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Short-Term Forecasting of Gold Prices in the Forex Market Using Deep Neural Networks and Price Action Strategy

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ABSTRACT

Gold is widely recognized as one of the most volatile and potentially profitable financial instruments, yet it can also result in significant losses. Consequently, even small price movements can generate substantial gains or losses for traders. In the present study, we developed a machine learning model for short-term forecasting of gold prices with a minimum expected accuracy of 60%. The forecasting problem was formulated as a binary classification task. Considering sound capital management principles, a model with 60% predictive accuracy can enable a trader to achieve profitability in the financial market. Assuming an initial capital of $100 per trade, a profit of $1 per successful trade, a loss of $1 per unsuccessful trade (i.e., a risk-reward ratio of 1:1), and a model success rate of at least 60%, one could achieve a net gain of $10 or a 10% return over 100 trades—an acceptable result. After building and optimizing the model, we achieved an accuracy of 66%, approximately 6% higher than the baseline assumption. To further improve model reliability and validate predictions, we tested the model using weekly and monthly data. The model performed poorly on weekly data, likely due to the limited sample size at this time scale. In contrast, the model demonstrated acceptable accuracy on monthly data, suggesting its utility for validating daily predictions. Monthly data typically contain lower noise and volatility than other time frames, which may explain the higher accuracy observed at this scale. For comparison with previous studies, we selected two articles that predicted gold prices as a regression task and one article that predicted price direction. Results indicate that the proposed method has two key advantages over prior approaches: 1) the predictive power of deep neural networks and 2) the effectiveness of incorporating the price action methodology—particularly the inside bar technique—in forecasting gold price direction.

1. INTRODUCTION

In a Forex transaction, one sells a currency and simultaneously buys another. If the currency purchased appreciates relative to the currency sold, a profit is realized. Retail traders typically conduct these transactions through online

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brokers using well-known trading platforms. However, only about 2% of retail traders successfully predict currency movements, making forecasting in the Forex market one of the most challenging tasks. Machine learning algorithms, along with their derivatives and hybrid models, have increasingly gained popularity in forecasting market price trends and are rapidly developing.

Capital management is a fundamental principle in financial trading. Win rate and risk-to-reward ratio are two essential components of capital management, which, according to experts, play a critical role in the sustained long-term success of traders. The win rate refers to the percentage of trades that yield a profit. For instance, if a trader executes 100 trades and 60 are successful while 40 result in losses, the win rate is 60%. The risk-to-reward ratio, on the other hand, refers to the amount of capital risked for a given potential profit. For each trade, a trader must define a stop-loss and take-profit level.

Assuming an initial capital of $100, with a stop-loss and take-profit both set at $1 per trade (i.e., a 1:1 risk-to-reward ratio), a hypothetical trader executing 100 trades with a 60% win rate would gain $60 and lose $40, resulting in a net profit of $20 or a 20% return—considered highly satisfactory. Therefore, if we can develop an artificial intelligence system, particularly based on deep neural networks, that achieves predictive accuracy exceeding 60%, it effectively becomes a successful trading system—a capability lacking for over 90% of global financial market traders.

2. RELATED WORK

In [1], a study analyzed gold price forecasting using Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Radial Basis Function Networks (RBFN). Each of these methods leveraged short-term gold price factors. The study is particularly relevant for gold rate analysis and investment planning and provides insights for entrepreneurs, investors, and gold traders.

In [2], text mining methods were applied to gold price volatility. This approach assessed how academic articles could influence gold price instability. Selected sources included various financial indices, such as Treasury bill auctions, the red book index, retail activity, financial transactions, and others. The authors utilized Support Vector Machines (SVM), ordinary least squares, and other classification methods such as k-Nearest Neighbors (k-NN) and Naïve Bayes to evaluate predictive accuracy, finding SVM achieved 87.52%, outperforming other methods.

In [3], a hybrid approach combining Support Vector Regression and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) was proposed to forecast gold prices. Performance metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) indicated that SVR outperformed ANFIS.

In [4], a multivariate linear regression model was introduced for gold price prediction while addressing uncertainty. Using five years of data, the model demonstrated effective prediction capabilities and highlighted the importance of understanding gold investment, especially during volatile periods.

In [5], Random Forest (RF) methods were employed to predict gold price volatility trends. Extensive experiments on real-world data revealed that data mining techniques, particularly RF, provide robust predictions for upward or downward gold price trends, showing strong adaptability to complex datasets with high accuracy.

In [6], classification methods were used to forecast gold price direction. Algorithms including decision trees, SVM, k-NN, and linear regression were evaluated using RapidMiner software. Among these, k-NN achieved superior performance.

In [7], a forecasting model integrating machine learning and statistical prediction methods was developed using stock market data. Comparing SVM and regression-based methods, results indicated that stock indices can serve as strong predictors of gold price movements.

In [8], a multivariate Random Forest model was proposed for forecasting the prices of gold, silver, and two other precious metals. The model outperformed univariate RF models in predictive accuracy.

In [9], the relationship between gold price and several descriptive economic indicators was investigated. Using four machine learning algorithms—linear regression, SVM, vector autoregressive regression, and integrated moving average autoregressive regression—the study concluded that linear regression provided the highest predictive accuracy, while the integrated moving average autoregressive regression performed the worst.

In [10], a novel method combining correlation rules with long short-term memory (LSTM) networks was proposed. Using Yahoo Finance data from January 2010 to December 2020, correlation rules selected features associated with the U.S. Dollar Index (DXY). Simulation results indicated that the LSTM-GS-DXY model achieved low mean absolute percentage error and outperformed simple, weighted, and exponential moving averages as well as integrated moving average autoregressive models.

3. PROPOSED METHOD

In this study, we aim to develop a classification system capable of predicting the next day's (or next period's) price movement with an accuracy exceeding 60%. Since the system is designed to predict only the direction of price movement—up or down—rather than its magnitude, we combine technical price analysis concepts, particularly the popular Price Action strategy, with modern artificial intelligence technology, specifically deep learning. Price Action concepts have been well-established and widely accepted as a reliable approach in financial market analysis and trading. We hypothesize that integrating these concepts into an AI model will yield promising results.

The core idea of the current research is based on the "Inside Bar" technique, a modern and widely used Price Action pattern, combined with deep learning networks. Inside Bar candles are defined as candlesticks whose high and low are entirely contained within the high and low of the preceding period. Our system aims to predict whether the first price that breaks the previous candle's high or low will be upward or downward—that is, whether it will exceed the current candle's high or fall below its low.

By leveraging the Inside Bar pattern, our system provides a robust tool for forecasting the direction of the next period's price. Typically, after the high or low of the Inside Bar pattern is broken, a continuation of the movement in the same direction can be expected. Therefore, our system functions as a binary classification model, where the output corresponds to the first significant upward or downward price movement. Figure 1 illustrates the Inside Bar technique within the Price Action strategy.

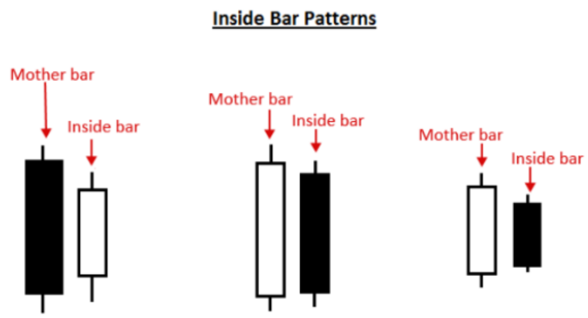

Fig. 1. The Inside Bar Technique in Price Action Trading

In the Inside Bar technique, it is assumed that when the next candlestick breaks the previous period's high (i.e., a breakout occurs), an upward trend can be expected, and vice versa for a downward breakout. Our idea is based on this technique, and the goal of our system is to predict whether the first price to break the current candlestick's high or low will be upward or downward. In other words, we aim to investigate whether, based on the characteristics of the current candlestick and training the model on previous samples, it is possible to predict whether the price will rise (break above the current candle's high) or fall (break below the current candle's low). The rationale behind this approach is that, given the value of small movements in gold prices, even predicting these minor movements can lead to profitable trading opportunities in financial markets.

4. IMPLEMENTATION

Our machine learning task is a binary classification problem. Specifically, based on the features in the dataset, each sample is classified into either an upward or downward category. Given the proven capabilities of the Keras library in Python for constructing deep neural networks, we implemented the proposed system using Python and the Keras library. The implementation environment was Spyder (version 5.2.1).

The dataset used in this study was obtained from Investing.com and contains daily gold price data from August 12, 2008, to February 5, 2023, totaling 3,762 samples. The dataset includes the following features:

1. **Date**: The date of each time period.
2. **Open**: The price at which the first gold trade occurred in the corresponding period.
3. **Close**: The price at which the last gold trade occurred in the corresponding period (labeled as “Price” in our dataset).
4. **High**: The highest price gold reached during the period.
5. **Low**: The lowest price gold reached during the period.
6. **Volume**: The trading volume in the corresponding timeframe.

The data files are in CSV format and can be easily loaded into memory using the Pandas library in Python.

To implement this idea using deep neural networks, all samples were processed chronologically from the oldest date. For each sample, we searched for the first price that exceeded the high or fell below the low of the current candle. Based on this price, a binary label was assigned: 1 if the price broke above the current candle’s high, and 0 if it fell below the current candle’s low.

In this study, we employed a Dense neural network. Dropout layers were also used to reduce overfitting. After extensive experimentation, the best-performing model achieved 66% accuracy, with 6 layers, 128 neurons per layer, the Nadam optimizer, and 250 epochs. Figure 2 illustrates the accuracy curve of the best model.

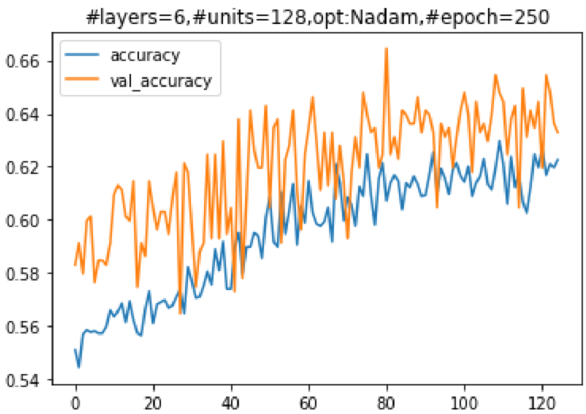

Fig. 2. Accuracy Curve of the Best Model

5. COMPARISON OF THE PROPOSED METHOD WITH PREVIOUS APPROACHES

In the proposed work, both the direction and magnitude of gold prices were predicted using deep neural networks. To evaluate the performance of our method, we selected three relevant studies for comparison: two articles focused on price prediction (regression) and one on price direction prediction.

Selecting comparable studies presented several challenges. For example, due to the novelty of our approach, very few studies focus on binary classification of gold price direction. Additionally, many previous studies have focused on longer timeframes, such as monthly or yearly data, whereas our work is concentrated on daily data. Moreover, reported metrics vary widely across studies; for instance, the MSE is sometimes reported on scales of 10, 100, or even 1,000, making direct comparison difficult. In some cases, methodological details were not fully provided, further complicating fair comparison.

Considering these challenges, we identified the most relevant studies with sufficient implementation details and re-executed their methods on our dataset. Hyperparameter tuning was performed extensively, and the best results were used for comparison. The classification accuracy of our proposed method is 66.26%, obtained using a deep neural network combined with the inside bar technique and features derived from open, close, high, and low prices.

In study [11], a fuzzy logic-based approach was applied using a large dataset, including the Dow Jones Industrial Index, USD-CNY index, other metals (e.g., copper and silver), oil prices, and several news sentiment indices. We collected the publicly available indices and commodity price data from the internet and tested them with our proposed deep network using the same configurations. The resulting model achieved an accuracy of 64.65%, which is approximately 2% lower than our proposed approach.

The regression-based prediction of gold prices using our proposed deep network achieved the following metrics: MAE = 10.73, MSE = 233.29, and RMSE = 15.27.

In study [12], various tree-based regression models were employed, including Random Forest Regression, AdaBoost Regression, XGBoost Regression, and Gradient Boost Regression. Gradient Boost Regression achieved the best performance. We implemented this method using Python's sklearn library on our dataset, prepared identically to the proposed method. The prediction results using Gradient Boost Regression were: MAE = 11.35, MSE = 257.83, and RMSE = 16.06. Comparing the two approaches, the MAE of our proposed method is approximately 0.62 lower than that of Gradient Boost Regression, indicating improved performance.

In study [13], two methods were used for gold price prediction: 1) ARIMA statistical model and 2) MLP neural network. The MLP outperformed ARIMA significantly; hence, we compared our method with MLP. Using sklearn, we implemented the MLP network, prepared the data identically to our approach, and fed it into the network. The regression results were: MAE = 11.12, MSE = 245.37, and RMSE = 15.66. Compared to this MLP model, our proposed deep LSTM network reduces MAE by approximately 0.39, demonstrating superior predictive performance.

From the results above, two clear advantages of the proposed method can be identified:

The predictive power of deep neural networks for gold price direction, and

The effectiveness of integrating the price action strategy, particularly the inside bar technique.

Figures 3, 4, and 5 illustrate the superiority of the proposed method compared to previous approaches.

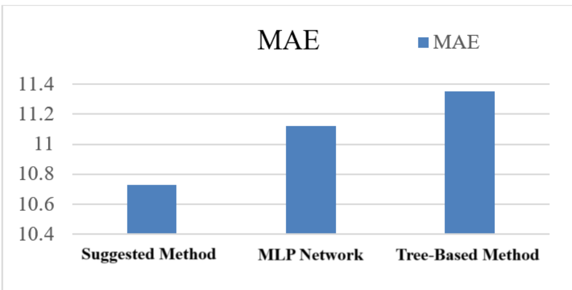

Fig. 3. Comparison of the Proposed Method with Other Approaches Based on MAE

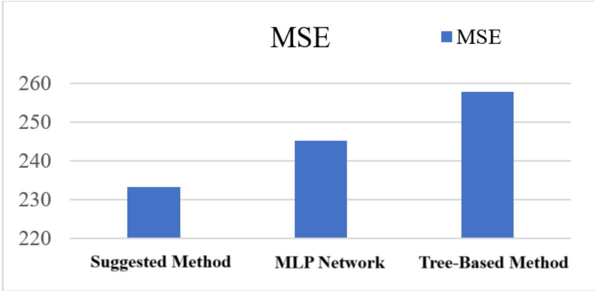

Fig. 4. Comparison of the Proposed Method with Other Approaches Based on MSE

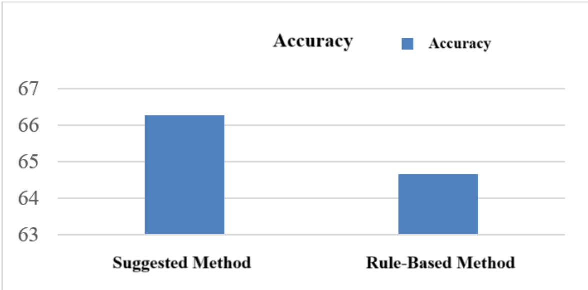

Fig. 5. Comparison of the Proposed Method with Other Approaches in Terms of Gold Price Direction

6. CONCLUSION

The hypothesis of the present study was to develop a machine learning model with a minimum accuracy of 60% to predict the short-term trend of gold prices. We formulated the problem as a binary classification task. Considering capital management principles, having a system with 60% predictive power can make a trader profitable in financial markets.

After building and optimizing the model, we achieved an accuracy of 66%, which is approximately 6% higher than our initial hypothesis. The adequacy of this accuracy depends on the application domain. However, given the highly unpredictable nature of financial markets, significant volatility, and underlying influencing factors, even a predictive power of 60%, combined with proper capital management, can yield reasonable and acceptable profits.

For comparison with previous works, two studies focusing on price value prediction (regression) and one on price direction prediction were selected. The comparison results indicated that the proposed method offers two main advantages over previous approaches: 1) the power of deep neural networks, and 2) the effectiveness of incorporating the Price Action strategy, particularly the Inside Bar technique, in predicting gold price direction.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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