting gold prices. Studies that are close to our study are the study by (Dinesh et al., 2021), (Makala & Li, 2021) and (Livieris et al., 2020). This study uses the moving average of time series (Dinesh et al., 2021) as an independent variable when predicting gold prices using MLR, SVM and CNN-LSTM. Furthermore, this study integrated the moving average of Fibonacci retracement to improve the accuracy of prediction using MLR, SVM and CNN LSTM. Fibonacci retracement is a widely utilized technical analysis tool in financial markets and stock exchange markets (Tsinaslanidis et al., 2022). The Fibonacci retracement captures the relationship between gold price and time. The main finding in this study is we find that integrating the Fibonacci retracement level as an independent variable improves the accuracy of prediction using MLR, SVM and CNN LSTM.

2. Literature Review

Multivariate prediction

Gold price prediction has been a focal point for researchers and investors due to the precious metal's significant economic and financial impact. One of the common methods employed in predicting gold prices is linear regression, a statistical technique that models the relationship between a dependent variable and one or more independent variables. Many explored the correlation between gold prices and various economic indicators. A study by (Tully & Lucey, 2007), (Manjula & Karthikeyan, 2019) examined the relationship between gold prices and the exchange rates, interest rates, and oil prices. Their findings indicated that gold prices were significantly influenced by other variables outside the pattern of historical gold prices, providing a basis for developing predictive models using linear regression or machine learning methods.

Time series or univariate prediction

Instead, use other economic indicators for predicting gold prices. The early use of linear regression for gold price prediction primarily involved modelling the relationship between gold prices and time. The use of linear regression based on time series data for predicting future gold prices has evolved significantly, from simple models moving average, linear regression to deep learning methods. In this section, we explained the previous study and the contribution of our study to the prediction of gold prices based on the time series approach. The classic method to predict time series is the famous moving average, linear regression and ARIMA. Some studies by (Annuar et al., 2021) (Dinesh et al., 2021) (Setiawan, 2024)use moving averages to predict the future of gold prices based on time series data. Furthermore, a study by (Xin, 2023) integrated moving averages with MLR to predict future gold prices based on time series data. Instead of using classical methods, many studies use machine learning algorithms to predict gold prices based on time series data. Some studies by (Makala & Li, 2021) (S. K. Singh et al., 2021)(Dubey, 2016) use a support vector machine (SVM) to predict gold prices, their finding shows that SVM outperformed ARIMA when predicting gold prices based on time series data. Recent studies used deep learning methods to predict gold prices based on time series. Some studies by (Hansun & Suryadibrata, 2021) and (Livieris et al., 2020) used LSTM to predict gold prices based on time series. Furthermore (Livieris et al., 2020) show that the combination of CNN with LSTM has better performance than using LSTM only. Studies that is close to our study is the study by (Xin, 2023), (Makala & Li, 2021) and (Livieris et al., 2020). This study uses the moving average of time series (Xin, 2023) as an independent variable when predicting gold prices using MLR, SVM and CNN-LSTM. Furthermore, this study integrated the moving average of Fibonacci retracement to improve the accuracy of prediction using MLR, SVM and CNN LSTM. Fibonacci retracement is a widely utilized technical analysis tool in financial markets (Tsinaslanidis et al., 2022).

Fibonacci Retracement Level

Fibonacci retracement is is a popular technical analysis tool used by traders and investors to predict potential reversal levels in financial markets (Tsinaslanidis et al., 2022), including forex trading (Gaucan, 2011) and stock exchange (Mirjanic & Dušica, 2022). Fibonacci retracement derived from the Fibonacci sequence, the retracement levels are based on key Fibonacci ratios (23.6%, 38.2%, 50%, 61.8%, and 76.4%) which help identify points at which prices might retrace before continuing their original direction(Gaucan, 2011)(Kumar, 2014). An example of Fibonacci retracement is shown in Figure 1.

Fig. 1. Fibonacci Ratios, Graphics Illustration(Gaucan, 2011).

In this study, we use the Fibonacci retracement level to capture the relationship between gold price and time for modelling the the relationship between gold prices and time.

3. Research Methods

This section contains a complete and detailed description of the steps undertaken in conducting the research in this study. Our methodology is described in Fig 2 as follows:

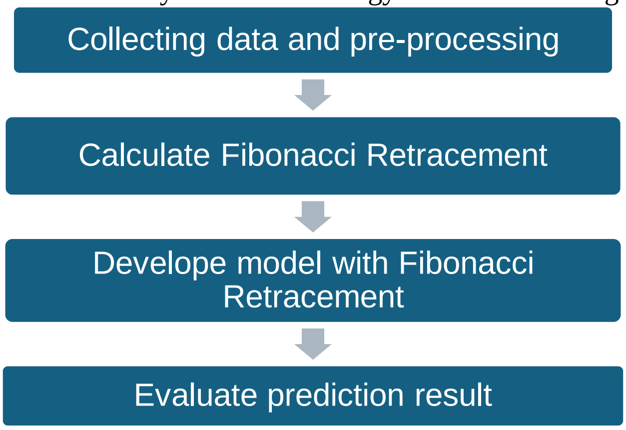


Fig. 2. Diagram of Methodology

Collecting data

Previous studies in the prediction of gold prices collected gold price data from Yahoo Finance (Mombeini & Yazdani-Chamzini, 2015)(Hansun & Suryadibrata, 2021) (Livieris et al., 2020). This study also collected gold price data from Yahoo Finance from July 2022 to July 2024. The example of data is shown in the table I. This study used the Close variable as the gold price in a day. After collecting data, the Fibonacci retracement is calculated explained in detail in the section Calculate Fibonacci Retracement. In this study, the dataset is divided into training and testing, 80 % for training and 20 % for testing.

Table 1 - Gold dataset from Yahoo Finance July 2022 – July 2024

Date	Open	High	Low	Close
2022-07-18	1712.2	1712.4	1709.2	1709.2
2022-07-19	1712.3	1714.4	1706.1	1710
2022-07-20	1707.1	1708.5	1699.5	1699.5
2022-07-21	1687	1715.5	1679.8	1712.7
2022-07-22	1713.3	1735	1713	1727.1

2022-07-25	1727	1732	1719	1719
…	…	…	…	…
2024-07-10	1719.1	1719.1	1719.1	1719.1
2024-07-11	1732.3	1755	1732	1750.3

Calculate Fibonacci Retracement

The algorithm for calculating the level of Fibonacci in this study is described as follows:
High = max(data)
Low = min(data
Fib100% = High
Fib764 = Low + (Diff * 0.764)
Fib618 = Low + (Diff * 0.618)
Fib50 = Low + (Diff * 0.5)
Fib382 = Low + (Diff * 0.382)
Fib236 = Low + (Diff * 0.236)
Fib0 = Low

The Fibonacci retracement of the gold prices in our study is shown in Figure 3.

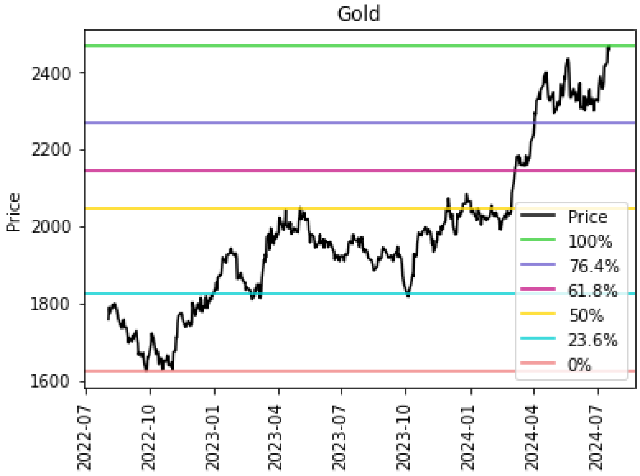


Fig. 3. Fibonacci retracement of gold price July 2022- July 2024.

Develop Model

Multiple linear regression model

A regression model is a fundamental predictive tool designed to estimate the equation that best captures the relationship between a continuous dependent variable (y) and an independent variable (x) (Liu, 2022)(Marcellino et al., 2023). When the model includes multiple independent variables, it is referred to as a multiple regression model. If the relationship between the dependent variable (y) and the independent variables ($x_1, x_2, ..., x_i$) is linear, it is specifically called a multiple linear regression (MLR) model (Krkač et al., 2020)(P. Singh et al., 2024)(Rath et al., 2020)(Priambodo & Ahmad, 2017).

This study empowers the moving average of gold price and Fibonacci level ratio for the past 3 days, 6 days and 9 days as explanatory variables the equation is shown in (1).

$$y = \beta_0 + \beta_1 PriceMv3 + \beta_2 PriceMv6 + \beta_3 PriceMv9 + \beta_4 FibMv3 + \beta_5 FibMv6 + \beta_6 FibMv9 \quad (1)$$

Support Vector Machine Model

Support Vector Machine (SVM) is a type of supervised learning method, which means should have a dependent or output variable (y)(Montesinos López et al., 2022)(Lei et al., 2024). SVM has been widely used for predicting regression in many areas (Roy & Chakraborty, 2023), (Xu et al., 2023), (Xu et al., 2023), (Agyeman et al., 2022), (Dhahi et al., 2023). In the finance and investment area, many studies use SVM to predict traffic gold prices (Makala & Li, 2021)

(S. K. Singh et al., 2021)(Dubey, 2016). In this study, the moving average of gold price and Fibonacci level ratio for the past 3 days, 6 days and 9 days are utilized for prediction through the Support Vector Machine (SVM) method. The problem can be formally defined using the following formula. (2).

$$D = \{(x_i, y_i), x_i \in R^n, y \in \{-1, 1\}\}_{i=1}^{m}$$
$$B = \min_{i=1 \dots m} |w \cdot x + b$$
$$H = \max_{i=1 \dots s} \{h_i | B_i\} \tag{2}$$

D is the dataset, where x is the moving average of gold price and Fibonacci level ratio for the past 3 days, 6 days and 9 days and y is the gold prices. B is computed for each training data, and B is the smallest β that obtained. Each H hyperplanes, each of them will have a B_i value, and finally, the hyperplane with the largest B_i Value is selected.

CNN LSTM

The CNN-LSTM architecture combines both CNN and LSTM methods(Alshingiti et al., 2023)(Alhussein et al., 2020)(Lu et al., 2020). A convolutional neural network (CNN) is a type of neural network that relies on large, labelled datasets for training(Garcia et al., 2020). CNNs are highly effective in addressing various challenges, including image classification, object recognition, phishing detection, and medical disease diagnosis to leverage the strengths of each approach and achieve outstanding performance(Garcia et al., 2020)(Al-Jabbar et al., 2023). CNN models are useful in extracting valuable features and may filter out the noise of the input data(Agyeman et al., 2022). Apart from CNN, there are other methods for feature extraction(Nugroho et al., 2021) and dimensional reduction, such as principal component analysis(Priambodo et al., 2023), local binary pattern (Priambodo et al., 2024), and grey level co-occurrence matrix(Priambodo et al., 2021). LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) that excels in processing time-series data by effectively addressing challenges such as vanishing gradients and managing long-term dependencies(Alshingiti et al., 2023). This integration is particularly effective, as both CNN and LSTM in handling tasks such as classification, detection, and recognition (Alshingiti et al., 2023). This study empowers the moving average of gold price and Fibonacci level ratio as input for the CNN LSTM model. The core concept of applying these models to time-series data is that LSTM networks effectively capture sequential pattern information, while CNN models excel at extracting valuable features and filtering out noise from the input data (Alhussein et al., 2020). The architecture of our CNN LSTM model follows (Livieris et al., 2020). The architecture is arranged as follows first is the Convolutional layer with 32 filters of size (2,), continue with the Convolutional layer with 64 filters of size (2,), Max pooling layer with size (2,) and LSTM layer with 50 units. More detail is shown in Table 2.

Table 2 - Architecture of proposed CNN LSTM model

Name	Type	Shape
Convolution	Filter	(None, None, 3, 32)
Convolution	Filter	(None, None, 3, 64)
Max Polling	Pool	(None, None, 1, 64)
Flatten	Flatten	(None, None, 64)
lstm	LSTM	(None, 50)
dense	Dense	(None, 32)
dense_1	Dense	(None, 64)
dense_2	Dense	(None, 1)

Evaluate Model

This study uses the R^2 Score and RMSE to evaluate the performance of the prediction result. R-squared (R^2) is a number that shows how well the independent variable(s) in a

statistical model explain the variation in the dependent variable. In other words, the R^2 score shows how well an independent variable predicts the outcome of observed data (dependent variable). In this study, the Fibonacci retracement level is evaluated whether this improves the prediction of gold prices or not. It ranges from 0 to 1, where 1 indicates a perfect fit of the model to the data. In our study, the R^2 score is used to compare how well the independent variable is with the Fibonacci retracement level and without the Fibonacci retracement level.
The R^2 Score formula is explained in (3)

$$R^2 = 1 - \frac{SS_{res}}{SS_{total}} \tag{3}$$

SS_{res} : residual sum of squares
SS_{total} : the total sum of squares

Root Mean Square Error (RMSE) represents the standard deviation of the residuals, which are the differences between predicted values and observed data points. Residuals indicate the distance of data points from the regression line, while RMSE quantifies the dispersion of these residuals. RMSE formula is followed (Makala & Li, 2021) shown in (4). In our study these metrics will show how many errors the accuracy between prediction using the Fibonacci retracement level and without the Fibonacci retracement level. The lowest RMSE score means a higher accuracy of prediction.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(A_t - F_t)^2}{n}} \tag{4}$$

Where:
- A_t is the actual value for the ith observation.
- F_t is the predicted value for the ith observation.
- N is the number of observations.

4. Results and Discussions

Result

We compare MLR with Fibbonacci and MLR without Fibbonacci. The result of the prediction is shown in the figure 4. Figure 4 shows that the prediction result using multiple linear regression is close to the actual value.

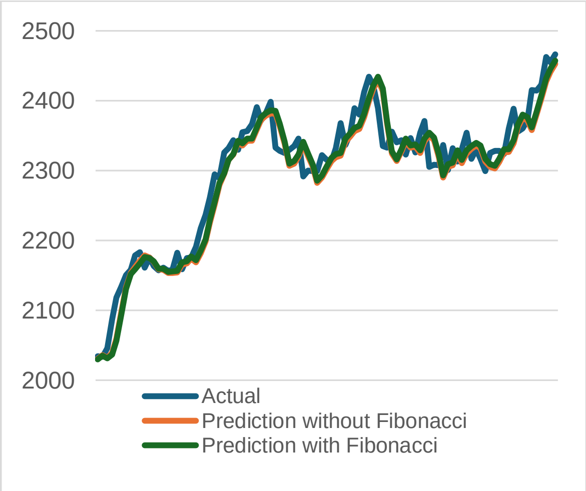


Fig. 4. Prediction Result Of Gold Price Using Multiple Linear Regression

The experiment results the accuracy of MLR with Fibonacci and without Fibonacci is almost similar. The R^2 Score and RMSE metrics are then used to analyse the performance of both methods. The R^2 Score in Figure 5 shows that MLR with the Fibonacci (blue colour) ratio has a higher value than without the Fibonacci ratio (red colour). This shows that MLR with the Fibonacci has better performance than without the Fibonacci retracement level.

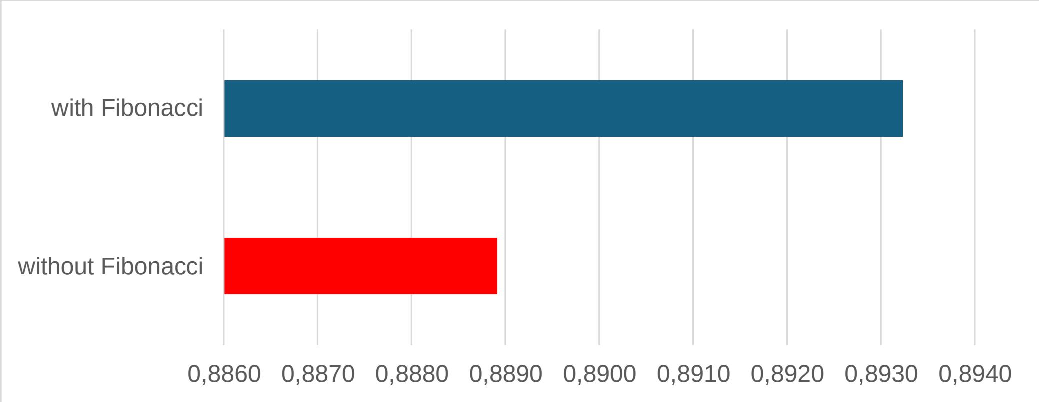


Fig. 5. Comparison of R^2 Score using MLR

The RMSE Score in Figure 6 shows that MLR with Fibonacci (blue colour) has a lower RMSE value than MLR without Fibonacci (red colour), this explains that MLR with Fibonacci has better accuracy than without Fibonacci retracement level.

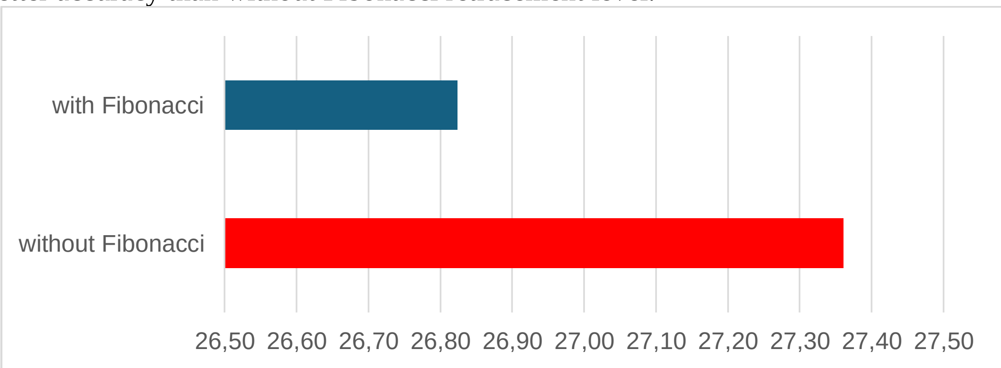


Fig. 6. Comparison of RMSE Score using MLR

The R^2 Score in Figure 7 shows that prediction using SVR with the Fibonacci ratio (blue colour) has a higher value than without the Fibonacci ratio (red colour). This shows that SVR with the Fibonacci has better performance than without the Fibonacci retracement level.

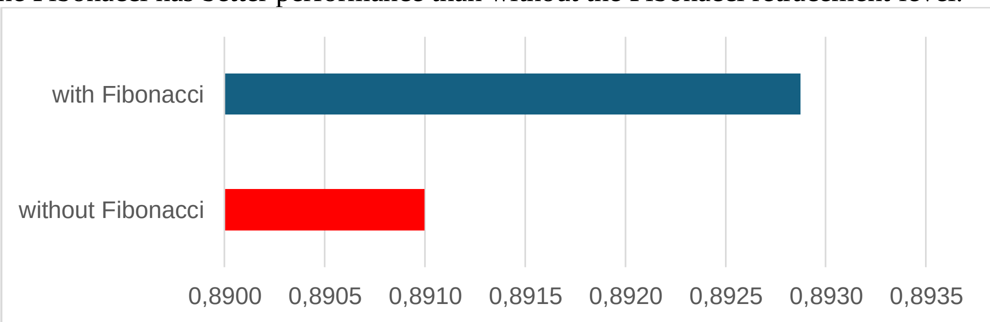


Fig. 7. Comparison of Score using SVR

The RMSE Score in Figure 8 shows that prediction using SVR with Fibonacci (blue colour) has a lower RMSE value than SVR without Fibonacci (red colour), this explains that SVR with Fibonacci has better accuracy than without Fibonacci retracement level.

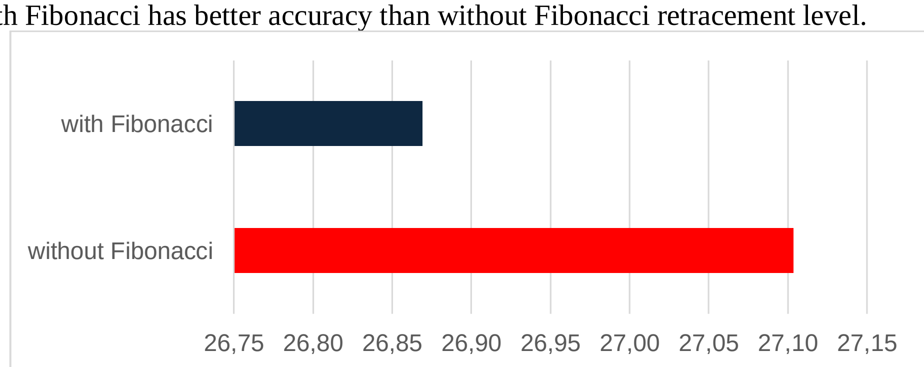


Fig. 8. Comparison of RMSE Score using SVR

The R^2 Score in Figure 9 shows that prediction using CNN LSTM with the Fibonacci ratio (blue colour) has a higher value than without the Fibonacci ratio (red colour). This shows that CNN LSTM with the Fibonacci has better performance than without the Fibonacci retracement level.

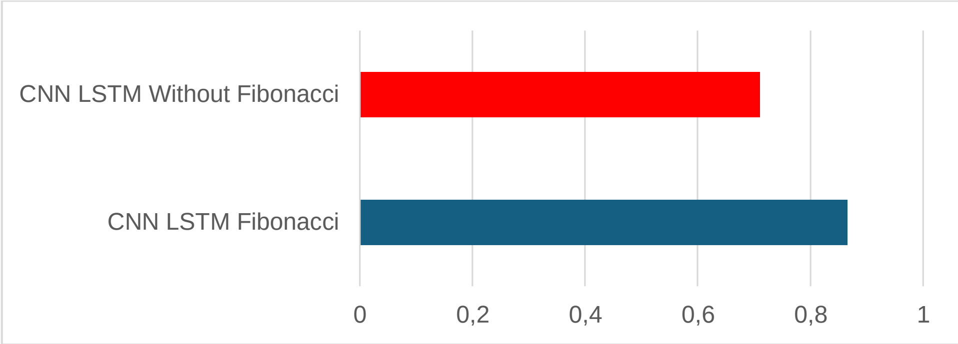


Fig. 9. Comparison of R^2 Score using CNN-LSTM

The RMSE Score in Figure 10 shows that prediction using CNN LST with Fibonacci (blue colour) has a lower RMSE value than CNN LSTM without Fibonacci (red colour), this explains that CNN LSTM with Fibonacci has better accuracy than without Fibonacci retracement level.

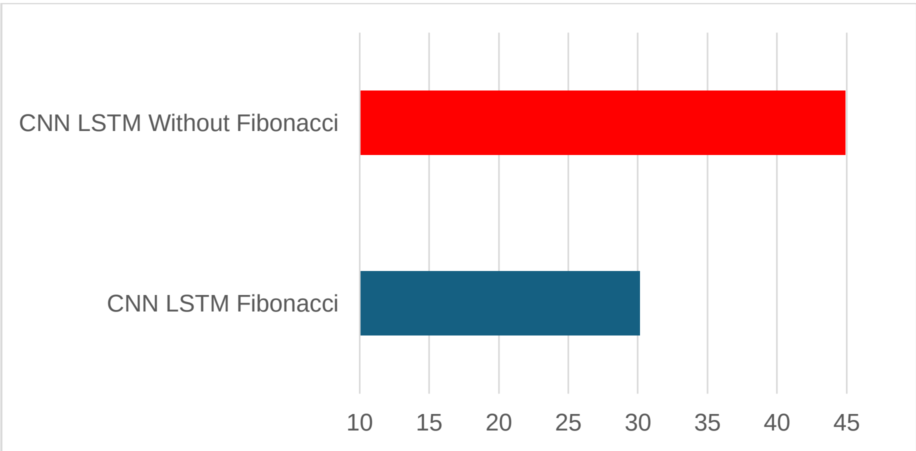
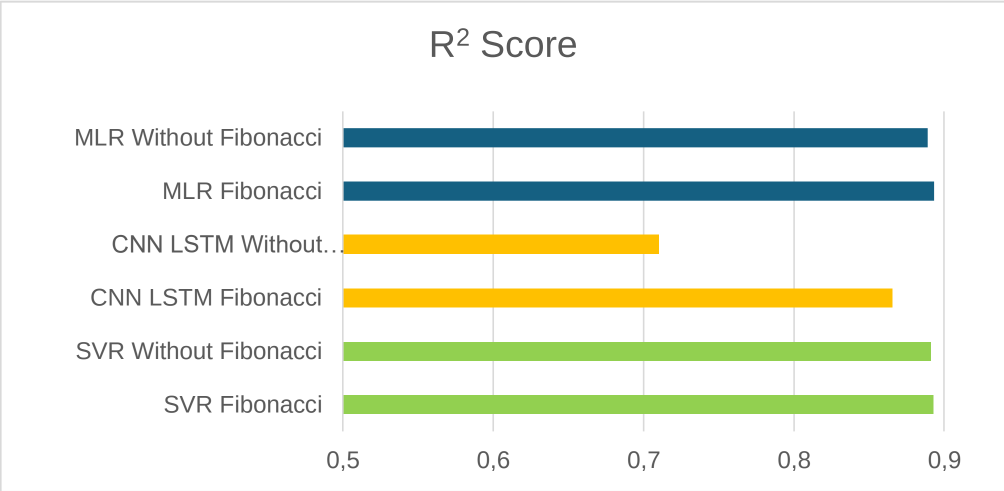


Fig. 10. Comparison of RMSE Score using CNN-LSTM

Discussion

Most methods used in time series gold price predictions are the moving average (Annuar et al., 2021) (Dinesh et al., 2021) (Xin, 2023) (Setiawan, 2024), multiple linear regression(Manoj & Suresh, 2019) (Sekar et al., 2017)(E et al., 2019)(Gaspareniene et al., 2018)(Manjula & Karthikeyan, 2019)(Xin, 2023), support vector machine (Makala & Li, 2021)(S. K. Singh et al., 2021)(Dubey, 2016) and deep learning (Hansun & Suryadibrata, 2021)(Livieris et al., 2020)(Zhang & Ci, 2020). Studies that are close to our study are the study by (Xin, 2023), (Makala & Li, 2021), (Livieris et al., 2020). A study by (Xin, 2023) found that MLR performance is better than ARIMA. A study by (Makala & Li, 2021) found that SVM outperformed ARIMA, and a study by (Livieris et al., 2020) found that combination CNN LSTM outperformed LSTM only. Our proposed approach integrated the moving average of the Fibonacci retracement level (Tsinaslanidis et al., 2022) to improve the accuracy of prediction using MLR (Xin, 2023), SVM (Makala & Li, 2021) and CNN-LSTM (Livieris et al., 2020), while the independent variables follow (Xin, 2023). The metrics R^2 scores and RMSE are used to evaluate the result of the experiment.

The comparison of R^2 scores in Figure 9 illustrates that the inclusion of Fibonacci retracement leads to an increase in the R^2 value. A high R^2 score implies that a considerable portion of the variance in the dependent variable is predictable from the independent variables. The use of Fibonacci levels has resulted in a higher R^2 score, showing that these levels enhance the accuracy of gold price predictions and strengthen the overall reliability of gold price



forecasts.

Fig. 11. Comparison of R^2 Score between using Fibonacci and without Fibonacci

Further analysis, Figure 10 presents a comparison of RMSE errors of all models, revealing that the use of Fibonacci retracement results in a lower RMSE compared to predictions made without it.

This finding indicates that the implementation of Fibonacci retracement levels enhances the accuracy of gold price predictions using MLR, SVM and CNN-LSTM. However, in this study, we are not predicting the future level of Fibonacci retracement level.

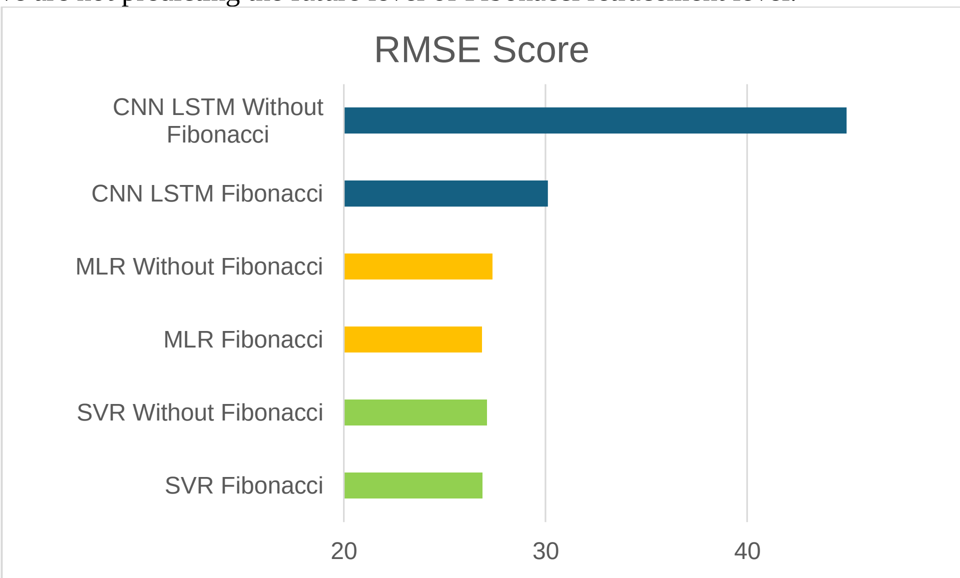


Fig. 12 Comparison Of RMSE Score Between Using Fibonacci And Without Fibonacci

Gold is one of the foremost investment instruments for companies engaging globally and for any nation, The high accuracy of integrating the Fibonacci level in the gold price prediction might help in making informed investment decisions or managing economic risks. Furthermore, this result may apply to the prediction of other commodities like metal, energy, livestock and meat, and agricultural products.

5. Conclusion

The study concludes that incorporating Fibonacci retracement levels into models significantly enhances the accuracy of gold price predictions in time series analysis, whether using MLR, SVM or CNN LSTM. Integrating the Fibonacci retracement level offers valuable insights for market participants, enabling more informed investment decisions and effective risk management strategies. This improvement in predictive accuracy highlights the value of combining machine learning with technical analysis for financial forecasting. The are other technical analyses in financial forecasting like Elliot Wave. In the future, we will use another technique in financial forecasting like Elliot Wave for predicting commodities values.

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