Indonesian Journal of Data and Science

Volume 7 Issue 2
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v7i2.394

Research Article

Hybrid Deep Learning Models For Gold Price Prediction: Enhancing Forecast In Volatile Financial Markets

NI Luh Wiwik Sri Rahayu Ginantra[1*]; Ni Wayan Yeni Pratiwi [2]; Christina Purnama Yanti[3]; Wayan Gede Suka Parwita[4]

[1] Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, wiwik@instiki.ac.id
[2] Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, 2201010403@student.instiki.ac.id
[3] Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, christinapy@instiki.ac.id
[4] Politeknik Negeri Bali, Bali, gede.suka@pnb.ac.id

Correspondence should be addressed to Author; wiwik@instiki.ac.id

Received 10 March 2026; Accepted 15 April 2026; Published 31 July 2026

Abstract:
Introduction: Gold is widely regarded as a long-term store of value and a hedge against inflation, yet its short-term price volatility creates significant challenges for investment decision-making and requires accurate forecasting methods. This study evaluates a hybrid deep learning approach combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to capture both short-term fluctuations and long-term temporal dependencies in gold price movements. **Method**: Historical daily gold closing-price data comprising 2,735 observations from 2015 to 2025 were collected and normalized using Min-Max Scaling. The data were divided chronologically into 80% training and 20% testing sets. A hybrid CNN–LSTM model was trained using the Adam optimizer with a learning rate of 0.0001, dropout of 0.2, a timestep of 30, and batch sizes of 16, 32, and 64. Model performance was evaluated using Root Mean Square Error (RMSE). **Results and Discussion**: The batch size of 16 achieved the best performance, producing the lowest validation RMSE of 0.0929 and an RMSE of 11.518535% after denormalization, outperforming batch sizes of 32 and 64. The model also followed actual gold-price trends more closely, while the inclusion of Dense and Dropout layers improved generalization. **Conclusion**: The CNN–LSTM hybrid model, particularly with a batch size of 16, provides an effective approach for forecasting volatile gold prices by integrating local pattern extraction with long-term temporal modeling.

Keywords: Gold price prediction; Hybrid Deep Learning; Convolutional Neural Network; Long Short-Term Memory.

1. Introduction

Gold is a valuable metal that is important as an investment and a safe place to keep money in the global financial system. Investors are very interested in gold because it can hold its value even when the econ-omy is unstable. This is especially true during times of inflation, changes in exchange rates, and geopo-litical tensions [1]. Changes in the price of gold are also often used as signs of how the global economy is doing, which is why gold price analysis and prediction are important topics in finance and computational economics [2]. Gold prices are generally stable over the long term; however, they can change a lot in the short term because of global events and macroeco-nomic conditions [3]. The dynamic, non-linear, and time series characteristics of gold prices pose challenges in identifying optimal investment strategies [4].

Predicting the price of gold is no simple task due to a number of challenges. To begin with, gold price movements are affected by intricate global and macroeconomic factors, which result in a very complicated behavior as it is highly volatile and non-linear [5]. Additionally, traditional predictive methods can be limited and are often unable to effectively recognize short-term variations, as well as long-term dependencies in time-series data [6]. Lastly, the selection of optimal model architectures and training configurations is fundamental and an inadequate setting can have an impact on prediction accuracy leading to model instability and poor overall performance [7].

However, With the development of technology, artificial intelligence-based approaches, particularly machine learning and deep learning, have been widely used in financial data analysis due to their ability to capture complex patterns from historical data [8]. Previous studies have applied gold price prediction methods such as Support Vector Regression (SVR), linear regression, and Long Short-Term Memory (LSTM). Moreover, traditional forecasting techniques like Fuzzy Time Series and simple linear regression have been extensively adopted to deal with lots of the time series prediction problems in practice with satisfactory performance. Yet still they have their limitations in capturing complex non-linear patterns and long-term temporal dependencies [9]. However, the use of a single model is often not optimal in handling short-term fluctuations and long-term temporal dependencies simultaneously [10]. Therefore, this study proposes a hybrid deep learning approach by combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), where CNN plays a role in extracting short-term local patterns, while LSTM captures long-term temporal relationships in time series data [11]. The hybrid CNN–LSTM approach has been proven to improve prediction accuracy in various time series forecasting problems compared to single models. This study aims to design and evaluate a hybrid CNN–LSTM model in predicting gold prices and analyzing the effect of batch size variation on model performance [12].

In the context of time series forecasting, deep learning models such as CNN and LSTM show better performance than classical methods. CNN is effective in extracting local patterns or short-term fluctuations from time series data [13], while LSTM excels at capturing long-term temporal dependencies. However, the use of a single model is often not optimal for handling both characteristics simultaneously. Therefore, the hybrid CNN–LSTM approach has been widely developed to combine the advantages of each architecture [14].

A recent study conducted by [15] proposed a hybrid Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) architecture for multi-sector export forecasting, published in the Indonesian Journal of Data and Science (IJODAS). The study demonstrated that combining CNN for local feature extraction and BiLSTM for capturing bidirectional temporal dependencies significantly improved forecasting accuracy compared to single deep learning models. Their findings highlight the effectiveness of hybrid deep learning architectures in modeling complex time series data influenced by multiple economic factors. This prior work supports the application of hybrid CNN–LSTM models in financial forecasting contexts, including gold price prediction, where both short-term fluctuations and long-term temporal patterns must be effectively captured.

The uniqueness of this study resides in the application of a hybrid CNN–LSTM methodology for forecasting gold prices and the assessment of its training framework. The proposed model combines CNN and LSTM to take advantage of the best features of both architectures. It has been shown to make predictions more accurately than single models [16]. This study also shows real data on how batch size affects how well the model works, which helps improve financial time series fore-casting using deep learning.

2. Method

This research was conducted through several main stages that were arranged systematically, starting from data collection, preprocessing, data division, model design, training, to model evaluation. The overall research flow is shown in **Figure 1**.

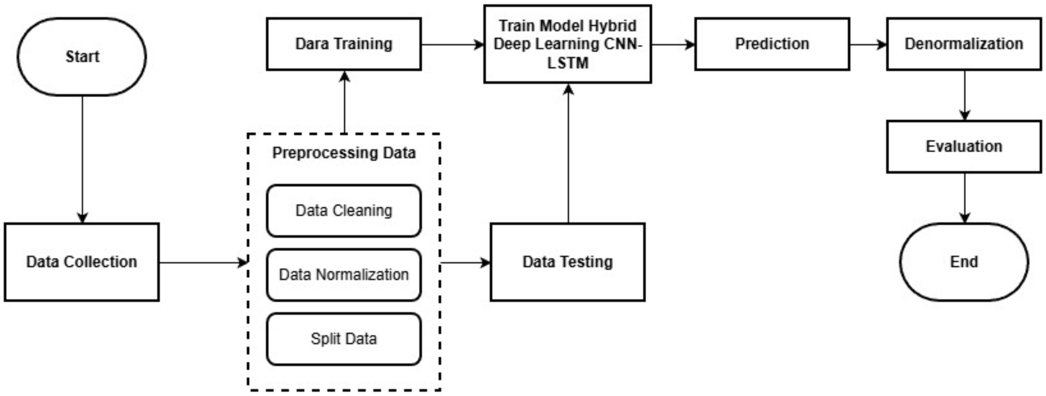

Figure 1. Workflow Diagram

Data Collection

This study uses historical daily gold price data from finance.yahoo.com, one of the most reliable finan-cial data sources and widely used in academic research. The collected information is the final gold price in USD. There are 2,735 historical gold price data points in this dataset from 2015 to 2025. This long time period was chosen to simulate a variety of market conditions, both stable and volatile, allowing the model to better analyze gold price movement patterns. An example of this data collection is shown in **Table 1**.

Table 1. Gold Price Dataset

No	Date	Close
1	2-Jan-15	1,186.00
2	5-Jan-15	1,203.90
3	6-Jan-15	1,219.30
4	7-Jan-15	1,210.60
5	8-Jan-15	1,208.40
…	…	…
2.735	28-Oct-25	3,955.30

Pre-processing Data

Improving data quality before using it in model training is the goal of the pre-processing phase. Data filtering, normalization, and cleaning are part of this process [17].

1) Data Cleaning
Inconsistencies and missing values are identified using data inspection. We convert missing values in the closing price column to NaN and then remove them to prevent them from affecting the model training process [18].
2) Normalization
After data cleaning, it is normalized using Min-Max Scaling, which transforms data values into the range [0,1]. To improve CNN and LSTM model training stability and accelerate convergence, the data is nor-malized to be proportional [19]. Min-max normalization calculation:

$$x' = \frac{x_i - x_{min}}{x_{imax} - x_{min}} \quad (1)$$

Description:
x' = Normalization Result
x_i = Data to-i
x_{min} = Minimum Data Value

x_{max} = Maximum Data Value

Split Data

After the dataset was normalized, it was split into training and testing data in an 80%:20% ratio. To maintain time sequence, a time series splitting technique was used to divide the data. This method en-sures that the model is tested on more recent data and trained on older data. This means that the test results will accurately reflect the conditions used to generate the forecast [20].

Model Design and Training

Utilizing the Hybrid CNN–LSTM model, this study combines the advantages of Long Short-Term Memory (LSTM) with Convolutional Neural Networks (CNN). Long-term temporal relationships are learned by LSTM, whereas CNN retrieves local patterns or short-term variations from time series data [21]. The model has an input layer, a Conv1D layer, a max pooling layer, a dropout layer, an LSTM layer, and a dense output layer with one neuron and a linear activation function. The hyperparameter configu-ration in **Table 2** was used to train the model. Additionally, this study performed a comparative analysis between the base model CNN–LSTM and the CNN–LSTM model enhanced by the incorporation of Dense and Dropout layers subsequent to the LSTM layer, aiming to assess the impact of architectural modifications on predictive accuracy and model generalization abilities.

Table 2. Hyperparameter Training Model

Hyperparameter	
Learning Rate	0.0001
Kernel Size	3
Batch Size	16, 32, 64
Epochs	100
Optimizer	Adam
Timestep	30
Train Loss	
Val Loss	
RMSE	

Denormalization

After testing the model and obtaining prediction results from the prediction process, before calculating the accuracy of the prediction results, denormalization must be performed, which is changing the data by transforming the prediction values into actual values. This is because the prediction results are still in the form of range interval data performed in data normalization. The purpose of denormalization is to make the output easy to read and understand [22]. The formula for calculating data denormalization is as follows:

$$x = x'(x_{max} - x_{min}) + x_{min} \tag{2}$$

Description:

x_i = Denormalization Result

x' = Data to be Denormalized

x_{min} = Minimum Data Value

x_{max} = Maximum Data Value

Evaluation Metric

Researchers used the Root Mean Square Error (RMSE) to assess how well the model performed. RMSE tells us how far apart the actual value is from the predicted value. Researchers used RMSE because it provides a harsher penalty for large errors in prediction, which is beneficial for highly volatile gold price data [23].

As the model improves at predicting gold prices, the RMSE decreases and approaches zero. This study used the RMSE evaluation results to determine the best way to adjust the model.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{3}$$

Description:
A_t = Actual Demand Value
F_t = Predicted Value
n = Amount of Data

3. Result and Discussion

This section presents and discusses the experimental results obtained from training the Hybrid Deep Learning models to forecasting the gold price.

Result

A hybrid deep learning CNN–LSTM model was used in testing to predict gold prices. The model used preprocessed and normalized historical data. The experiment aimed to see how different batch sizes 16, 32, and 64 affected the model's performance. The Adam optimizer trained each model for 100 epochs, using a learning rate of 0.0001 and a timestep of 30.

The training results showed that all settings were able to gradually decrease the loss and RMSE values during the training process. This indicates that the CNN–LSTM model successfully understood how gold prices changed over time. However, the model's stability and generalization ability varied depending on the batch size.

Model performance evaluation was conducted using the Root Mean Square Error (RMSE) metric on training and validation data in the normalized data scale. The quantitative evaluation results are shown in Table 3. Based on this table, the model with a batch size of 16 produced the best performance with a validation RMSE value of 0.0929, which was lower than the batch sizes of 32 and 64, which had validation RMSE values of 0.1150 and 0.1191, respectively. A smaller RMSE value indicates a lower prediction error rate, so the model with a batch size of 16 has better prediction accuracy.

Table 3. Model Training Result

Model Training Results				
BatchSize	**Train RMSE**	**Val RMSE**	**Train Loss**	**Val Loss**
16	0.0153	0.0929	2.3485e-04	0.0086
32	0.0159	0.1150	2.5404e-04	0.0132
64	0.0171	0.1191	2.9103e-04	0.0142

The excellent performance of FastText can be explained by its subword-level modeling. FastText breaks down words These results show that using a smaller batch size allows the model to update weights more frequently, enabling it to learn gold price data patterns in greater detail and produce better generalization on the validation data.

Prediction performance analysis was conducted by comparing the model's prediction results with actual gold price data in the test data, as shown in Figure 2 to Figure 4. Visually, the model with a batch size of 16 produced prediction curves that were closest to the actual data, both in terms of long-term trends and short-term price fluctuations. Conversely, batch sizes of 32 and 64 show greater deviation, especially during periods of high price volatility.

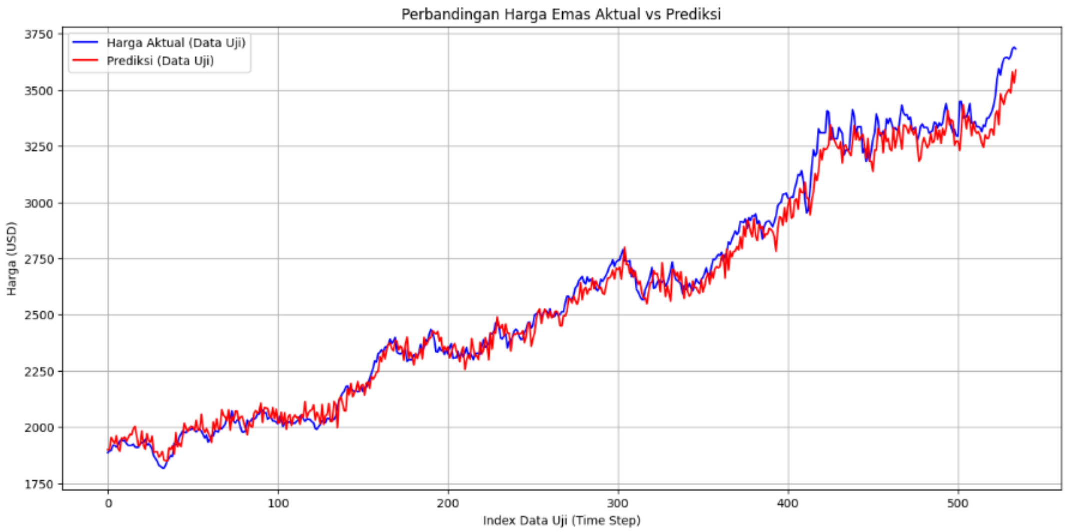

Figure 2. Workflow Actual Gold Price Comparison Chart with Batch Size 16 Model Prediction

Figure 2 shows a comparison between actual gold prices and the predicted results of the CNN–LSTM model on test data with a batch size of 16. Visually, the prediction curve appears very close to the actual price curve and is able to consistently follow price movement patterns, both in upward and downward trends. The differences that appear at several points are relatively small and do not significantly affect the direction of movement.

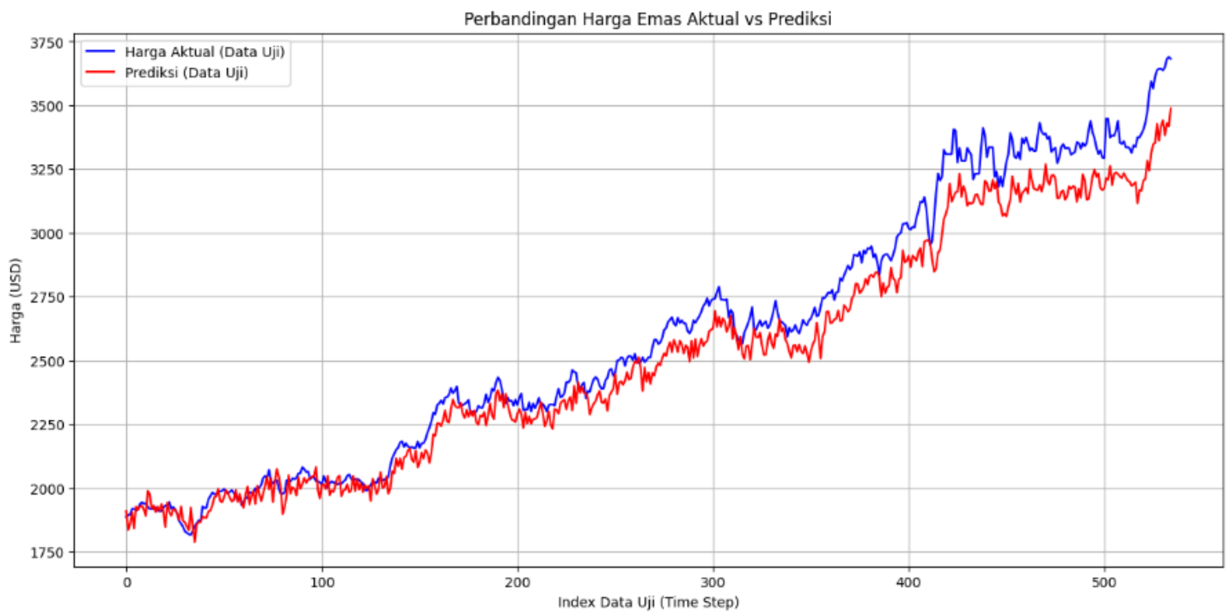

Figure 3. Workflow Actual Gold Price Comparison Chart with Batch Size 32 Model Prediction

Figure 3 shows a comparison between actual gold prices and the prediction results of the CNN–LSTM model on test data with a batch size of 32. The graph shows that the prediction results are still able to follow the general pattern of actual gold price movements, especially in major trend changes. However, there is a larger discrepancy in some periods compared to batch size 16, so that the accuracy of the prediction has relatively decreased even though the direction of price movements can still be represented quite well.

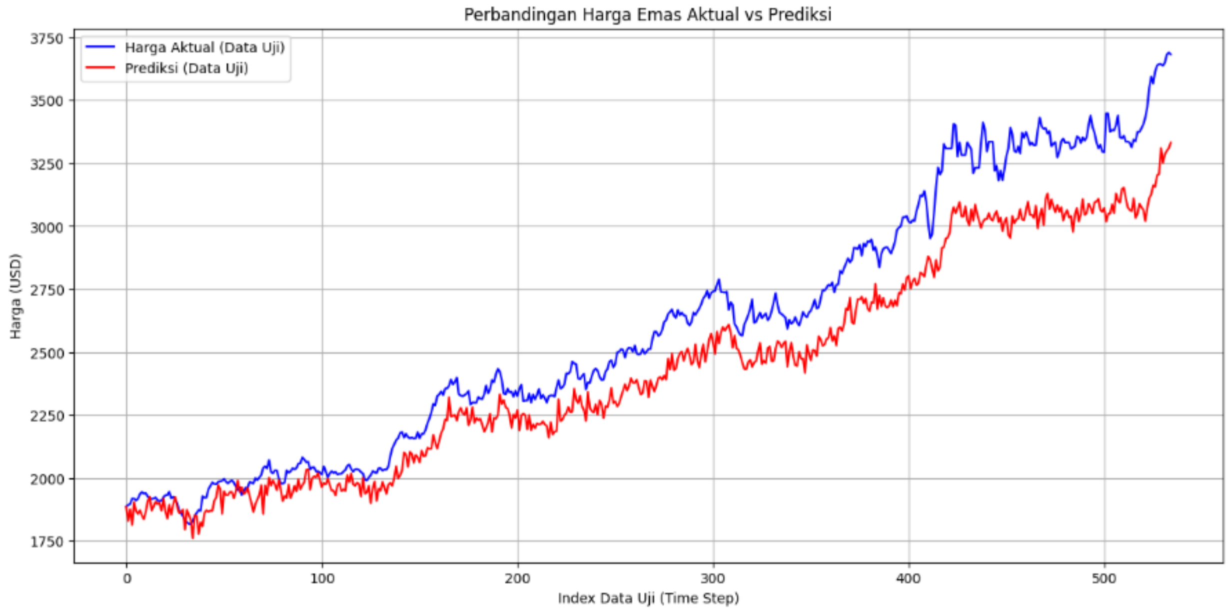

Figure 4. Workflow Actual Gold Price Comparison Chart with Batch Size 64 Model Prediction

Figure 4 shows a comparison between actual gold prices and the CNN–LSTM model's predictions on test data with a batch size of 64. From the visualization results, the model is still able to capture the general trend of gold price movements, but differences between the prediction curve and actual data appear more frequently. This condition indicates that the use of a larger batch size causes the model's ability to predict gold prices to be less optimal compared to a smaller batch size.

To support the visual analysis in **Figure 2** to **Figure 4**, prediction error patterns were analyzed by observing the difference between actual gold prices and predicted values. As is common with gold price data, the quantitative analysis in Table 4 shows that forecast errors tend to increase when prices change rapidly. However, under relatively normal market conditions, the CNN–LSTM model with a batch size of 16 consistently produces lower error values than other batch size combinations. This indicates a more stable prediction.

Table 4. Result of Batch Size Comparison Evaluation

Hyperparameter			
Batch Size	16	32	64
Epoch	100	100	100
Optimasi	Adam	Adam	Adam
Learning Rate	0.0001	0.0001	0.0001
DropOut	0.2	0.2	0.2
Timestamp	30	30	30
Train Loss	0.000246	0.000253	0.000285
Val Loss	0.008627	0.013236	0.014178
RMSE	305.175555	377.998966	391.226518
RMSE %	**11. 518535%**	14.267179%	14.766439%

An analysis was done to find the best model configuration after training the CNN–LSTM model with three different batch sizes: 16, 32, and 64. The assessment results showed that the model with a batch size of 16 did the best. This model was used to predict gold prices for the next 30 days. The prediction results were then shown in graph form to show the trend of the expected changes in the price of gold.

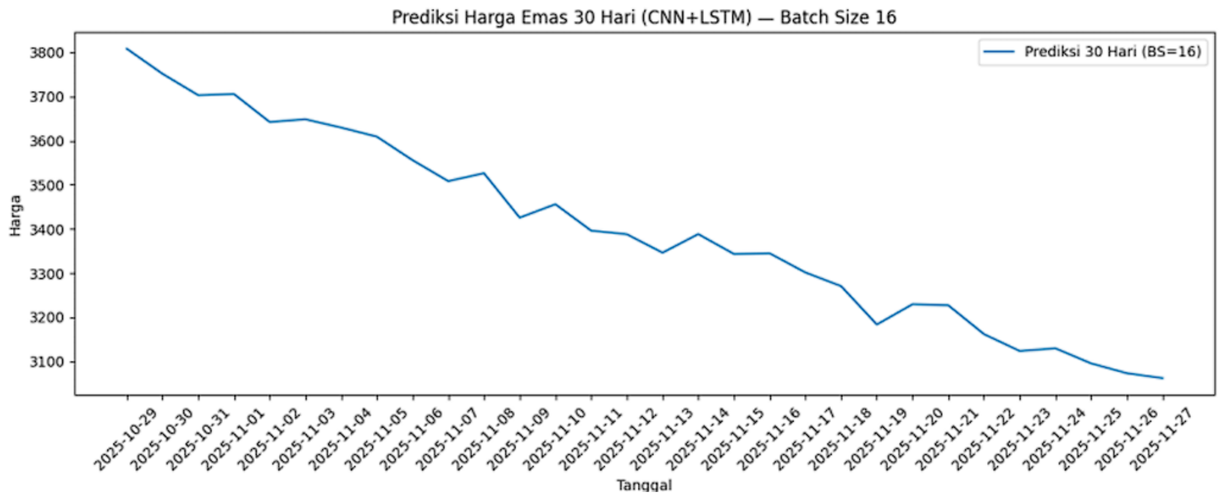

Figure 5. 30-Day Gold Price Forecast Chart

Using a CNN-LSTM hybrid model with a batch size of 16, **Figure 5** shows the predicted gold price for the next 30 days. This setup is the best because it has the lowest value for RMSE. The time frame for the forecast is from October 29 to November 27. The graph shows that the price of gold will slowly go down over a number of time periods, with only small changes. The price of gold is higher at the start of the forecast range than it is at the end. After that, it usually goes down until the end of the range. The CNN–LSTM model with a batch size of 16 can accurately show the patterns in historical gold price data over time and make strong short-term predictions, according to these results.

The model design was then evaluated by comparing the implementation of dropout and dense layers. This test used the best model, which had a batch size of 16 and was trained on a variety of previous batch sizes. **Table 5** shows the evaluation results. The model with dropout and dense layers had a lower validation RMSE value than the model without them. This means that dropout makes neurons less dependent on each other during training, while dense layers help transfer discovered characteristics to better predictive outputs. Therefore, using dropout and dense layers together makes the model better at generalizing and less likely to overfit, making it more reliable and accurate in predicting gold prices on previously unseen data.

Table 5. Result of Layer Comparison Evaluation

Hyperparameter		
With Dense & Dropout		
Parameter	Yes	No
Epoch	100	100
Optimasi	Adam	Adam
Learning Rate	0.0001	0.0001
Dropout	0.2	0.2
Timestep	30	30
Train Loss	0.000246	0.000234
Val Loss	0.008627	0.011706
RMSE	305.175555	355.489649
RMSE %	11. 518535%	13.417588%

The results show that the hybrid CNN–LSTM model makes the best predictions for gold prices when it is set up correctly with a batch size of 16. This model works so well because the CNN can find short-term changes and local patterns, and the LSTM can find long-term temporal dependencies. These results show that both CNN and LSTM can handle the time series and non-linear parts of gold price data very well. This means that you can use either one to guess what the price of gold will be in the future.

Discussion

The experimental results demonstrate that batch size significantly influences the performance of the CNN–LSTM model in forecasting gold prices. Among the tested configurations, batch size 16 consistently achieved the lowest validation RMSE and loss values, indicating better generalization capability compared to batch sizes 32 and 64. This suggests that smaller batch sizes allow more frequent weight updates, enabling the model to learn detailed temporal patterns in gold price movements. The visual comparison graphs further confirm that the batch size 16 model produces prediction curves that more closely follow actual price trends, especially during stable market conditions.

In addition, the evaluation of dropout and dense layers shows that their inclusion improves model performance by reducing overfitting and enhancing feature representation. The hybrid CNN–LSTM architecture proves effective because CNN captures short-term fluctuations and local patterns, while LSTM models long-term dependencies in time series data. These findings align with theoretical expectations that hybrid deep learning models are well-suited for complex, non-linear financial data such as gold prices, and highlight the importance of proper hyperparameter tuning to achieve optimal forecasting accuracy.

4. Conclusion

This study finds that the use of the Hybrid Deep Learning CNN-LSTM model is successful in fore-casting gold prices using historical time series data. The experimental results indicate that CNN-LSTM model with batch size 16 is the best performer with the lowest RMSE of 11.518535% and the prediction pattern that is closest to the actual. This claim holds true in the numerical evaluation and prediction graph; therefore, the method may be considered reasonable and scientifically valid. This agrees with the theory and other research stating that hybrid models outperform individual models in detecting and reflecting the non-linear and time-dependent patterns in time series data. This study adds to the empirical works that hybrid deep learning architectures improve the accuracy of the prediction of prices of commodities by establishing the potentials of CNN in the capture of local attributes and LSTM in the modeling of long-term dependencies. More so, this study enhances the body of knowledge in financial forecasting with a hybrid approach, in particular to gold price forecasting.text domains.

References:

[1] S. Aprizal dan M. N. Harahap, “Determinants of Gold Prices in Indonesia Period of 2018-2022.”

[2] A. Amini dan R. Kalantari, “Gold price prediction by a CNN-Bi-LSTM model along with automatic parameter tuning,” *PLoS One*, vol. 19, no. 3 March, Mar 2024, doi: https://doi.org/10.1371/journal.pone.0298426.

[3] G. Taneva-Angelova, S. Raychev, dan G. Ilieva, “A Framework for Gold Price Prediction Combining Classical and Intelligent Methods with Financial, Economic, and Sentiment Data Fusion,” *International Journal of Financial Studies*, vol. 13, no. 2, Jun 2025, doi: https://doi.org/10.3390/ijfs13020102.

[4] S. Sathyanarayana dan T. Mohanasundaram, “The Surge in Gold Price Volatility: Macroeconomic Drivers, Geopolitical Risk, and Market Dynamics,” *IRA-International Journal of Management & Social Sciences (ISSN 2455-2267)*, vol. 21, no. 1, hlm. 15, Apr 2025, doi: https://doi.org/10.21013/jmss.v21.n1.p2.

[5] M. M. Ataey dan A. K. Azizi, “Forecasting Gold Price Volatility Using Econometric and Machine-Learning Models,” *Journal of Social Sciences and Humanities*, vol. 3, no. 1, hlm. 173–188, Jan 2026, doi: https://doi.org/10.62810/jssh.v3i1.231.

[6] Afiz Adewale Lawal, Omogbolahan Alli, Aishat Oluwatoyin Olatunji, Enuma Ezeife, dan Ehizele Dean Okoduwa, “Time series analysis and forecasting in finance: A data mining approach,” *Open Access Research Journal of Science and Technology*, vol. 9, no. 1, hlm. 075–075, Okt 2023, doi: https://doi.org/10.53022/oarjst.2023.9.1.0045.

[7] R. P. dos Santos, J. P. Matos-Carvalho, dan V. R. Q. Leithardt, “Deep learning in time series forecasting with transformer models and RNNs,” *PeerJ Comput. Sci.*, vol. 11, 2025, doi: https://doi.org/10.7717/peerj-cs.3001.

[8] S. Joddy, “Comparative Analysis of CNN, LSTM, and CNN-LSTM for Indonesian Stock Prediction,” vol. 7, no. 3, hlm. 283–289, 2025, doi: https://doi.org/10.21512/emacsjournal.v6.

[9] Ni Luh Sri April Yanti, Ni Wayan Jeri Kusuma Dewi, I Gede Made Yudi Antara, Desak Made Dwi Utami Putra, dan Putu Wirayudi Aditama, "Sales Forecasting Analysis Using Fuzzy Time Series and Simple Linear Regression Methods at Toko Ari," *Indonesian Journal of Data and Science*, vol. 6, no. 3, hlm. 473–480, Des 2025, doi: https://doi.org/10.56705/ijodas.v6i3.368.

[10] I. W. Krisna Gita Santika, S. Sa'adah, dan P. E. Yunanto, "Gold price prediction using Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM)," *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, Agu 2021, doi: https://doi.org/10.22219/kinetik.v6i3.1253.

[11] "Deep Learning for Financial Forecasting: A Review of Recent Trends."

[12] Z. Dong dan Y. Zhou, "A Novel Hybrid Model for Financial Forecasting Based on CEEMDAN-SE and ARIMA-CNN-LSTM," *Mathematics*, vol. 12, no. 16, Agu 2024, doi: https://doi.org/10.3390/math12162434.

[13] S. M. Chishti, "Hybrid Deep Learning Architectures for Time-Series Forecasting," *International Journal of Engineering & Extended Technologies Research (IJEETR) | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal* | |, vol. 7, no. 4, hlm. 10252, doi: https://doi.org/10.15662/IJEETR.2025.0704003.

[14] B. J. Kim dan I. W. Nam, "A Review of Hybrid LSTM Models in Smart Cities," 1 Juli 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: https://doi.org/10.3390/pr13072298.

[15] D. Anggreani, ; Nurmisba, ; Aedah, dan A. Rahman, "A Hybrid Convolutional Neural Network and Bidirectional LSTM Architecture for Multi-Sector Export Forecasting: A Macroeconomic Time Series Analysis of Indonesia," *Indonesian Journal of Data and Science*, vol. 6, 2025, doi: https://doi.org/10.56705/ijodas.v5i3.330.

[16] X. Zhou, "Stock Price Prediction using Combined LSTM-CNN Model," dalam *Proceedings - 2021 3rd International Conference on Machine Learning, Big Data and Business Intelligence, MLBDBI 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, hlm. 67–71. doi: https://doi.org/10.1109/MLBDBI54094.2021.00020.

[17] C. Fan, M. Chen, X. Wang, J. Wang, dan B. Huang, "A Review on Data Preprocessing Techniques Toward Efficient and Reliable Knowledge Discovery From Building Operational Data," 29 Maret 2021, *Frontiers Media S.A.* doi: https://doi.org/10.3389/fenrg.2021.652801.

[18] P. Koukaras dan C. Tjortjis, "Data Preprocessing and Feature Engineering for Data Mining: Techniques, Tools, and Best Practices," 1 Oktober 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: https://doi.org/10.3390/ai6100257.

[19] A. Alsarhan, F. Hussein, S. Moh, dan F. S. El-Salhi, "The Effect of Preprocessing Techniques, Applied to Numeric Features, on Classification Algorithms' Performance," 2021, doi: https://doi.org/10.3390/data.

[20] H. Bichri, A. Chergui, dan M. Hain, "Investigating the Impact of Train / Test Split Ratio on the Performance of Pre-Trained Models with Custom Datasets," 2024.

[21] K. O. Adefemi dan M. B. Mutanga, "A Robust Hybrid CNN–LSTM Model for Predicting Student Academic Performance," *Digital*, vol. 5, no. 2, Jun 2025, doi: https://doi.org/10.3390/digital5020016.

[22] A. Hidayatur, M. Idhom, dan W. Syaifullah, "Hybrid Prediction Model Fuzzy Time Series-LSTM on Stock Price Data with Volatility Variation," *bit-Tech*, vol. 8, no. 2, hlm. 1625–1636, Des 2025, doi: https://doi.org/10.32877/bt.v8i2.3014.

[23] G. Airlangga, "Performance Evaluation of Machine Learning Models for Predicting Household Energy Consumption: A Comparative Study," *Indonesian Journal of Artificial Intelligence and Data Mining*, vol. 8, no. 1, hlm. 76, Des 2024, doi: https://doi.org/10.24014/ijaidm.v8i1.32791.