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Comparative Analysis of Deep Learning and Machine Learning Models for Forecasting Global Gold Prices and Indonesian Gold Stocks

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COMPARATIVE ANALYSIS OF DEEP LEARNING AND MACHINE LEARNING MODELS FOR FORECASTING GLOBAL GOLD PRICES AND INDONESIAN GOLD STOCKS

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ABSTRACT

Gold has long been recognized as a global store of value and a prominent safe-haven asset; however, its price dynamics have become increasingly volatile and nonlinear over the past decade (2015–2025). This study proposes an integrated cross-asset forecasting framework to model global gold prices (XAU/USD) and Indonesian gold-related equities, including ANTM, BRMS, ARCHI, PSAB, MDKA, and HRTA. Using an adaptive modeling approach, the study compares the predictive performance of deep learning architectures, namely Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), with machine learning models, including Random Forest and XGBoost, alongside a Moving Average baseline model. Forecasting performance was evaluated using MAE, RMSE, and MAPE metrics based on an 80:20 chronological data split. The findings indicate that no single model consistently outperforms others across all assets; instead, predictive effectiveness depends on asset-specific volatility regimes and market characteristics. CNN models demonstrated superior robustness in forecasting highly volatile assets such as ANTM and BRMS, whereas XGBoost achieved stronger performance for assets characterized by more structured price behavior, such as MDKA. In addition, the sensitivity analysis revealed heterogeneous relationships between global gold prices and local equities, including a significant inverse sensitivity in downstream firms such as HRTA $\beta=-4.18$. These findings contribute to the Adaptive Market Hypothesis by highlighting the dynamic nature of informational efficiency in emerging markets and provide practical implications for asset-specific forecasting strategies in portfolio risk management.

Keywords : Gold Price Forecasting; Deep Learning; Machine Learning; Indonesian Stock Exchange; Adaptive Market Hypothesis; Sensitivity Analysis.

I. INTRODUCTION

Gold is widely recognized as a global store of value and a safe-haven asset, often functioning as a borderless financial instrument in the international monetary system (Zhu et al., 2018). As a strategic reserve asset held by central banks, gold plays a crucial role in shaping monetary policy, stabilizing financial systems, and facilitating international trade. Gold serves as a defensive asset and an effective instrument for portfolio diversification during periods of global uncertainty (Amini & Kalantari, 2024; Zhao et al., 2025). Gold price forecasts are widely used by investors and policymakers to support strategic decision-making and anticipate future economic trends (Jabeur et al., 2024).

Over the past decade, particularly from 2015 to 2025, gold price movements have become increasingly complex and volatile (Beckmann et al., 2019). This heightened volatility is driven by the interaction of multiple macroeconomic and geopolitical factors, including global

financial uncertainty, monetary tightening cycles, and major geopolitical conflicts such as the Russia–Ukraine war and escalating tensions in the Middle East. These events have intensified investors' demand for safe-haven assets, thereby amplifying fluctuations in gold prices (Fan et al., 2014; Fang et al., 2018; Hu et al., 2020). Prior studies suggest that gold price dynamics are influenced not only by commodity market fundamentals but also by nonlinear interactions among economic variables, making accurate forecasting increasingly challenging.

In the context of emerging markets, Indonesia represents a particularly relevant case due to its substantial gold reserves and rapidly growing mining sector. The Indonesian gold mining industry contributes significantly to national economic development and government revenue. Several gold mining companies are publicly listed on the Indonesia Stock Exchange, such as PT Aneka Tambang Tbk (ANTM), PT Archi Indonesia Tbk (ARCHI), PT J Resources Asia Pasifik Tbk (PSAB), PT Hartadinata Abadi Tbk (HRTA), and PT Merdeka Copper Gold Tbk (MDKA). These firms operate across various stages of the gold value chain, including exploration, development, and production, with differing exposure to global commodity price fluctuations. The stock performance of these firms is closely linked to global gold price movements, although the degree and nature of this relationship may vary across firms due to differences in operational structure, diversification, and market exposure.

Forecasting is essential as gold prices and mining stock values are influenced by uncertain and complex market conditions (Beckmann et al., 2019). A data-driven predictive approach provides a systematic basis for investment decision-making by capturing underlying patterns in historical data and improving the reliability of risk–return assessments (Cohen & Aiche, 2023). Comparing Indonesian gold mining stocks with global gold price movements enables the identification of stock-specific sensitivity and responsiveness, which may vary across firms due to differences in operational and market characteristics. Identifying the most appropriate predictive model is crucial, as different approaches vary in their ability to capture underlying data patterns, thereby influencing the reliability of forecasting results (Parwita et al., 2025).

A growing body of literature has explored gold price forecasting using a wide range of approaches, including econometric models, machine learning, deep learning, and hybrid techniques. Recent studies have focused on improving predictive accuracy and capturing the nonlinear and volatile nature of financial time series. For instance, advanced models such as Quantile Regression Deep Learning and ensemble learning frameworks have been developed to produce more robust predictions under uncertainty. Other studies have integrated feature selection techniques with nonlinear models such as Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) to enhance predictive performance. However, empirical findings remain mixed. For example, Gong (2024) demonstrates that traditional Linear Regression can outperform LSTM models in predicting short-term price direction under specific conditions.

Hybrid approaches combining methods such as CEEMDAN, Support Vector Regression (SVR), Grey Wolf Optimizer (GWO), Convolutional Neural Networks (CNN), and Polynomial Regression have also been proposed to address the nonlinear, chaotic, and noisy characteristics of financial data (Durairaj & Mohan, 2022; Lu et al., 2022). In parallel, econometric models such as FGARCH have been employed to improve interpretability and model stability under volatile market conditions (Mustafa & Bajwa, 2022). In

terms of market relationships, previous studies indicate that the interaction between gold prices and stock markets is not always negative; instead, both can move in the same direction during periods of financial stress, particularly under conditions of negative real interest rates (Drake, 2022). Additionally, Shah et al. (2022) find that LSTM models are more effective in price prediction, while CNN models perform better in capturing trend dynamics.

Despite these advancements, existing studies exhibit several important limitations. First, most prior research focuses on either a single asset (e.g., gold prices) or a single modeling approach, thereby limiting their ability to capture cross-asset interactions. Second, comparative analyses between machine learning and deep learning models are often conducted in isolation, without integrating both approaches within a unified predictive framework. Third, empirical evidence from emerging markets, particularly in Southeast Asia, remains limited. These gaps hinder a comprehensive understanding of the nonlinear and dynamic transmission mechanisms between global commodity markets and local equity markets.

To address these limitations, this study proposes an integrated cross-asset forecasting framework that simultaneously models global gold prices (XAU/USD) and Indonesian gold related stocks, including BRMS, ANTM, ARCHI, PSAB, and UNTR. The study employs and compares multiple predictive approaches, encompassing both machine learning models (Random Forest and XGBoost) and deep learning architectures (Convolutional Neural Networks and Long Short-Term Memory networks). By integrating these approaches, this study aims to capture complex nonlinear dependencies, temporal dynamics, and cross-market interactions more effectively.

This study contributes to the literature in three main ways. First, it provides a comprehensive comparative evaluation of machine learning and deep learning models in forecasting both global gold prices and gold-related equities within a unified analytical framework. Second, it offers new empirical insights into the nonlinear and dynamic relationship between global gold prices and Indonesian gold related stocks, highlighting patterns of cross-market transmission and sensitivity. Third, it identifies the most suitable predictive modeling approach for capturing the characteristics of financial time series in emerging markets, thereby providing practical implications for investors, portfolio managers, and policymakers.

II. LITERATURE REVIEW

II.1 Gold Price Dynamics

The global gold market during the period 2023–2026 reflects significant structural shifts in the international financial system (*JP Morgan, 2026*) and (*CBS News, 2026)*. Gold has reinforced its role as a dominant hedging instrument amid escalating systemic risks (Madani & Ftiti, 2022). The sustained increase in gold prices over recent years is driven not only by conventional supply and demand mechanisms but also by the convergence of geopolitical uncertainty and global monetary policy adjustments (Ameur et al., 2024).

Prolonged conflicts in Eastern Europe and geopolitical instability in the Middle East have empirically strengthened the positive correlation between geopolitical risk indices and demand for safe-haven assets, commonly referred to in the financial literature as the “flight to quality” (Han, 2026).

From a macroeconomic perspective, gold's strengthening is driven by global economic volatility, characterized by persistent inflation and fluctuating central bank interest rate policies (Ampudia & Van den Heuvel, 2022; Wang, 2025). Amid the risk of fiat currency depreciation, gold serves

as an effective store of value, helping preserve purchasing power. Furthermore, institutional behavior has shifted toward large-scale accumulation of gold reserves by central banks, particularly in emerging economies. This trend reflects a broader de-dollarization strategy aimed at enhancing monetary sovereignty and reducing exposure to external risks associated with US dollar-based assets (Ponsot, 2025). Consequently, gold has evolved beyond a speculative commodity into a core component of global portfolio risk management in an era of multidimensional uncertainty.

II.2 Indonesian Gold Stocks

This study examines stocks of companies involved in Indonesia's gold industry, including PT Bumi Resources Minerals Tbk (BRMS), PT Aneka Tambang Tbk (ANTM), PT Archi Indonesia Tbk (ARCHI), PT J Resources Asia Pasifik Tbk (PSAB), PT Hartadinata Abadi Tbk (HRTA), and PT Merdeka Copper Gold Tbk (MDKA) (*BRMS*; *ARCI*; *ANTM*; *MDKA*; *PSAB*). These firms are selected due to their direct involvement in the gold value chain, spanning upstream mining activities to downstream processing and distribution.

PT Bumi Resources Minerals Tbk focuses on gold production development through its subsidiary, PT Citra Palu Minerals, in Central Sulawesi, continuously expanding production capacity and reserves(*BRMS*). PT Aneka Tambang Tbk is a state-owned enterprise under the MIND ID mining holding, operating an integrated business model from upstream mining to downstream refining, including gold bullion production(ANTM). PT Archi Indonesia Tbk is one of Southeast Asia's largest gold producers, operating the Toka Tindung gold mine in North Sulawesi (*ARCI*). PT J Resources Asia Pasifik Tbk manages a diversified portfolio of mining assets across Indonesia and Southeast Asia, focusing on long-term expansion of production capacity(*PSAB*). PT Hartadinata Abadi Tbk operates in the downstream gold sector, specializing in refining, jewelry manufacturing, and distribution, with performance influenced more by consumer demand than mining activity(HRTA). PT Merdeka Copper Gold Tbk manages a multi-commodity portfolio, including gold, copper, and nickel, with gold serving as a major revenue contributor alongside strategic mineral development initiatives (MDKA).

III. METHODOLOGY

III.1 Data Collection

This study utilizes daily time-series data obtained from Investing.com, covering global gold prices represented by XAU/USD and stock prices of Indonesian gold-sector companies, namely BRMS, ANTM, ARCHI, PSAB, HRTA, and MDKA. The data spans different observation periods for each asset, depending on data availability and listing history. Specifically, the dataset covers the following date ranges: Hartadinata Abadi (2017–2025), Merdeka Copper Gold (2015–2025), Aneka Tambang (2012–2025), J Resources (2012–2025), Archi Indonesia (2021–2025), Bumi Resources Minerals (2012–2025), and XAU/USD (2006–2025). These variations reflect differences in market entry and data accessibility across assets. The primary variable used in this study is the closing price, which is further processed during the preprocessing stage. Table 1 presents the descriptive statistics of the dataset, including minimum, quartiles, maximum, mean, and standard deviation, providing an overview of the distribution and variability of each asset. All data processing, analysis, and model development in this study are implemented using Python 3, leveraging relevant libraries for time-series analysis, machine learning, and deep learning.

Tabel 1. Descriptive Statistics Close Price

Ticker	Date Range	Min	25%	50%	75%	Max	Mean	Std
Hartadinata Abadi Stock (HRTA)	2017-06-22 to 2025-12-30	175	222.5	265	374	808	323.82	147.32
Merdeka Copper Gold (MDKA)	2015-06-22 to 2025-12-30	312	576	1815	2690	5700	1920.42	1317.85
Aneka Tambang Persero (ANTM)	2012-03-02 to 2025-12-30	287	785	1055	1805	3670	1326.17	721.18
J Resources (PSAB)	2012-03-26 to 2025-12-30	83	184	244	535	1661	409.38	395.77
Archi Indonesia Tbk (ARCI)	2021-06-29 to 2025-12-30	230	322	348	476	1028	430.62	201.44
Bumi Resources Mineral (BRMS)	2012-03-12 to 2025-12-30	44	56	135	232	773	175.38	151.58
XAU_USD	2006-01-03 to 2025-03-17	2643.44	2668.17	2692.73	2709.49	2755.02	2693.6	33.54

III.2 Data Preprocessing

The data preprocessing stage is conducted to ensure data quality and consistency prior to modeling. Several sequential steps are performed in this study. First, date column detection and formatting are applied by converting the date column into a standard *datetime* format. The dataset is then sorted chronologically from the earliest to the most recent observations, and the date column is set as the index of the Data Frame to preserve the time-series structure. Second, data cleaning is performed on the closing price variable to ensure consistency in numerical formatting, including the removal of non-numeric characters and standardization of decimal values. Third, missing value handling is conducted using a time-based interpolation method, which estimates missing values based on the temporal trend between adjacent data points. For any remaining missing values at the beginning or end of the series, forward fill and backward fill methods are applied to maintain continuity. Fourth, duplicate data removal is carried out to ensure data integrity. In cases where multiple entries exist for the same date, only the most recent record is retained (*keep = 'last'*), while the remaining duplicates are removed. Finally, outlier detection and treatment are implemented using the Interquartile Range (IQR) method. Upper and lower bounds are calculated using a 3×IQR threshold. Instead of removing extreme values, this study applies a capping approach, where values beyond the defined limits are adjusted to the respective boundary values. This approach preserves the data structure while reducing the impact of extreme fluctuations that may distort model performance. After completing the preprocessing steps, the dataset for each stock is divided into training and testing subsets using an 80:20 ratio. The split is performed chronologically to maintain the temporal dependency of the data and to avoid data leakage during model evaluation. The training set (80%) is used to build and optimize the forecasting models, while the testing set (20%) is used to evaluate the predictive performance of the trained models on unseen data.

III.3 Modelling Approach

This study employs a hybrid forecasting framework consisting of baseline, machine learning, and deep learning models. The baseline model is represented by the Simple Moving Average (SMA), which serves as a benchmark for evaluating model performance. Furthermore, machine learning

models, including Random Forest and XGBoost, are utilized to capture nonlinear relationships between macroeconomic variables and gold prices. In addition, deep learning models, namely Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN), are implemented to model temporal dependencies and extract complex patterns from time-series data.

III.4 Machine Learning Models

III.4.1 Random Forest

The Random Forest component in the hybrid model brings external macroeconomic variables into the forecasting framework. This ensemble learning method builds many decision trees using bootstrap sampling and random feature selection. With this approach, the model can capture complex nonlinear links between macroeconomic indicators and gold price dynamics. As a result, the model is better at accounting for external shocks and market forces not fully reflected in past price data. (Numerous studies demonstrate the superiority of Random Forest in forecasting stocks, commodities, and cryptocurrencies (Oyewola et al., 2021, 2021; Silva de Souza et al., 2019; Visharad et al., 2025; Wu et al., 2026; Zhao & Zhao, 2025). The prediction of Random Forest in a regression task is formulated as follows:

$$\hat{y} = \frac{1}{T} + \sum_{t=1}^{T} f_t(x)$$

where Tdenotes the number of trees and $f_t(x)$represents the prediction from the t-th tree.

By introducing randomness in both data sampling and feature selection, Random Forest effectively captures complex nonlinear relationships between macroeconomic variables and gold price movements.

XGBoost

Extreme Gradient Boosting (XGBoost) is an advanced machine learning method that optimizes the gradient boosting framework. XGBoost is popular in data science for its predictive accuracy and computational efficiency. In boosting, models are trained in sequence. Each subsequent model corrects the mistakes of the previous one, gradually improving predictions.

XGBoost was introduced by Tianqi Chen and Carlos Guestrin. They proposed a tree-based learning framework that handles data sparsity. This feature enables the model to quickly identify features with minimal contribution (Chen & Guestrin, 2016). As a result, it improves computational efficiency while retaining high predictive performance. Numerous studies demonstrate the effectiveness of the XGBoost algorithm in forecasting various financial instruments, including gold prices, Bitcoin, and Ethereum (Asgari & Hashemi, 2026a; Bagheri & Giudici, 2025; Jabeur et al., 2024).

The objective function of XGBoost is defined as:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $l$represents the loss function and $\Omega(f_k)$is the regularization term that penalizes model complexity.

XGBoost incorporates regularization to prevent overfitting and uses second-order gradient information for efficient optimization, making it highly effective in financial forecasting tasks.

III.5 Deep Learning Models

III.5.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a variant of the Recurrent Neural Network (RNN) designed to model sequential data and capture long-term dependencies in time

series. LSTM uses memory cells controlled by input, forget, and output gates, enabling the model to retain relevant information while discarding irrelevant signals during learning.

In finance, LSTM is widely used for forecasting stock prices, volatility, and market movements due to its ability to learn complex temporal patterns. This capability makes LSTM one of the most widely used deep learning methods for financial time series forecasting.

Several studies demonstrate the application of Long Short-Term Memory (LSTM) models in various prediction contexts developed an LSTM model combined with an attention mechanism and data preprocessing using wavelet transform, resulting in improved prediction accuracy for stock prices in the S&P 500, DJIA, and HSI indices. Furthermore. (Budiharto, 2021) applied LSTM to predict stock prices in Indonesia during the COVID-19 pande mic and found that using short-term historical data produced more optimal results. Selain itu (L. Peng et al., 2018) proposed a DE-LSTM model, in which LSTM is optimized using a differential evolution algorithm, enabling more effective electricity price predictions across different regions.

III.5.2 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning architecture that extracts spatial patterns from data via convolutional operations (Goel et al., 2023; Pan et al., 2023; Wu et al., 2026). The model comprises key components, including convolutional, pooling, and fully connected layers, enabling automatic feature extraction.

In recent years, CNN has been increasingly applied to financial time series analysis by transforming data into visual representations or feature matrices (Asgari & Hashemi, 2026b; Mertzanis, 2025; NoorMohammadzadehMaleki et al., 2026; P. Peng et al., 2024). This approach allows hidden patterns within the data to be identified more effectively.

III.6 Hyperparameters Tuning

To obtain optimal model performance, each forecasting model in this study is optimized through a hyperparameter tuning process. Hyperparameter tuning plays a critical role in improving model generalization by identifying the most suitable configuration for each model based on the underlying data characteristics.

Two main approaches are employed, namely Grid Search and Randomized Search, depending on the complexity and computational requirements of each model. For machine learning models such as Random Forest and XGBoost, the tuning process is conducted using RandomizedSearchCV with a time series split strategy to preserve temporal dependencies and prevent data leakage. In contrast, for deep learning models (LSTM and CNN), manual grid search combined with early stopping is applied to efficiently determine optimal configurations while avoiding overfitting. The baseline model, Simple Moving Average (SMA), is also tuned by varying the window size to capture different levels of temporal smoothing.

The detailed tuning configurations and parameter ranges are presented in Table 2.

Tabel 2. Hyperparameter Tuning Configurations

Model	Tuning Approach	Tuned Hyperparameters	Tested Values
Moving Average	Grid Search Manual	Window Size (w)	7 - 60 days

XGBoost	RandomizedSearchCV (Time Series Split)	n_estimators max_depth learning_rate subsample	[100, 300, 500] [3, 5, 7] [0.01, 0.05, 0.1] [0.7, 0.8, 0.9]
Random Forest	RandomizedSearchCV (Time Series Split)	n_estimators max_depth min_samples_leaf	[100, 200, 400] [10, 20, None] [1, 2, 4]
LSTM	Grid Search Manual (Early Stopping)	units dropout lr (Learning Rate)	Set 1: 64, 0.2, 0.001 Set 2: 128, 0.3, 0.0005
CNN	Grid Search Manual (Early Stopping)	filters (Filter Conv1D)	[32, 64]

The range of hyperparameters presented in Table 2 is determined based on a combination of prior studies, domain knowledge in financial time series forecasting, and empirical considerations to balance model performance and computational efficiency. For the Simple Moving Average (SMA) model, the window size is varied between 7 and 60 days to capture both short-term fluctuations and medium-term trends, where smaller windows reflect higher sensitivity to price changes and larger windows provide smoother signals. For XGBoost, the number of estimators (100–500), maximum depth (3–7), learning rate (0.01–0.1), and subsample ratio (0.7–0.9) are selected to control model complexity, ensure stable convergence, and improve generalization through stochasticity. Similarly, for Random Forest, the number of trees (100–400), maximum depth (10, 20, and unlimited), and minimum samples per leaf (1–4) are tuned to balance ensemble diversity and prevent overfitting. For deep learning models, the LSTM configurations (64 and 128 units, dropout rates of 0.2 and 0.3, and learning rates of 0.001 and 0.0005) are chosen to represent different levels of model capacity while maintaining training stability and mitigating overfitting. Meanwhile, the CNN model varies the number of convolutional filters (32 and 64) to capture local temporal patterns at different levels of abstraction.

The tuning process is executed independently for each stock, enabling each asset to possess a unique optimal model configuration. This methodology recognizes that different stocks demonstrate diverse patterns concerning trend, volatility, and noise, which may necessitate varying model preferences. Consequently, the study employs an adaptive modeling strategy, wherein the best-performing model is chosen individually for each stock based on evaluation metrics.

III.7 Evaluation Metrics

To evaluate the performance of the forecasting models, this study employs three widely used error metrics in time series analysis, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are selected to provide a comprehensive assessment of model accuracy from different perspectives, including absolute error, squared error, and relative percentage error. A lower value of

MAE, RMSE, and MAPE indicates better model performance.

The Mean Absolute Error (MAE) measures the average magnitude of prediction errors without considering their direction. It provides a straightforward interpretation of the average absolute deviation between actual and predicted values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

The Root Mean Squared Error (RMSE) emphasizes larger errors by squaring the differences before averaging and then taking the square root. This makes RMSE more sensitive to outliers and large deviations compared to MAE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

The Mean Absolute Percentage Error (MAPE) expresses the prediction error as a percentage, making it easier to interpret the model performance relative to the scale of the data.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} |$$

where y_i represents the actual value, $\hat{y}_i$ denotes the predicted value, and n is the total number of observations.

III.8 Sensitivity Analysis

After identifying the best-performing model for each stock, a sensitivity analysis is conducted to examine the relationship between stock price movements and global gold prices represented by XAU/USD. This analysis aims to quantify how strongly Indonesian gold-related stocks respond to fluctuations in the global gold market.Two main approaches are employed in this study, namely Pearson correlation analysis and beta coefficient estimation**.**

The Pearson correlation coefficient is used to measure the strength and direction of the linear relationship between stock returns and gold price returns. The value of the correlation coefficient ranges from -1 to 1, where values close to 1 indicate a strong positive relationship, values close to -1 indicate a strong negative relationship, and values near 0 indicate little to no linear relationship.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where x_i and y_i represent the return values of the stock and XAU/USD respectively, while $\bar{x}$ and $\bar{y}$ denote their mean values.

In addition to correlation, the beta coefficient is estimated using a simple linear regression model to quantify the sensitivity of stock returns to changes in global gold prices. Beta reflects how much the stock return changes in response to a unit change in gold price return.

$$R_{stock} = \alpha + \beta R_{gold} + \epsilon$$

The beta coefficient (β) can be estimated as follows:

$$\beta = \frac{Cov(R_{stock}, R_{gold})}{Var(R_{gold})}$$

A higher beta value indicates greater sensitivity of the stock to movements in global gold prices. Specifically, $beta > 1$ indicates high sensitivity, $betaapprox1$ indicates proportional movement, and $beta < 1$indicates lower sensitivity.

IV. RESULTS AND DISCUSSION

IV.1 Comparative Model Performance in Forecasting

To address the first research question regarding the comparative performance of machine learning and deep learning models, this study evaluates multiple models across different Indonesian gold-related stocks and global gold prices.

IV.1.1 Distribution Characteristics of Returns

The distribution of daily returns across all observed stocks generally exhibits a pattern that approximates a normal distribution, characterized by a bell-shaped form with most values concentrated around zero. This indicates that, under typical market conditions, daily price changes tend to be relatively small and stable. Such patterns are particularly evident in several Indonesian gold-related stocks, including HRTA, MDKA, and ANTM, which display pronounced peaks around the zero-return level.

However, the return distributions do not fully conform to the assumption of normality, as they exhibit key characteristics commonly found in financial time series data, namely **f**at tails and slight skewness**.** The presence of fat tails suggests a higher probability of extreme returns compared to a normal distribution, reflecting the occurrence of market shocks or unexpected events. These extreme observations are present on both the negative and positive sides, indicating that sharp price movements either declines or increases are inherent features of market dynamics.

ANTM and MDKA show relatively symmetric distributions around zero, although they still display extended tails, implying that extreme events, while infrequent, remain significant. In contrast, J Resources (PSAB/JRES) demonstrates a more dispersed distribution with a notably long right tail, indicating higher volatility and the potential for substantial positive price jumps during certain periods.

Meanwhile, HRTA and ARCI exhibit distributions that remain centered around zero but with slight skewness, suggesting that return distributions are not perfectly symmetric. On the other hand, BRMS presents a wider spread of returns compared to the other stocks, indicating a relatively higher level of risk. This is reflected in the greater variability of returns on both the negative and positive sides of the distribution.

IV.1.2 Price Trends and Volatility Patterns

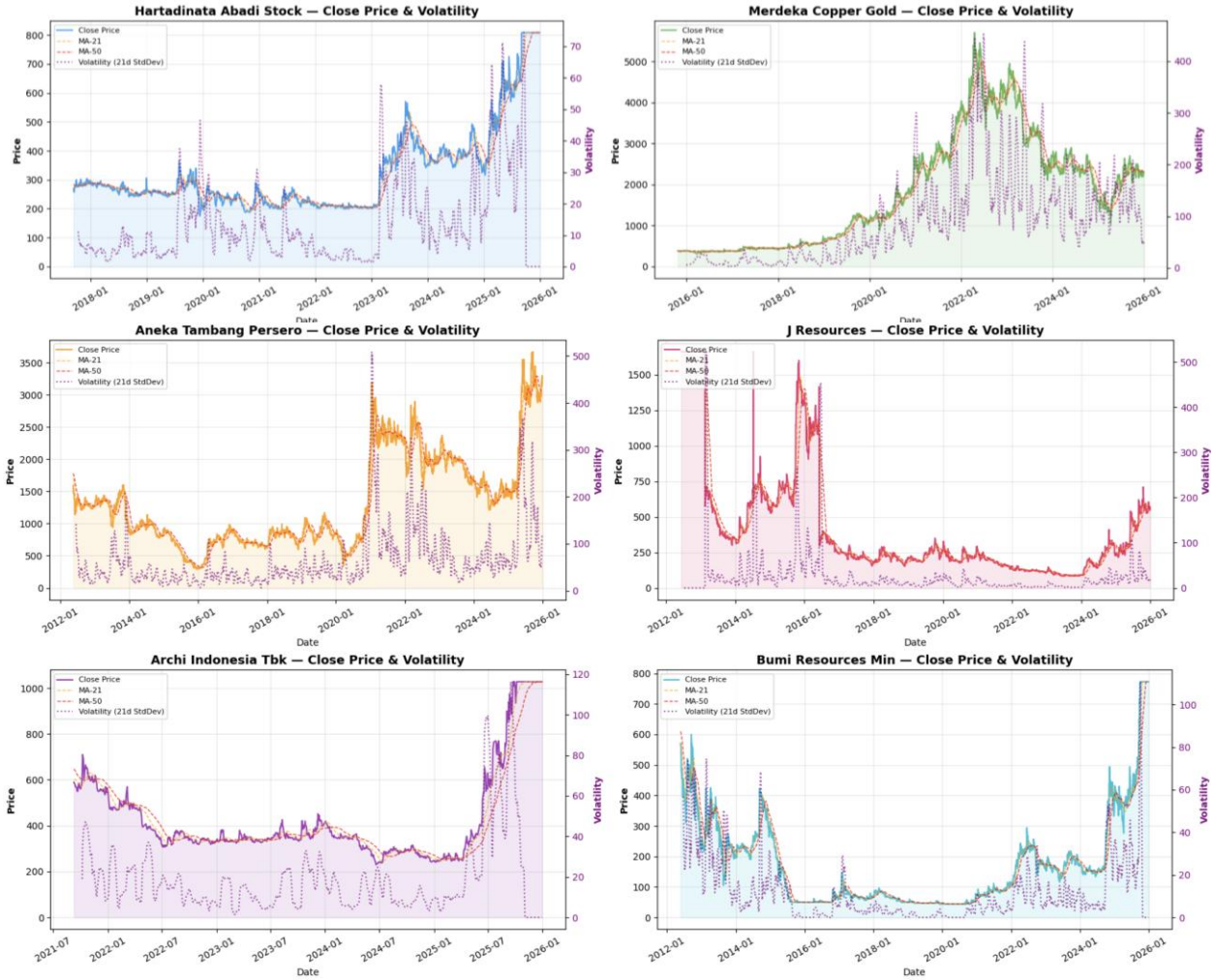


Figure 2. Closing Price Trends and Volatility of Indonesian Gold Stocks

Figure 2 illustrates the closing price dynamics and volatility patterns of Indonesian gold-related stocks over the observation period. Overall, the price movements exhibit a non-linear and fluctuating long-term trend, characterized by alternating phases of growth (bullish) and correction (bearish). These patterns reflect the complex nature of financial markets, which are influenced by macroeconomic conditions and global commodity price movements, particularly gold.

Periods of elevated volatility are clearly observed during 2020–2021 and 2024–2025, indicating the presence of market shocks and heightened uncertainty. These fluctuations suggest that external factors, such as global economic disruptions and commodity price surges, play a significant role in shaping stock price behavior.

From a technical perspective, the application of Moving Averages (MA) provides insight into trend direction. The short-term moving average (MA21) responds more rapidly to price changes, capturing short-term dynamics, while the medium-term moving average (MA50) reflects a smoother and more stable trend. The interaction between MA21 and MA50 generates meaningful trading signals, where MA21 crossing above MA50 indicates a bullish trend, whereas the opposite condition signals a bearish trend.

At the individual stock level, distinct movement patterns are observed. HRTA exhibits a prolonged sideways phase between 2018 and 2022, followed by a strong upward movement during 2023–2025, accompanied by increased volatility, suggesting a delayed response to global gold price movements. MDKA demonstrates a strong bullish trend until 2022, followed by a correction and consolidation phase, with high volatility indicating strong sensitivity to global market sentiment.

ANTM shows a cyclical pattern with significant price surges during 2020–2021 and again in 2025, accompanied by sharp volatility increases. This behavior indicates a strong dependence on global commodity price fluctuations. PSAB presents a long-term downward trend followed by a stabilization phase and gradual recovery, reflecting a potential price reversal pattern. Meanwhile, ARCI exhibits a declining trend that transitions into a consolidation phase before experiencing a strong breakout toward the end of the period, marked by increased volatility. BRMS, on the other hand, shows a prolonged downtrend from 2013 to 2019, followed by a recovery phase starting in 2020 and a strong upward trend in 2025. Volatility spikes are particularly evident during the early recovery and breakout phases, indicating increased market activity and uncertainty.

IV.1.3 Forecasting Performance Comparison

Table 3. Forecasting Performance Comparison and Optimal Hyperparameters for Each Stock

Emiten	Model	MAE	RMSE	MAPE (%)	Parameter Terbaik
Aneka Tambang Persero	Tuned CNN	47,32088	71,02035	2,26454	Filters: 64
Archi Indonesia Tbk	Tuned MA (w=7)	24,03313	41,2504	4,150245	Window Size (w): 7
Bumi Resources Min	Tuned CNN	12,05368	18,46628	3,818067	Filters: 64
Hartadinata Abadi Stock	Tuned CNN	13,89377	20,33462	2,622536	Filters: 32
J Resources	Tuned XGBoost	13,82556	21,37323	8,039314	subsample: 0.7, n_estimators: 300, max_depth: 3, learning_rate: 0.05
Merdeka Copper Gold	Tuned XGBoost	60,04992	78,94997	2,890945	subsample: 0.8, n_estimators: 300, max_depth: 3, learning_rate: 0.05

The evaluation results indicate that no single model consistently outperforms others across all observed stocks. Instead, model performance is highly dependent on the underlying characteristics of each stock, particularly in terms of price dynamics, volatility levels, and data complexity. Overall, machine learning and deep learning models that incorporate hyperparameter tuning generally achieve better performance

compared to simpler approaches, although the results vary across different assets.

For Aneka Tambang (ANTM), the tuned CNN model demonstrates the best performance, achieving an MAE of 47.32088, RMSE of 71.02035, and MAPE of 2.26454%, with an optimal configuration of 64 filters. This result suggests that CNN is effective in capturing local temporal patterns in highly fluctuating and volatile time series data.

In contrast, for Archi Indonesia (ARCI), the best performance is achieved by the simple Moving Average model with a window size of 7, resulting in an MAE of 24.03313, RMSE of 41.2504, and MAPE of 4.15025%. This finding indicates that for relatively stable and less complex data patterns, simpler models can still provide competitive performance.

For Bumi Resources Minerals (BRMS), the tuned CNN model again achieves the best results, with an MAE of 12.05368, RMSE of 18.46628, and MAPE of 3.81807%, using 64 filters. This further reinforces the ability of CNN to capture complex temporal dependencies and localized fluctuations.

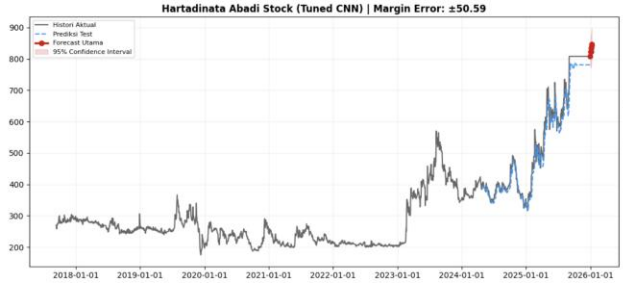
Similarly, for Hartadinata Abadi (HRTA), CNN remains the best-performing model, with an MAE of 13.89377, RMSE of 20.33462, and MAPE of 2.62254%, using 32 filters. This suggests that convolutional-based architectures are particularly effective when local patterns dominate the data structure.

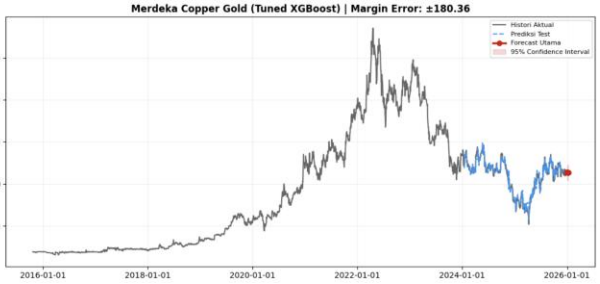
On the other hand, for J Resources (PSAB), the tuned XGBoost model achieves the best performance, with an MAE of 13.82556, RMSE of 21.37323, and MAPE of 8.03931%. The optimal configuration (subsample = 0.7, n_estimators = 300, max_depth = 3, and learning rate = 0.05) indicates that a moderately complex model is sufficient to capture the data patterns while preventing overfitting.

A similar pattern is observed for Merdeka Copper Gold (MDKA), where the XGBoost model delivers the best results, with an MAE of 60.04992, RMSE of 78.94997, and MAPE of 2.89095%, using a comparable parameter configuration. This highlights the effectiveness of boosting-based models in modeling non-linear relationships in volatile financial data.

Overall, the findings confirm that the selection of the best-performing model is highly data-dependent. Deep learning models, particularly CNN, tend to perform better for stocks with complex patterns and high volatility due to their ability to capture local temporal structures. Meanwhile, machine learning models such as XGBoost are effective in modeling non-linear relationships with controlled complexity. Notably, simpler methods such as Moving Average remain relevant under specific conditions, especially when the data exhibits relatively stable and less complex behavior. These results demonstrate that increasing model complexity does not necessarily guarantee improved performance, emphasizing the importance of adopting an adaptive model selection strategy.

IV.1.4 Forecasting Results and Prediction Accuracy





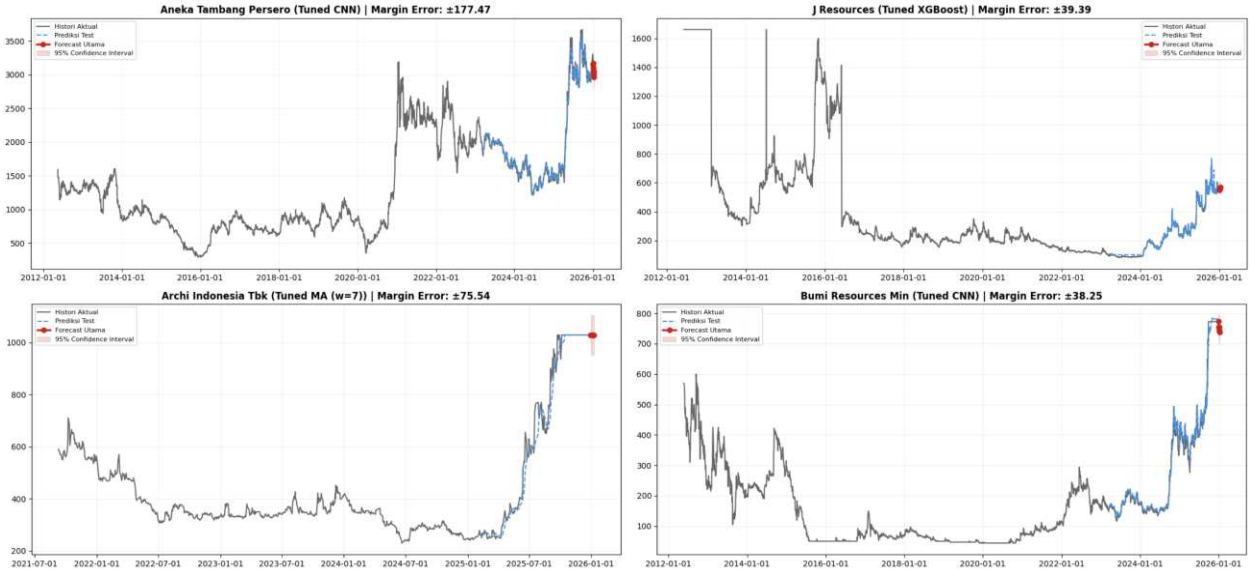


Figure 3. Forecasting Results of Best Models for Each Stock

Table 4. Forecasting Results and Prediction Intervals for Each Stock Based on Best-Performing Models

Emiten / Aset	Model Terbaik	Data Terakhir	2026-01-02	2026-01-05	2026-01-06	2026-01-07	2026-01-08	2026-01-09
Hartadinata Abadi Stock	Tuned CNN	2025-12-30	823.47 (772.88 - 874.06)	823.47 (772.88 - 874.06)	833.81 (783.22 - 884.40)	836.13 (785.54 - 886.72)	843.71 (793.12 - 894.30)	847.14 (796.56 - 897.73)
Merdeka Copper Gold	Tuned XGBoost	2025-12-30	2,266.87 (2,086.51 - 2,447.23)	2,265.24 (2,084.88 - 2,445.60)	2,264.71 (2,084.35 - 2,445.07)	2,272.63 (2,092.27 - 2,452.99)	2,272.31 (2,091.94 - 2,452.67)	2,272.31 (2,091.94 - 2,452.67)
Aneka Tambang Persero	Tuned CNN	2025-12-30	3,172.86 (2,995.39 - 3,350.34)	3,106.71 (2,929.23 - 3,284.18)	3,080.59 (2,903.11 - 3,258.06)	3,051.86 (2,874.38 - 3,229.33)	3,004.19 (2,826.71 - 3,181.66)	2,966.33 (2,788.86 - 3,143.81)
J Resources	Tuned XGBoost	2025-12-30	562.04 (522.65 - 601.43)	564.89 (525.51 - 604.28)	559.61 (520.22 - 598.99)	562.54 (523.16 - 601.93)	558.13 (518.74 - 597.52)	567.94 (528.56 - 607.33)
Archi Indonesia Tbk	Tuned MA (w=7)	2025-12-30	1,028.00 (952.46 - 1,103.54)	1,028.00 (952.46 - 1,103.54)	1,028.00 (952.46 - 1,103.54)	1,028.00 (952.46 - 1,103.54)	1,028.00 (952.46 - 1,103.54)	1,028.00 (952.46 - 1,103.54)
Bumi Resources Min	Tuned CNN	2025-12-30	755.29 (717.04 - 793.54)	755.29 (717.04 - 793.54)	754.87 (716.63 - 793.12)	745.70 (707.45 - 783.95)	740.82 (702.57 - 779.07)	737.58 (699.33 - 775.83)

The visualization results in Figure 3 indicate that the tuned models are generally able to follow historical price patterns with good accuracy, although performance varies across stocks as reflected by the margin of error and prediction intervals. The predicted values closely align with actual data during the testing period, confirming that the models successfully capture the main trend dynamics before being used for forward forecasting.

A more detailed quantitative summary is presented in Table 4. For Hartadinata Abadi (HRTA), the forecast shows a stable upward trend, with predicted

values ranging from approximately 823.47 to 847.14 and prediction intervals between 772.88 and 897.73. With a margin of error of ±50.59, the CNN model demonstrates relatively high accuracy and confidence in short-term forecasting.

In contrast, stocks with higher volatility, such as Merdeka Copper Gold (MDKA) and Aneka Tambang (ANTM), exhibit wider prediction intervals. For MDKA, the predicted values remain around 2264–2272 with intervals ranging from 2084.35 to 2452.99 and a margin of error of ±180.36. Similarly, ANTM shows predicted values between 2966.33 and 3172.86, with intervals spanning approximately 2788.86 to 3350.34 and a margin of error of ±177.47. These results reflect the higher uncertainty associated with complex and highly volatile price movements.

For J Resources (PSAB), the model produces relatively stable predictions, with values ranging from 559.61 to 567.94 and narrower intervals between 520.22 and 607.33, accompanied by a lower margin of error (±39.39). This indicates that more structured and less volatile data can be modeled with higher confidence using XGBoost.

Meanwhile, Archi Indonesia (ARCI) shows constant predicted values around 1028.00, with intervals between 952.46 and 1103.54 and a margin of error of ±75.54. This behavior reflects the smoothing nature of the Moving Average model, which effectively captures the overall trend but is less responsive to rapid changes.

For Bumi Resources Minerals (BRMS), the forecast indicates a relatively stable trend with slight downward movement, with predicted values ranging from 737.58 to 755.29 and intervals between 699.33 and 793.54. The relatively low margin of error (±38.25) suggests moderate uncertainty and consistent model performance.

Overall, the results demonstrate that prediction accuracy and confidence are strongly influenced by the volatility and structural complexity of each stock. Stocks with stable patterns tend to produce narrower intervals and lower errors, while highly volatile stocks result in wider intervals and greater uncertainty. Therefore, the inclusion of prediction intervals is essential, as it provides not only point estimates but also a range of possible outcomes, offering a more comprehensive basis for decision-making under uncertainty.

IV.2 Cross-Asset Relationship Between Gold and Stocks

To address the second research question, this study examines the relationship between global gold prices (XAU/USD) and Indonesian gold-related stocks using correlation analysis, as presented in Figure 4.

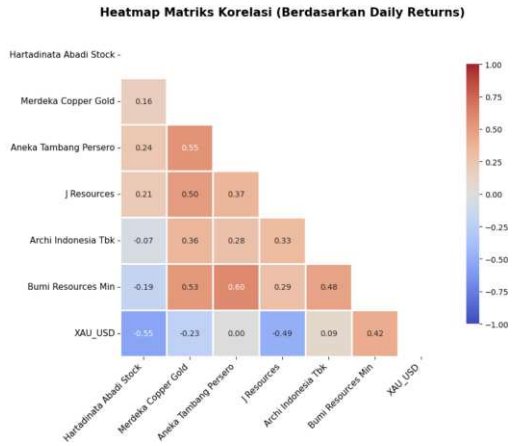


Figure 4. Correlation Heatmap of Daily Returns Among Indonesian Gold Stocks and XAU/USD

The correlation heatmap in Figure 4 reveals that the relationship between Indonesian gold-related stocks and global gold prices is heterogeneous and non-uniform. This indicates that the interaction between the two markets varies across different firms and is not consistently aligned.

Based on the results, Bumi Resources Minerals (BRMS) exhibits a positive correlation of 0.4165 with global gold prices. This indicates that increases in gold prices are associated with increases in the stock price of BRMS, suggesting that this stock tends to move in the same direction as the global gold market.

In contrast, Archi Indonesia (ARCI) and Aneka Tambang (ANTM) show correlations that are close to zero. These findings suggest that both stocks have weak relationships with global gold price movements, indicating that other factors beyond gold prices may play a more dominant role in influencing their price behavior.

Interestingly, several stocks exhibit negative correlations, including Hartadinata Abadi (HRTA) (-0.5541) and J Resources (PSAB) (-0.4905). These values indicate an inverse relationship, where stock prices tend to move in the opposite direction of global gold prices.

Overall, the results confirm that the relationship between Indonesian gold stocks and global gold prices is not uniform. While certain stocks exhibit positive relationships and move in line with gold price dynamics, others show weak or inverse relationships, reflecting the influence of firm-specific factors, market structure, and external economic conditions. These findings suggest that correlation alone is insufficient to fully explain the responsiveness of gold-related stocks to global gold price movements, thereby necessitating further analysis using sensitivity (beta) measures.

IV.3 Sensitivity of Gold Stocks to Global Gold Prices

To address the third research question, sensitivity analysis is conducted using beta coefficients, as presented in Figure 5.

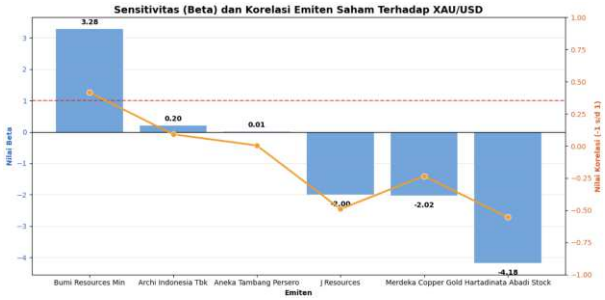


Figure 5. Sensitivity (Beta) of Indonesian Gold Stocks to XAU/USD

The sensitivity (beta) analysis reveals that the responsiveness of Indonesian gold-related stocks to global gold price movements varies significantly across firms. This analysis aims to quantify the magnitude and direction of each stock's response to changes in global gold prices.

Based on the results, Bumi Resources Minerals (BRMS) exhibits the highest beta value at 3.2792. This indicates that BRMS is highly sensitive to global gold price movements, where increases in gold prices are associated with disproportionately larger increases in stock prices. This behavior is clearly reflected in Figure 5, where BRMS is positioned significantly above the reference line of $\beta = 1$, indicating its role as a high-leverage proxy to gold price dynamics.

In contrast, Archi Indonesia (ARCI) and Aneka Tambang (ANTM) show relatively low beta values of 0.2011 and 0.0104, respectively. These findings suggest that both stocks have low sensitivity to global gold price movements, meaning that changes in gold prices have only a minimal impact on their stock prices.

Interestingly, several stocks exhibit negative beta values, including J Resources (PSAB) (-1.9983), Merdeka Copper Gold (MDKA) (-2.0221), and Hartadinata Abadi (HRTA) (-4.1755). These values indicate an inverse relationship, where stock prices tend to move in the opposite direction of global gold prices.

Among these, HRTA demonstrates the most extreme negative beta, suggesting a strong inverse sensitivity. This phenomenon may be attributed to firm-specific factors, business diversification, or the influence of domestic macroeconomic conditions that outweigh the impact of global gold price movements.

Visually, these stocks are positioned below the zero axis in Figure 5, reinforcing the presence of a negative relationship between stock prices and global gold price movements.

Overall, the results confirm that sensitivity to global gold prices is not uniform across Indonesian gold-related stocks. While certain stocks, such as BRMS, exhibit strong positive sensitivity and may serve as proxies for gold price movements, others show weak or inverse sensitivity, indicating the influence of non-commodity factors.

These findings have important implications for investors, particularly in portfolio diversification and risk management strategies. Not all gold-related stocks can be effectively used as hedging instruments against global gold price fluctuations. Therefore, asset selection should consider both the magnitude and direction of sensitivity to the underlying commodity, enabling more informed and risk-aware investment decisions.

V. CONCLUSION

This study offers a robust evaluation of computational intelligence in forecasting global commodities and emerging market equities through the proposed Adaptive Modeling Framework. The findings demonstrate that the effectiveness of deep learning and machine learning architectures is contingent upon asset-specific volatility regimes and structural complexity, rather than the existence of a universally superior predictive model. Specifically, Convolutional Neural Networks (CNNs) exhibit greater resilience in modeling highly volatile, non-linear assets such as ANTM and BRMS, while XGBoost performs more effectively in assets characterized by comparatively structured price formation, including MDKA and PSAB.

From a theoretical perspective, this study extends the Adaptive Market Hypothesis by empirically demonstrating that market efficiency in Indonesia's mining and gold-related equities is dynamic, state-dependent, and sensitive to volatility regimes. The superior performance of non-linear architectures during periods of market disruption (2020–2025) suggests that emerging markets transition across varying informational efficiency states, thereby requiring adaptive computational strategies. Moreover, the identification of Hartadinata Abadi's pronounced inverse sensitivity to gold price movements highlights a potential value-chain differentiation mechanism, suggesting that downstream firms may respond differently to commodity shocks than upstream extraction-based firms.

These findings provide strategic implications for portfolio managers, institutional investors, and domestic market participants by supporting an asset-specific model deployment strategy. CNNs may be better suited for high-volatility speculative environments, whereas XGBoost may offer superior utility during more stable growth phases. Additionally, the identification of HRTA's negative beta profile suggests potential internal hedging opportunities within sector-specific portfolios.

This study is constrained by its primary emphasis on historical price-based

modeling and limited integration of broader macroeconomic or sentiment-driven variables. Future research should expand this framework by incorporating multimodal architectures that combine time-series forecasting with Natural Language Processing (NLP), macroeconomic indicators, and geopolitical sentiment analysis to enhance predictive robustness across increasingly complex crisis environments.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Specifically, the authors hold no financial stakes, board positions, or consultancy roles in PT Aneka Tambang Tbk, PT Bumi Resources Minerals Tbk, or any of the other Indonesian gold equities analyzed in this study.

Funding Statement

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Ethics Statement and Data Integrity

The authors confirm that the data used in this study were obtained from publicly available sources, specifically Investing.com. No proprietary or confidential corporate data were utilized. All data processing, including interpolation for missing values and outlier treatment via the Interquartile Range (IQR) method, was conducted with transparency to maintain the integrity of the time-series analysis.

Data Availability Statement

The raw data supporting the conclusions of this article (closing prices for XAU/USD and Indonesian tickers) are available through Investing.com. The specific preprocessed datasets and Python code used for the adaptive modeling framework are available from the corresponding author upon reasonable request.

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