International Journal of Management Science and Information Technology
IJMSIT

E-ISSN: 2774-5694 P-ISSN: 2776-7388 OPEN ACCESS

Volume 6 (2), July-December 2026, 1807-1816
DOI: https://doi.org/10.35870/ijmsit.v6i2.8297

A Web-Based Gold Price Prediction Model Using Geopolitical Sentiment from Social Media and Gated Recurrent Unit (GRU)

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Article history:
Received August 5, 2026
Revised August 11, 2026
Accepted August 12, 2026

Abstract

Gold is widely recognized as a safe-haven asset whose price is sensitive to economic and geopolitical uncertainty. This study develops a web-based international gold price prediction system using the Gated Recurrent Unit (GRU) algorithm and evaluates the contribution of geopolitical sentiment from the X social media platform. The study uses historical XAUUSD data and English-language posts related to the Iran–United States–Israel conflict. Text data were processed through cleaning, case folding, tokenization, stopword removal, lemmatization, TF-IDF transformation, and sentiment analysis using VADER. The resulting daily sentiment scores were integrated with historical gold price features and used as an additional input to the GRU model. Two experimental scenarios were evaluated: GRU without sentiment and GRU with sentiment. The results show that the GRU model without sentiment achieved an MAE of 55.07, RMSE of 69.81, MAPE of 1.17%, and R^2 of 0.9629, while the model with sentiment achieved an MAE of 80.87, RMSE of 92.93, MAPE of 1.72%, and R^2 of 0.9342. These findings indicate that incorporating daily aggregated social media sentiment did not improve prediction performance for the dataset used. The developed Flask-based web application provides prediction, sentiment analysis, visualization, and model evaluation features, demonstrating the practical implementation of the proposed approach.

Keywords:
Gold Price Prediction; Geopolitical Sentiment; X Social Media; Gated Recurrent Unit (GRU); Sentiment Analysis.

1. INTRODUCTION

Gold is one of the most widely preferred investment instruments because it is considered a safe-haven asset during periods of economic and geopolitical uncertainty. In times of high inflation, recession risks, or international conflicts, investors tend to shift their assets toward gold to preserve investment value, resulting in significant fluctuations in gold prices (Adams et al., 2023; Agusmawati et al., 2023). The dynamic nature of gold price movements has made gold price forecasting an important research topic, particularly for supporting more accurate investment decision-making.

Gold price movements are influenced by various economic and non-economic factors. Economic variables such as inflation, interest rates, exchange rates, and global market conditions have been extensively employed in previous gold price forecasting studies. However, the rapid advancement of information technology and social media has introduced new sources of data capable of representing public opinion regarding global events. The social media platform X enables users to express their opinions, perceptions, and reactions to economic and geopolitical issues in real time, generating large volumes of textual data that can be utilized for sentiment analysis (Dalimunthe et al., 2025; Ehsan et al., 2025).

One of the geopolitical issues that has attracted significant global attention in recent years is the Iran–United States–Israel conflict. This conflict has increased uncertainty in global financial markets and influenced investor behavior in determining investment strategies. Geopolitical instability often drives higher demand for safe-haven assets such as gold, thereby affecting international gold prices (Hadinegoro & Sulistiyo., 2025). Furthermore, public sentiment expressed on social media regarding geopolitical conflicts may also influence market perception and investment decisions. Therefore, sentiment analysis of public opinion provides a valuable source of information for improving gold price prediction.

Sentiment analysis is a branch of Natural Language Processing (NLP) that aims to identify opinions, attitudes, and perceptions expressed in textual data. Previous studies have demonstrated that sentiment extracted from social media is significantly associated with financial market conditions and can improve forecasting performance compared with approaches that rely solely on numerical data (Dalimunthe et al., 2025; Ehsan et al., 2025). Public sentiment on the X platform has also been reported to correlate with fluctuations in stock prices and gold prices, making it a promising additional variable for financial market prediction models (Harmain et al., 2025; Hendra et al., 2026).

With the rapid development of artificial intelligence, deep learning methods have become increasingly popular for modeling time-series data because of their ability to capture complex nonlinear patterns. Several previous studies have applied Long Short-Term Memory (LSTM), Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM), and Gated Recurrent Unit (GRU) models to gold price forecasting. Agusmawati et al. (2023) reported that the GRU model achieved satisfactory forecasting performance on historical gold price data. Similarly, Meriani and Rahmatulloh (2024) found that GRU outperformed both LSTM and Linear Regression in time-series-based gold price prediction. Harmain et al. (2025) obtained a Mean Absolute Percentage Error (MAPE) of 1.107% using a GRU model optimized with the Nadam optimizer, while Hendra et al. (2026) concluded that GRU is more stable and computationally efficient than LSTM for modeling gold price data. In addition, Septiana et al. (2025) employed a CNN–LSTM model to predict Indonesian gold prices and demonstrated that deep learning techniques can produce highly accurate predictions based on historical data.

Despite the considerable amount of research on gold price prediction, most previous studies have primarily focused on historical price data, economic indicators, and other financial variables. Meanwhile, sentiment analysis has been more frequently applied to stock market and cryptocurrency forecasting than to gold commodities (Kusuma et al., 2025). Furthermore, studies integrating public sentiment regarding the Iran–United States–Israel geopolitical conflict extracted from the X platform with a GRU-based gold price prediction model remain limited. This limitation highlights an important research gap concerning the integration of geopolitical sentiment as an additional predictive feature for international gold price forecasting.

Based on this research gap, this study proposes a model for predicting international gold prices by integrating historical XAUUSD price data with public sentiment related to the Iran–United States–Israel conflict collected from the X platform. The textual data are transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF–IDF) method and analyzed using VADER to obtain sentiment scores. These sentiment scores are subsequently combined with historical gold price data and used as input features for a Gated Recurrent Unit (GRU) model. The objectives of this study are to develop a geopolitical sentiment-based gold price prediction model, investigate the impact of incorporating sentiment information on prediction performance, and evaluate the GRU model using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). The findings are expected to contribute to the development of sentiment-driven commodity price forecasting methods based on deep learning and to provide valuable insights for researchers and investors into the relationship between geopolitical sentiment and international gold price movements.

Although previous studies have demonstrated the effectiveness of deep learning models, particularly GRU and LSTM, for gold price forecasting, most studies primarily rely on historical price data and conventional economic variables. Meanwhile, social media sentiment has more frequently been investigated in stock and cryptocurrency forecasting than in international gold price prediction. In addition, limited studies have specifically examined geopolitical sentiment related to the Iran–United States–Israel conflict obtained from the X platform and integrated it into a GRU-based gold price forecasting framework. Another limitation concerns the nature of social media data, which is characterized by noise, informal language, heterogeneous opinions, and rapidly changing public reactions. Therefore, the contribution of geopolitical sentiment to gold price prediction cannot be assumed to be consistently positive. This study addresses this gap by empirically comparing a GRU model based solely on historical XAUUSD variables with a GRU model incorporating daily aggregated geopolitical sentiment extracted from X. This comparison allows the study not only to evaluate the predictive capability of GRU but also to determine whether the inclusion of social media sentiment provides additional predictive value.

2. RESEARCH METHOD

This study aims to predict international gold prices based on public sentiment regarding the Iran–United States–Israel geopolitical conflict on the X social media platform using the Gated Recurrent Unit (GRU) algorithm. The research framework serves as a systematic guideline for conducting the study, ensuring that each stage is logically connected and contributes to achieving the research objectives. The overall research framework is illustrated in Figure 1.

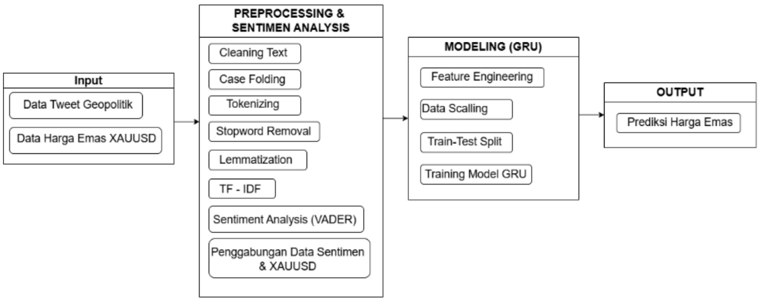

Figure 1. Research Framework

2.1. Data Collection

The dataset used in this study consists of two primary sources: historical international gold price (XAUUSD) data and public sentiment data collected from the X social media platform. Historical gold price data were obtained from trading records covering the period from April 2023 to May 2026. The dataset includes five numerical attributes: Open, High, Low, Close, and Volume, which represent the historical movement of gold prices.

Public sentiment data were collected from English-language tweets discussing the Iran–United States–Israel conflict. The data collection process was conducted through Python-based web scraping using the Apify platform. The collected tweets were subsequently used as the textual dataset for sentiment analysis.

2.2. Preprocessing and Sentiment Analysis

The preprocessing stage was performed to improve the quality of the textual data before sentiment analysis. This stage consisted of several sequential processes, including text cleaning, case folding, tokenization, stop-word removal, and lemmatization. After preprocessing, the cleaned text was transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF–IDF) method.

The TF–IDF weighting is calculated using EquationTF"-" IDF(t,d)=TF(t,d)×IDF(t), where TF represents the frequency of a term within a document and IDF measures the uniqueness of the term across the document collection.

Sentiment analysis was performed using the Valence Aware Dictionary and sEntiment Reasoner (VADER) lexicon-based approach. VADER produces four sentiment scores for each tweet: positive, negative, neutral, and compound. In this study, the compound score was selected as the overall sentiment representation because it summarizes the polarity of each tweet into a single normalized value.

Since multiple tweets may be posted on the same day, the compound sentiment scores were aggregated by calculating their daily average. The resulting daily sentiment values were then merged with the historical gold price dataset according to the corresponding dates. Consequently, the final dataset consisted of six input features: Open, High, Low, Close, Volume, and Sentiment Score.

2.3. Development of the Gated Recurrent Unit (GRU) Model

The Gated Recurrent Unit (GRU) model was developed to predict the closing price of international gold (XAUUSD). Two experimental scenarios were implemented to evaluate the contribution of geopolitical sentiment: a GRU model using historical gold price variables only and a GRU model incorporating geopolitical sentiment as an additional feature. For the sentiment-enhanced scenario, the input features consisted of Open, High, Low, Volume, and sentiment_score, while the target variable was the Close price..

Before model training, the input features and target variable were normalized using Min-Max Scaling to transform the values into a comparable numerical range. The dataset was divided chronologically into training and testing sets using an 80:20 ratio. The training data were used to develop the GRU model, while the testing data were reserved for evaluating the final prediction performance. Conventional random k-fold cross-validation was not applied because the dataset represents chronological financial time-series observations. Randomly shuffling the observations may cause temporal information leakage by allowing information from later observations to influence the training process. Therefore, the chronological order of the data was maintained during the training and testing process. However, systematic validation techniques such as rolling-window or walk-forward validation were not implemented in this study and are considered as potential approaches for future research to provide a more robust evaluation of model stability.

The training data were reshaped into a three-dimensional structure required by the GRU architecture, consisting of samples, time steps, and features. The GRU architecture used in this study consisted of one GRU layer with 64 neurons, followed by a Dropout layer with a rate of 0.2 to reduce the risk of overfitting. The output of the GRU layer was connected to a Dense layer containing 32 neurons with a ReLU activation function. Finally, a single-neuron Dense output layer was used to generate the predicted gold closing price.

The model was compiled using the Adam optimizer and Mean Squared Error (MSE) as the loss function. The model was trained for 100 epochs using a batch size of 16. The same GRU architecture and training configuration were applied to both experimental scenarios to ensure a consistent comparison between the model without sentiment and the model incorporating geopolitical sentiment. The detailed parameter of the model GRU is presented in Table 1.

Table 1. The Parameter of Model GRU

Parameter	Configuration
Model	Gated Recurrent Unit (GRU)
Input features	Open, High, Low, Vol., Sentiment Score
Target	Close
Normalization	Min-Max Scaling
Training data	80%
Testing data	20%
GRU layer	1 layer
Number of neurons	64
Dropout	0.2
Dense layer	32 neurons, ReLU activation
Output layer	1 neuron
Optimizer	Adam
Loss function	MSE
Epoch	100
Batch size	16
Training split	80%
Testing split	20%

2.4. Performance Evaluation

The predictive performance of the proposed model was evaluated by comparing the predicted values with the actual gold prices using four widely adopted evaluation metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2).

MAE measures the average magnitude of absolute prediction errors, while RMSE quantifies the overall deviation between predicted and actual values by assigning greater weight to larger errors. MAPE expresses prediction errors as percentages, facilitating model interpretation, whereas R^2 evaluates the proportion of variance in the actual data explained by the prediction model.

A lower value of MAE, RMSE, and MAPE, together with an R^2 value closer to 1, indicates better predictive performance and higher model accuracy.

3. RESULTS AND DISCUSSION

3.1. Results GRU Model

This study evaluated two experimental scenarios: (1) a GRU model trained solely on historical gold price data and (2) a GRU model incorporating both historical gold price data and public sentiment obtained through VADER sentiment analysis. Both models were trained using historical international gold price (XAUUSD) data, with 80% of the dataset allocated for training and 20% for testing. Model training was conducted for 100 epochs using the Gated Recurrent Unit (GRU) architecture.

3.1.1. GRU Model Without Sentiment Features

Figure 2 presents the training and validation loss curves of the GRU model trained without incorporating sentiment features.

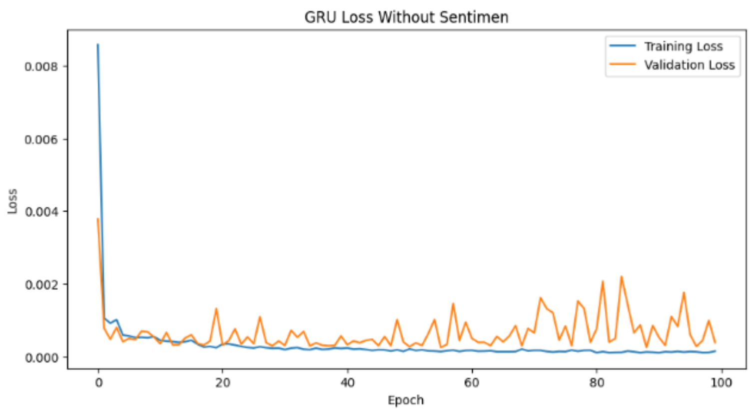

Figure 2. Epoch Loss GRU Without Sentiment

As illustrated in Figure 2, the training and validation loss curves show a substantial reduction during the initial epochs, followed by convergence toward relatively stable values. This pattern indicates that the GRU model successfully learned the dominant temporal patterns in the training data. The relatively small gap between training and validation loss during the later epochs suggests that the model did not exhibit severe overfitting. However, minor fluctuations in validation loss remain visible, indicating that the model is still sensitive to variations in the testing distribution and financial market dynamics.

The trained model was subsequently evaluated using the testing dataset. The comparison between the predicted and actual gold prices is presented in Figure 3.

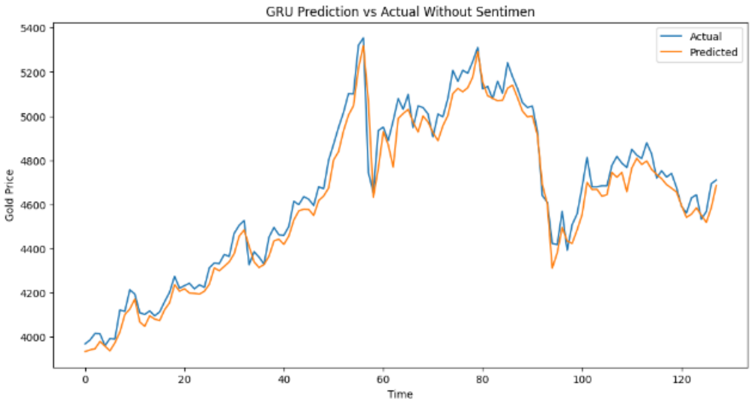

Figure 3. GRU Prediction vs Actual Without Sentimen

As shown in Figure 3, the predicted values closely followed the overall trend of the actual gold prices. Although slight deviations occurred during periods characterized by rapid price fluctuations, the model was generally able to capture both upward and downward market trends effectively.

Table 2. The Performance of GRU Without Sentimen

Metrics	Value
MAE	55,07
RMSE	69,81
MAPE	1.17%
R2	0,9629

The quantitative evaluation results are summarized in Table 2. The model achieved a Mean Absolute Error (MAE) of 55.07, indicating an average prediction error of approximately 55 gold price points. The Root Mean Squared Error (RMSE) was 69.81, suggesting that the prediction deviations remained relatively small. Furthermore, the Mean Absolute Percentage Error (MAPE) reached 1.17%, indicating excellent forecasting accuracy with an average percentage error below 2%. The Coefficient of Determination (R^2) was 0.9629, demonstrating that approximately 96.29% of the variance in gold prices could be explained by the proposed model.

3.1.2. GRU Model with Sentiment Features

In the second experimental scenario, public sentiment scores were incorporated as an additional input feature alongside the historical gold price variables. The training process of the GRU model with sentiment features is illustrated in Figure 4.

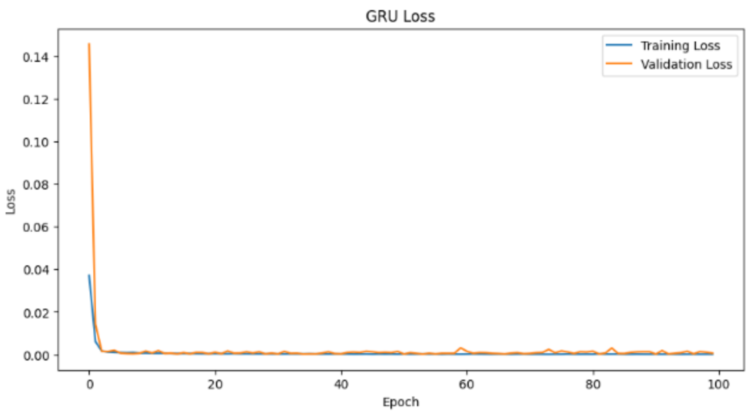

Figure 4. Epoch Loss GRU with Sentiment

The training and validation loss curves also show a substantial reduction during the initial epochs, followed by relatively stable convergence. This indicates that the GRU model was able to learn patterns from the combined gold price and sentiment features. However, fluctuations in the validation loss indicate that the model remained sensitive to variations in the data. Although the model converged during training, convergence alone does not guarantee that the additional sentiment feature improves generalization performance.

The trained model was then evaluated using the testing dataset, and the prediction results are presented in Figure 5.

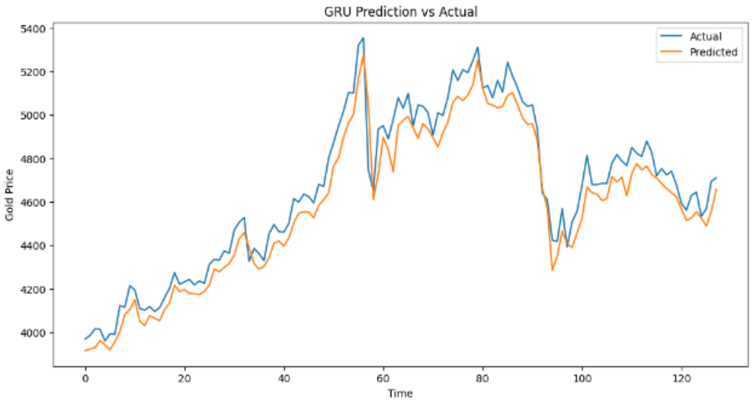

Figure 5. GRU Prediction vs Actual with Sentiment

The prediction results demonstrate that the model was able to capture the general trend of gold price movements. However, larger prediction errors were observed at several time points compared with the GRU model trained without sentiment information.

Table 3. The Performance of GRU With Sentimen

Metrics	Value
MAE	80,87
RMSE	92.93
MAPE	1.72%
R2	0,9342

The evaluation metrics are summarized in Table 3. The model achieved an MAE of 80.87, an RMSE of 92.93, a MAPE of 1.72%, and an R^2 value of 0.9342. These results indicate that, although the model maintained satisfactory predictive capability, its overall performance was inferior to that of the model utilizing only historical gold price data.

3.2. Results WEB Prediction

The proposed web application was implemented using the Flask framework to provide an accessible interface for the developed GRU model. The application integrates several functions, including historical gold price visualization, geopolitical sentiment visualization, gold price prediction, model evaluation, prediction history, and PDF report generation. The web interface allows users to perform predictions without directly interacting with the underlying Python implementation.

From a usability perspective, the application simplifies the prediction process by providing input forms and presenting the resulting predicted closing price in an interpretable format. The evaluation module also enables users to examine the model performance using MAE, RMSE, MAPE, and R^2.

However, the current implementation was designed primarily as a research prototype and has not been subjected to formal usability testing involving a large number of users. Similarly, comprehensive load testing and scalability evaluation were not conducted. These aspects represent limitations of the current implementation and should be addressed in future work if the system is intended for production-scale deployment.

From a security perspective, the system does not require users to provide sensitive personal information. Nevertheless, future deployment should implement standard web security practices, including input validation, protection against malicious text input, secure file handling, environment-based configuration of secret keys, and HTTPS communication.

The dashboard page of the application is presented in Figure 6. This page functions as the main interface of the system by providing an overview of the developed application. It displays a real-time TradingView chart of international gold prices (XAUUSD), historical gold price visualization, historical sentiment trends, and summary information regarding the prediction model. These visualizations allow users to monitor current market conditions while understanding historical price movements and sentiment fluctuations before conducting predictions.

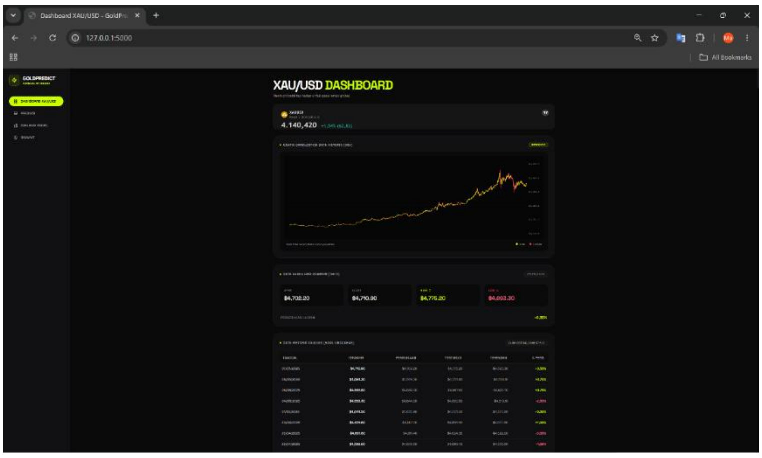

Figure 6. Page Dashboard WEB

The prediction page is illustrated in Figure 7. This page enables users to estimate future gold prices by entering the required input variables used during model training. The prediction process requires four historical market variables, namely Open, High, Low, and Volume, together with an optional geopolitical text input.

When textual input is provided, the system automatically performs several Natural Language Processing (NLP) stages, including text cleaning, case folding, tokenization, stop-word removal, lemmatization, TF-IDF feature extraction, and sentiment analysis using the VADER lexicon. The resulting compound sentiment score is then combined with the numerical gold price features and passed into the trained GRU model to predict the Close Price. If no text is entered, the system performs prediction solely based on the numerical market variables.

The prediction results are displayed immediately after processing, allowing users to compare the estimated gold closing price with the supplied market information.

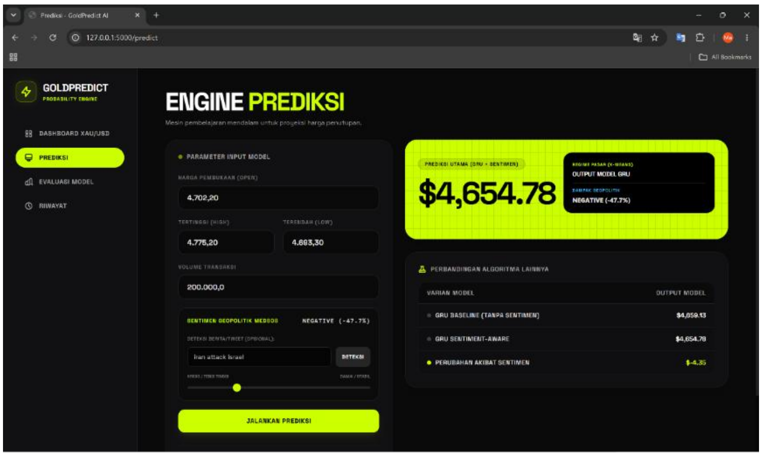

Figure 7. Page Prediction WEB

The evaluation page, shown in Figure 8, provides quantitative information regarding the predictive performance of the developed GRU model. The evaluation metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2).

Two experimental scenarios are presented on this page, namely the GRU model trained without sentiment information and the GRU model incorporating geopolitical sentiment. Based on the evaluation results, the model without sentiment achieved an MAE of 55.07, RMSE of 69.81, MAPE of 1.17%, and an R^2 value of 0.9629. Meanwhile, the GRU model with sentiment obtained an MAE of 80.87, RMSE of 92.93, MAPE of 1.72%, and an R^2 value of 0.9342. These results indicate that, for the dataset used in this study, historical gold price data alone produced better prediction performance than the integration of social media sentiment.

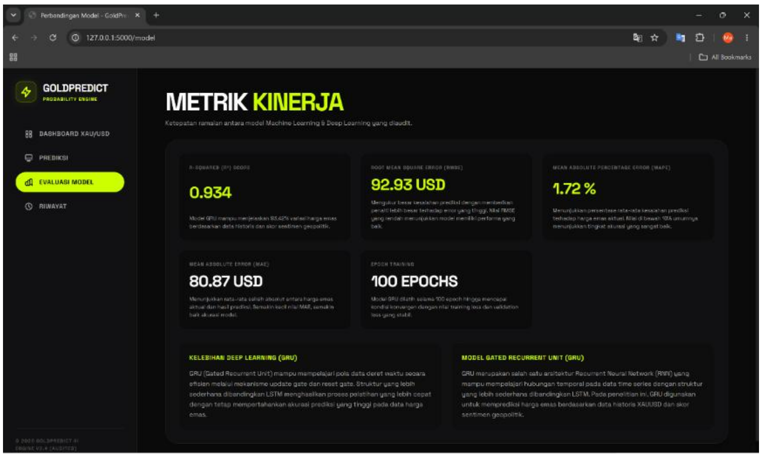

Figure 8. Page Evaluation Metrics WEB

The prediction history page is presented in Figure 9. This page stores every prediction generated by the system, including the prediction date, input parameters, sentiment score, sentiment category, and the predicted gold closing price. The prediction history enables users to review previous prediction results and monitor the consistency of the developed prediction model over time.

Furthermore, the system provides a feature for exporting prediction results into PDF format. This functionality allows prediction reports to be archived or shared conveniently, thereby improving the usability of the developed web application for both academic research and practical decision support.

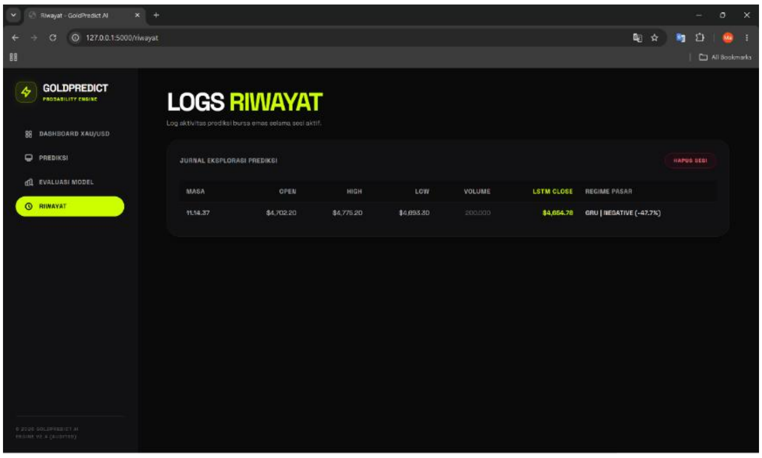

Figure 9. Page History WEB

3.3. Discussion

The comparative evaluation of both experimental scenarios indicates that the GRU model without sentiment features outperformed the model incorporating public sentiment. The detailed comparison of the evaluation metrics is presented in Table 3.

Table 3. The Performance of GRU Without Sentimen vs With Sentimen and Change

Matric	Without Sentiment	With Sentiment	Change
MAE	55,07	80,87	+46,84%
RMSE	69,81	92,93	+33,12%
MAPE	1.17%	1,72%	+47,01%
R2	0,9629	0,9342	-2,98%

The experimental results suggest that incorporating public sentiment extracted from social media did not improve the predictive performance of the GRU model. This finding is reflected by the increase in MAE, RMSE, and MAPE, together with the decrease in the R^2 value. Therefore, the sentiment information employed in this study did not provide a significant contribution to improving international gold price prediction.

Several factors may explain this outcome. First, sentiment data collected from social media are inherently dynamic and noisy, meaning that not all user-generated content accurately reflects actual market conditions. Consequently, the extracted sentiment scores may contain substantial irrelevant information that reduces their predictive value.

Second, the sentiment scores were aggregated into daily average values. Although this aggregation simplifies data integration, it may fail to capture rapid intraday changes in public opinion that could influence short-term market behavior.

Third, gold prices are influenced by numerous macroeconomic and financial variables beyond public sentiment. Factors such as inflation, interest rates, central bank monetary policies, the U.S. dollar exchange rate, and global economic conditions were not incorporated into the proposed prediction model. The omission of these influential variables may have limited the contribution of sentiment information to forecasting performance.

Despite these limitations, both experimental models achieved MAPE values below 2% and R^2 values exceeding 0.93, indicating that the GRU architecture is highly effective for modeling nonlinear time-series patterns in international gold prices. These findings demonstrate that GRU remains a robust deep learning approach for gold price forecasting.

The results further suggest that integrating public sentiment into gold price prediction remains a promising research direction. Future studies may improve predictive performance by adopting transformer-based sentiment analysis models such as BERT, RoBERTa, or FinBERT, incorporating additional macroeconomic indicators, and utilizing more relevant or higher-quality sentiment datasets. Such improvements may enable sentiment information to better capture market dynamics and enhance the overall forecasting capability of deep learning models.

The implementation of the web-based prediction system demonstrates that the proposed GRU model can be successfully integrated into a practical application for predicting international gold prices. Compared with executing prediction directly through Python scripts, the web application provides a more user-friendly interface that allows users to perform predictions without requiring programming knowledge.

In addition to prediction functionality, the application integrates sentiment analysis and data visualization into a unified platform. This integration enables users not only to obtain prediction results but also to understand the underlying market conditions through historical gold price trends, geopolitical sentiment information, and evaluation metrics.

The developed web application therefore extends the contribution of this study beyond algorithm development by providing a deployable decision-support system for gold price prediction based on deep learning techniques and geopolitical sentiment analysis. Such implementation demonstrates the practical applicability of the proposed research in the fields of information systems and financial data analytics.

4. CONCLUSION

This study developed and evaluated a web-based international gold price prediction system using the GRU algorithm and geopolitical sentiment obtained from the X social media platform. Two experimental scenarios were evaluated to determine whether the inclusion of geopolitical sentiment provided additional predictive value.

The experimental results demonstrate that the GRU model without sentiment achieved better predictive performance, with an MAE of 55.07, RMSE of 69.81, MAPE of 1.17%, and R^2 of 0.9629, compared with the sentiment-enhanced model, which achieved an MAE of 80.87, RMSE of 92.93, MAPE of 1.72%, and R^2 of 0.9342. Therefore, the inclusion of daily aggregated sentiment obtained using VADER did not improve prediction accuracy for the dataset examined in this study.

The main contribution of this study is the empirical evaluation of geopolitical sentiment from X as an additional feature for international gold price forecasting using GRU, together with its implementation in a web-based decision-support system. The findings demonstrate that adding a new data source does not necessarily improve forecasting performance when the information contains substantial noise or loses temporal information through aggregation.

Several limitations should be acknowledged, including the use of VADER for sentiment analysis, daily sentiment aggregation, the absence of macroeconomic variables, and the lack of extensive hyperparameter optimization and formal usability testing. Future research should investigate transformer-based sentiment models such as BERT, RoBERTa, or FinBERT, higher-frequency sentiment representations, additional macroeconomic variables, rolling-window validation, and hyperparameter optimization. These improvements may provide a more accurate assessment of whether geopolitical sentiment can contribute to international gold price forecasting.

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