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Prediction of Indonesian Banking Stock Prices Using a Hybrid LSTM and XGBoost Model with Optuna Based Hyperparameter Optimization

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Abstract

Stock price prediction is a critical task in investment decision-making, particularly in highly volatile financial markets such as the Indonesian banking sector. While Long Short-Term Memory (LSTM) networks are effective in modeling temporal dependencies, they often fail to capture nonlinear residual patterns in financial time-series data, and their performance is highly sensitive to hyperparameter selection. To address these limitations, this study proposes a residual learning–based hybrid LSTM–XGBoost framework optimized using Optuna for predicting stock prices of major Indonesian banking stocks, namely BBCA, BBNI, BBRI, and BMRI. LSTM is employed as the base learner to model log-return sequences, while XGBoost is used to learn nonlinear residual structures from LSTM predictions. Latent embeddings extracted from the LSTM are further refined using Principal Component Analysis (PCA) to reduce redundancy and improve generalization. Hyperparameters of the LSTM, PCA, XGBoost, and calibration components are jointly optimized using Optuna with a Tree-structured Parzen Estimator (TPE) strategy. Experimental results demonstrate that the Optuna-optimized hybrid model consistently outperforms the baseline hybrid model across all datasets, achieving lower Mean Absolute Percentage Error (MAPE) values of 1.196% for BBCA, 1.67% for BBNI, 1.53% for BBRI, and 1.70% for BMRI. Additional stability analyses confirm that the proposed framework delivers stable and reliable predictions on unseen data. These findings provide a scalable hybrid forecasting framework that contributes to the development of intelligent financial decision-support systems and demonstrates the effectiveness of adaptive hybrid deep learning optimization techniques in real-world time-series prediction problems within the field of informatics.

Keywords : *Financial Time Series, LSTM, Optuna, Residual Learning, Stock Price Prediction, XGBoost.*

1. INTRODUCTION

Stocks are investment instruments characterized by high volatility and are influenced by internal corporate factors, macroeconomic conditions, as well as global dynamics and market sentiment [1]. In the Indonesian capital market, banking sector stocks—particularly BBCA, BBRI, BBNI, and BMRI—play a dominant role as key investor benchmarks due to their strong fundamentals, high liquidity, and relatively robust capital stability [2]. Therefore, the banking sector represents a relevant and important object for stock price prediction research [3], [4].

Stock price prediction plays a crucial role in investment decision-making and risk management. However, conventional approaches such as fundamental analysis, technical analysis, and classical statistical methods still exhibit limitations in responding to rapid market changes and in capturing non-linear patterns and complex relationships in financial time-series data. The complexity and volatility of stock markets necessitate more adaptive modeling approaches [5], [6].

Along with technological advancements, Machine Learning (ML) and Deep Learning (DL) approaches have been widely adopted due to their ability to deliver higher predictive accuracy compared to classical methods [7], [8]. One of the most popular DL models is Long Short-Term Memory (LSTM),

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which is effective in learning long-term temporal dependencies in financial time-series data. For example, recent work has shown that LSTM networks can capture long-term dependencies effectively in volatile stock data [9]. Nevertheless, in highly dynamic data environments, LSTM models may still produce prediction residuals containing non-linear patterns that are not fully captured [10], [11], [12].

To overcome the limitations of single models in capturing complex relationships and temporal patterns in time-series data, hybrid approaches based on residual learning have been developed by integrating Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost). LSTM is effective in modeling long-term temporal dependencies, whereas XGBoost excels at learning non-linear relationships and correcting residual errors not captured by the primary model [13], [14], [15]. The combination of these models leads to more accurate and stable predictions compared to the use of individual models [16], [17], [18] **.**

Several studies have demonstrated that the LSTM–XGBoost framework outperforms single models by achieving higher predictive performance, improved consistency, and stronger generalization capabilities across various data types [2], [4], [19], [20]. Despite these advantages, the performance of hybrid models remains highly dependent on appropriate hyperparameter selection. Therefore, Optuna an adaptive search-based optimization framework with automatic pruning mechanisms is employed to efficiently identify optimal hyperparameter combinations. This approach has been shown to enhance predictive accuracy while simultaneously reducing computational costs [21], [22], [23], [24], [25].

Although previous studies have shown that hybrid LSTM–XGBoost models can outperform single forecasting models, several limitations remain. Most existing works focus mainly on residual correction without explicit refinement of latent feature representations, while hyperparameter tuning is often conducted using inefficient or non-adaptive strategies. To address these gaps, this study proposes an integrated framework that combines residual learning–based LSTM–XGBoost modeling with latent feature refinement using Principal Component Analysis (PCA) and Optuna-based adaptive hyperparameter optimization. This integration constitutes the main novelty of the proposed approach and is expected to improve prediction accuracy and robustness in highly volatile financial time-series data.

Based on these considerations, this study aims to develop a residual learning–based hybrid LSTM–XGBoost model optimized using Optuna for predicting stock prices in the Indonesian banking sector. This approach is expected to improve prediction accuracy and contribute methodologically to the development of hybrid forecasting techniques for financial time-series data.

2. METHOD

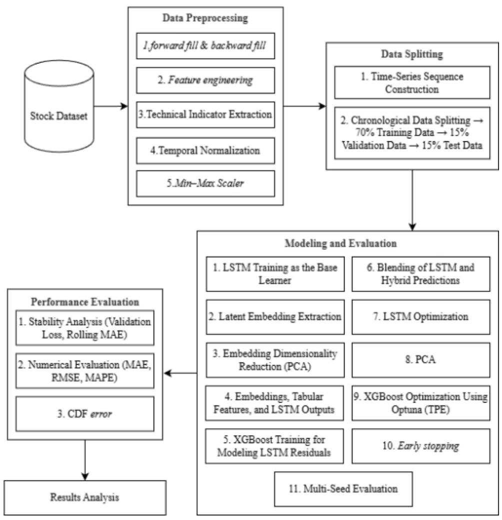

Figure 1. Experimental Workflow

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This study proposes a residual learning–based hybrid forecasting framework that integrates Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) optimized using Optuna. The methodological pipeline consists of data preprocessing, time-series sequence construction, LSTM-based temporal modeling, latent feature extraction, dimensionality reduction, residual correction using XGBoost, and comprehensive model evaluation. The overall research methodology and experimental workflow are illustrated in Figure 1.

2.1. Data Preprocessing

Let $P_t$denote the closing price of a stock at time t. Raw financial time-series data commonly contain missing values and exhibit scale heterogeneity, which may adversely affect model stability and estimation accuracy. Therefore, a structured data preprocessing pipeline is applied prior to analysis. The dataset consists of daily stock market records, including Date, Open, High, Low, Close, Adjusted Close, and Trading Volume, indexed by $t_1, t_2, \ldots, t_k$, as summarized in Table 1.

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Table 1. Sample of Raw Stock Price Data

Time	Date	Open	High	Low	Close	Adj Close	Volume
t_1	2019-01-01	5200	5200	5200	5200	4606.88	0
t_2	2019-01-02	5200	5245	5200	5240	4642.31	35,956,000
t_3	2019-01-07	5265	5325	5245	5245	4646.75	73,438,000
…	…	…	…	…	…	…	…
t_k	2025-02-13	9100	9150	9000	9000	9000	90,439,700
t_{k+1}	2025-02-14	9000	9075	8950	8975	8975	116,274,500
t_{k+2}	2025-02-17	8975	9325	8975	9325	9325	89,096,400

Missing Value Handling

Missing numerical values are handled using forward fill and backward fill techniques, which preserve temporal continuity and prevent artificial discontinuities in sequential data [26].

Logarithmic Return Transformation

Instead of directly modeling stock prices, this study employs logarithmic returns as the prediction target. Log returns exhibit superior statistical properties such as time additivity and variance stabilization compared to simple returns [27].

$$\boldsymbol{r_t = \log\left(\frac{P_t}{P_{t-1}}\right)} \tag{1}$$

Where : $\boldsymbol{rt}$denotes the logarithmic return at time step $\boldsymbol{t}$;

- $\boldsymbol{P_t}$represents the observed closing price at time $\boldsymbol{t}$;
- $\boldsymbol{P_{t-1}}$represents the closing price at the immediately preceding time step.

This transformation mitigates heteroskedasticity and scale dependency, which are common in financial price series.

Feature Engineering and Technical Indicators

To enrich the input space, several technical indicators are computed to capture momentum, trend, and volatility characteristics of stock price movements. The selected indicators are widely used in

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classical technical analysis and have also been adopted in recent deep learning–based stock prediction studies.

1. Relative Strength Index (RSI) :

The Relative Strength Index (RSI) is a momentum oscillator that measures the magnitude of recent price changes and is commonly used to identify overbought or oversold market conditions [28]. Its effectiveness as an input feature in modern deep learning–based stock price prediction models has been confirmed in recent studies [29].

$$RSI_t = 100 - \frac{100}{1 + RS_t} \tag{2}$$

Where :

- $\mathbf{RSI_t}$ is the Relative Strength Index at time $\mathbf{t}$;
- $\mathbf{RS_t}$ denotes the ratio of average gains to average losses over a predefined period.

RSItis the Relative Strength Index at time **t**;
RStdenotes the ratio of average gains to average losses over a predefined period.

2. Moving Average Convergence Divergence (MACD) :

Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator defined as the difference between two exponential moving averages . Recent hybrid and deep learning–based forecasting models also employ MACD to enhance trend representation [30].

$$MACD_t = EMA_{12}(P_t) - EMA_{26}(P_t) \tag{3}$$

Where :

- $MACD_t$ denotes the MACD value at time t;
- $EMA_{12}(P_t)$i and $EMA_{26}(P_t)$ represent the 12-period and 26-period exponential moving averages of the closing price P_t, respectively.

MACDtdenotes the MACD value at time ***t***;
EMA*12(*Pt*)**i and ***EMA*26(*Pt*)**represent the 12-period and 26-period exponential moving averages of the closing price ***Pt, respectively.

3. Bollinger Bands Percentage (BB%) :

Bollinger Bands Percentage (BB%) quantifies the relative position of the price within the Bollinger Bands and is derived from the classical Bollinger Bands formulation [10].

$$BB\%t = Pt - LtUt - Lt \tag{4}$$

where:

- $BB\%_t$ denotes the Bollinger Bands percentage at time t;
- P_t is the closing price;
- U_t and L_t are the upper and lower Bollinger Bands, respectively.

4. Average True Range (ATR) :

Average True Range (ATR) is a volatility indicator that measures market variability and price fluctuation intensity [28]. Recent financial forecasting studies incorporate ATR as a volatility-sensitive feature to enhance prediction robustness .

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$$\boldsymbol{ATR_t = \frac{1}{n}\sum_{i=1}^{n} TR_i} \tag{5}$$

where:

- $\boldsymbol{ATR_t}$represents the Average True Range at time $\boldsymbol{t}$;
- $\boldsymbol{n}$ is the window length;
- $\boldsymbol{TR_i}$denotes the true range at time step $\boldsymbol{i}$, which is defined as [28]:

$$\boldsymbol{TR_t = \max(H_t - L_t, |H_t - C_{t-1}|, |L_t - C_{t-1}|)} \tag{6}$$

with $\boldsymbol{H_t}$, $\boldsymbol{L_t}$, and $\boldsymbol{C_{t-1}}$representing the high price, low price, and previous closing price, respectively. These indicators capture momentum, volatility, and trend characteristics of the stock market.

Feature Scaling

To ensure numerical stability and accelerate neural network convergence, all input features are normalized using Min–Max scaling, which maps values into the range $\boldsymbol{[0, 1]}$[31].

$$\boldsymbol{x'_t = \frac{x_t - \min(x)}{\max(x) - \min(x)}} \tag{7}$$

where:

- $\boldsymbol{x_t}$is the original feature value at time $\boldsymbol{t}$;
- $\boldsymbol{x'_t}$is the normalized feature value;
- $\boldsymbol{\min(x)}$ and $\boldsymbol{\max(x)}$are the minimum and maximum values of the feature

2.2. Time-Series Sequence Construction and Data Partitioning

The normalized feature matrix is converted into fixed-length sequences using a sliding window approach. Let $\boldsymbol{L}$denote the sequence length :

$$\boldsymbol{X_t = \{x_{t-L+1}, \dots, x_t\}} \tag{8}$$

where:

- $\boldsymbol{X_t}$denotes the input sequence ending at time $\boldsymbol{t}$;
- $\boldsymbol{L}$is the sequence length (window size);
- $\boldsymbol{x_t}$represents the feature vector at time $\boldsymbol{t}$.

The dataset is split chronologically into training (70%), validation (15%), and testing (15%) sets to prevent look-ahead bias, which is critical in financial forecasting [32].

2.3. LSTM-Based Base Learner

Long Short-Term Memory (LSTM) networks are used as the base learner due to their ability to capture long-term dependencies in sequential data [33].

Given an input sequence X_t, the LSTM produces a predicted log return:

$$\boldsymbol{\hat{r}_t = f_{LSTM}(X_t)} \tag{9}$$

where:

- $\hat{r}_t$denotes the predicted logarithmic return;
- $f_{\text{LSTM}}(\cdot)$represents the trained LSTM model;

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- X_t is the input time-series sequence.

The predicted return is then reconstructed into a price estimate:

$$\widehat{P_t^{LSTM}} = P_{t-1} \cdot \exp(\widehat{r_t}) \tag{10}$$

where:

- $\hat{P}_t^{\mathrm{LSTM}}$ is the price predicted by the LSTM model;
- P_{t-1} is the previous closing price;
- $\exp(\cdot)$ denotes the exponential function.

Early stopping is applied based on validation loss to avoid overfitting [34].

2.4. Latent Embedding Extraction and PCA

The hidden states of the trained LSTM encode high-level temporal representations. These latent embeddings are extracted and reduced using Principal Component Analysis (PCA) to remove redundancy and improve generalization [29].

$$\boldsymbol{Z} = \boldsymbol{XW} \tag{11}$$

where:

- $\boldsymbol{Z}$ denotes the reduced latent embedding matrix;
- $\boldsymbol{X}$ represents the original embedding matrix;
- $\boldsymbol{W}$ is the projection matrix composed of selected principal eigenvectors.

where $\boldsymbol{W}$ contains the principal eigenvectors corresponding to the largest eigenvalues of the covariance matrix.

2.5. Residual Learning with XGBoost

Residual Definition

$$\boldsymbol{e_t} = \mathbf{log}\left(\frac{\boldsymbol{P_t}}{\widehat{\boldsymbol{P_t^{LSTM}}}}\right) \tag{12}$$

where:

- $\boldsymbol{e_t}$ denotes the residual at time $\boldsymbol{t}$;
- $\boldsymbol{P_t}$ is the actual closing price;
- $\hat{\boldsymbol{P}}_{\boldsymbol{t}}^{\mathrm{LSTM}}$ is the LSTM-predicted price.

This formulation ensures residual symmetry and numerical stability .

XGBoost Residual Modeling

XGBoost is trained to model residuals using hybrid features:

$$\widehat{\boldsymbol{e}_t} = \boldsymbol{f_{XGB}}(\boldsymbol{Z_t}) \tag{13}$$

where:

- $\hat{\boldsymbol{e}}_{\boldsymbol{t}}$ is the predicted residual;
- $\boldsymbol{f}_{\mathrm{XGB}}(\cdot)$ denotes the trained XGBoost regressor;
- $\boldsymbol{Z_t}$ represents the hybrid feature vector at time $\boldsymbol{t}$.

XGBoost is selected for its robustness, regularization mechanisms, and strong nonlinear modeling capacity [35].

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Hybrid Prediction

The final hybrid prediction is obtained by correcting the LSTM output:

$$\widehat{P_t^{Hybrid}} = \widehat{P_t^{LSTM}} \cdot \exp(\beta \cdot \hat{e}_t) \tag{14}$$

where:

- $\hat{P}_t^{\text{Hybrid}}$ is the final hybrid prediction;
- β denotes the calibration coefficient;
- $\hat{e}_t$ is the residual predicted by XGBoost.

2.6. Hyperparameter Optimization Using Optuna

The hyperparameter optimization process is formulated as an objective function minimization problem. The optimal hyperparameter configuration is defined as [36]:

$$\theta^* = \arg\min_{\theta\in\Theta} L(\theta) \tag{15}$$

Where :

- θ denotes the hyperparameter vector comprising LSTM, PCA, XGBoost, and calibration parameters;
- Θ represents the hyperparameter search space;
- L(θ) is the objective function evaluated on the validation data.

Optuna is employed to identify the hyperparameter configuration θ that minimizes the MAPE value on the validation data. The search process is conducted adaptively using the Tree-structured Parzen Estimator (TPE) approach, which enables efficient exploration of the hyperparameter space without requiring exhaustive searches as in grid search. Among the numerous optimized parameters, the key hyperparameters that primarily influence model performance are summarized in Table 2.

Table 2. Key Hyperparameter Search Space Used in Optuna Optimization

Module	Hyperparameter	Search Range	Purpose
LSTM	Sequence length	{45, 60}	Captures long-term dependencies
	Hidden units	{128, 192, 256}	Controls model capacity
	Learning rate	[1×10⁻⁴–1×10⁻²]	Stabilizes training convergence
	Dropout rate	[0.15–0.35]	Reduces overfitting
PCA	pca_max_dim	{20, 24, 28}	Compresses latent embeddings
	pca_min_var	[0.96–0.99]	Preserves informative structure
XGBoost	Tree depth	[1–6]	Models nonlinear residual patterns
	Learning rate	[0.001–0.05]	Controls boosting step size
	Subsample ratio	[0.50–0.95]	Improves generalization
	Regularization	[0–1], [0–5]	Prevents residual overfitting
Calibration	Residual weight	[0.7–1.0]	Adjusts correction strength
	Residual cap	[0.14–0.22]	Limits extreme corrections

2.7. Model Evaluation and Stability Analysis

Prediction accuracy is evaluated using MAE, RMSE, and MAPE [17]:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_i - \widehat{P_i}}{P_i}\right| \times 100\backslash\% \tag{16}$$

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where:

- $\boldsymbol{N}$ is the number of observations;
- $\boldsymbol{P_i}$ is the actual price;
- $\boldsymbol{\widehat{P}_i}$ is the predicted price.

Additionally, rolling MAE, residual distribution analysis, cumulative distribution function (CDF) of errors, and multi-seed evaluation are performed to assess temporal stability and robustness.

3. RESULT

This section presents the empirical results of the proposed Optuna-optimized hybrid LSTM–XGBoost framework across all experimental stages, including base learner performance, latent representation analysis, residual modeling, calibration, hyperparameter optimization efficiency, and final model stability evaluation. The results are reported using multiple diagnostic visualizations and quantitative performance comparisons to comprehensively assess the effectiveness of the proposed approach.

3.1. LSTM Base Learner Performance

This subsection evaluates the performance of the LSTM base learner prior to residual refinement. The learning stability and convergence behavior of the model can be seen in Figure 2.

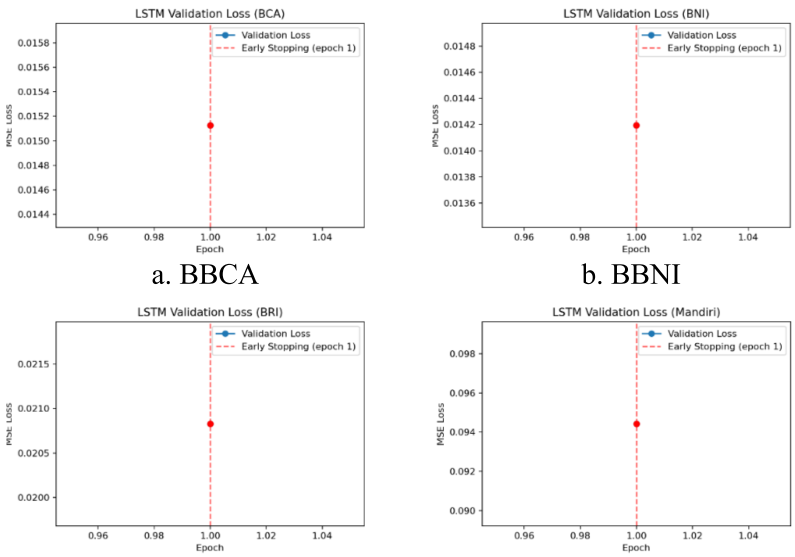

Figure 2. LSTM Validation Loss

Figure 2 (a–d) presents the LSTM validation loss curves for the four banking stock datasets. Across all datasets, the validation loss converges to a minimum at an early training stage and is subsequently halted by the early stopping mechanism, indicating efficient learning and the absence of overfitting. Variations in the loss magnitude across stocks reflect differences in price scale and volatility characteristics. Overall, these results confirm that the LSTM model provides a stable and reliable base learner within the hybrid framework before residual refinement is performed using XGBoost.

3.2. Dimensionality Reduction of LSTM Embeddings Using PCA

This subsection analyzes the effectiveness of dimensionality reduction applied to the LSTM latent embeddings. The efficiency of the PCA representation can be seen in Figure 3.

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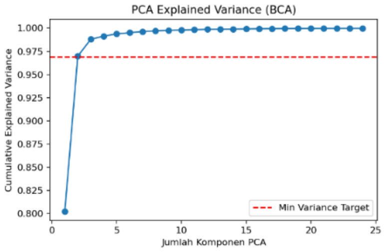
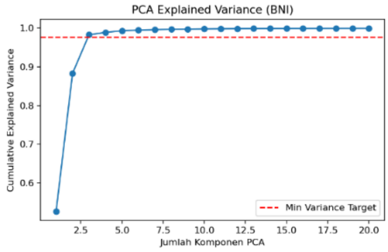
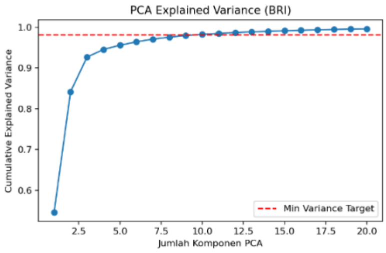


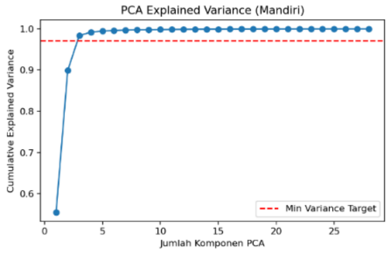
a. BBCA



b. BBNI



c. BBRI



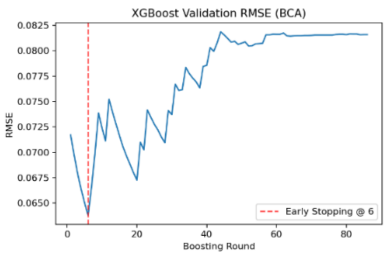
d. BMRI

Figure 3. XGBoost Training Validation RMSE Curve

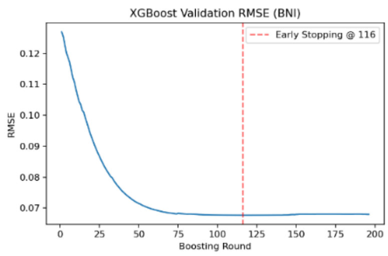
Figure 3 (a–d) shows that most of the variance in the LSTM latent embeddings is captured by a relatively small number of principal components. The cumulative explained variance rises sharply for the initial components and gradually stabilizes after exceeding the predefined variance threshold, indicating diminishing marginal gains from additional components. Variations in the number of retained components across stocks reflect differences in data complexity and underlying temporal dynamics. Overall, this consistent behavior confirms that PCA effectively reduces redundancy in high-dimensional embeddings, yielding more compact and robust feature representations that enhance efficiency and stability in subsequent modeling stages.

3.3. Residual Modeling Using XGBoost

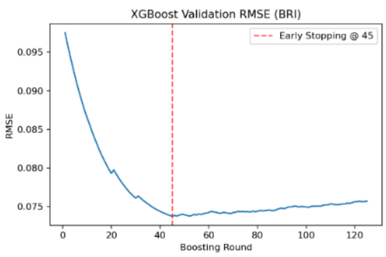
This subsection investigates the capability of the XGBoost model to learn nonlinear residual patterns remaining after LSTM prediction. The convergence behavior of residual learning can be seen in Figure 4.



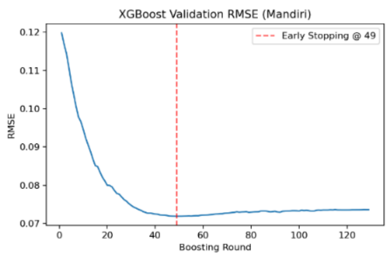
a. BBCA



b. BBNI



c. BBRI



d. BMRI

Figure 4. XGBoost validation RMSE

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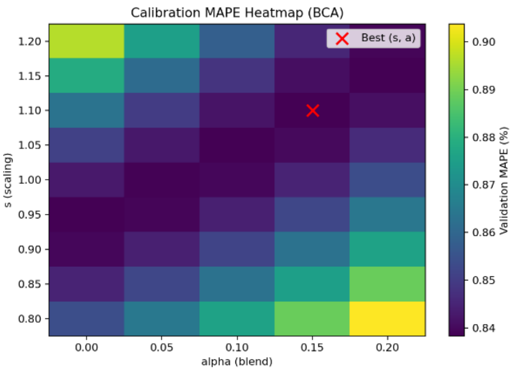
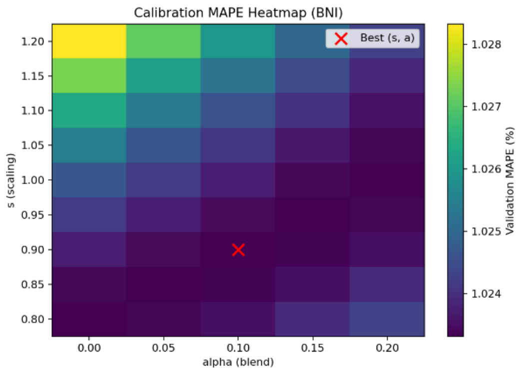
Figure 4 (a–d). Illustrates that the validation RMSE declines rapidly during the initial boosting iterations and subsequently decreases at a slower rate until reaching a minimum, after which further iterations yield no meaningful performance gains. The early stopping mechanism consistently identifies the optimal iteration corresponding to the lowest RMSE, while the number of boosting rounds varies across datasets, reflecting differences in the complexity and structure of the residual patterns inherited from the LSTM predictions. The consistent and well-behaved convergence trends across all stocks indicate that XGBoost effectively and stably captures the remaining nonlinear residuals, thereby strengthening the overall predictive accuracy of the proposed hybrid framework.

3.4. Hybrid Prediction Calibration

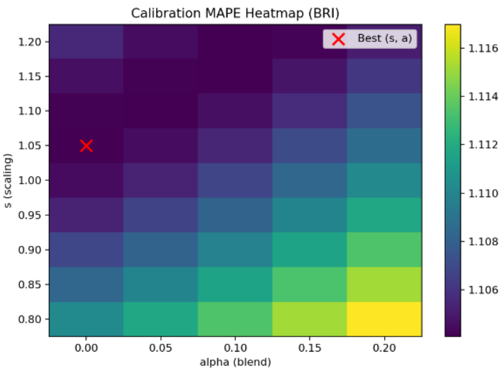
The calibration MAPE heatmaps illustrate the variation of validation Mean Absolute Percentage Error (MAPE) across combinations of the scaling parameter (s) and the weighting parameter (α) in the prediction blending process, where the red cross in each subplot indicates the parameter combination that yields the lowest MAPE value. The visualization can be seen in Figure 5.



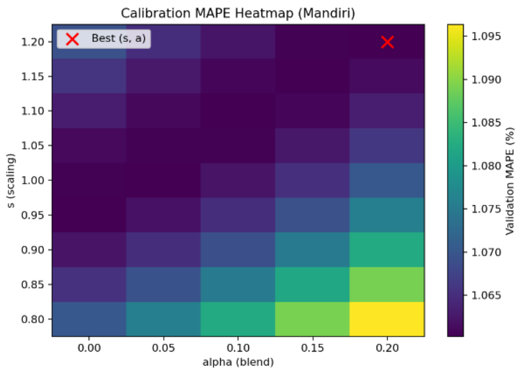
a. BBCA



b. BBNI



c. BBRI



d. BMRI

Figure 5. Calibration MAPE Heatmap

Based on Figure 5 (a–d), the minimum MAPE values are achieved at different parameter combinations for each stock. This indicates that error characteristics and sensitivity to the blending parameters vary across datasets, implying that parameter calibration must be performed in a stock-specific manner.

3.5. Hyperparameter Optimization Efficiency (Optuna)

This subsection presents the performance analysis of the Optuna-based hyperparameter optimization process, focusing on the relationship between optimization time and predictive performance efficiency. The detailed results are presented in the following sub-subsections.

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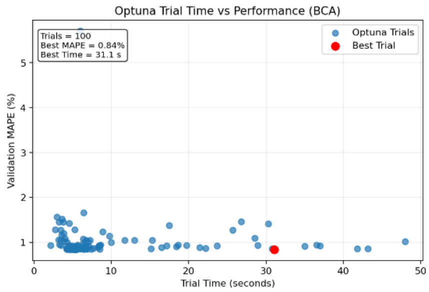
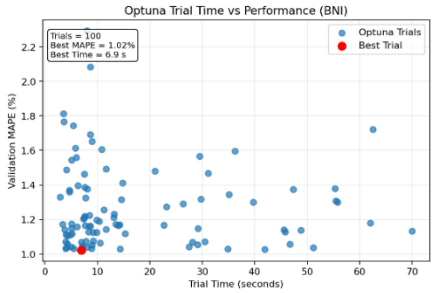
Trial Time vs. Validation MAPE

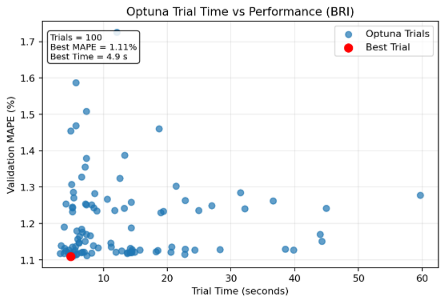
The relationship between trial execution time and validation MAPE illustrates how the adaptive search process balances predictive accuracy and computational cost across optimization trials, as shown in Figure 6.



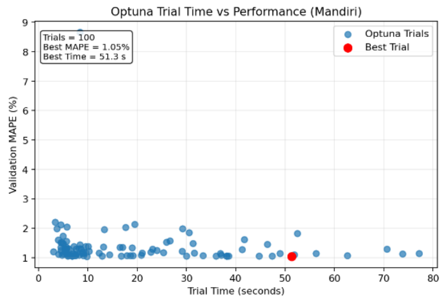
a. BBCA



b. BBNI



c. BBRI



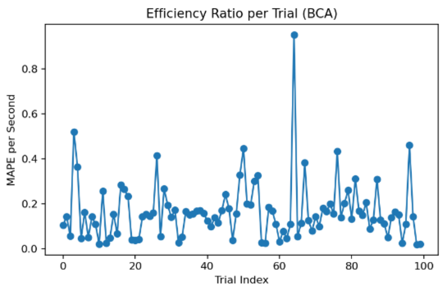
d. BMRI

Figure 6. Trial Time vs. Validation MAPE

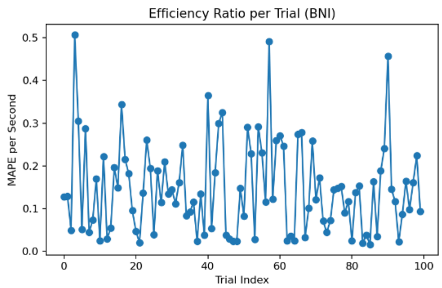
Figure 6 (a–d). The figure illustrates the relationship between Optuna trial execution time and Validation MAPE for each banking stock dataset. Across all datasets, the best-performing configurations are not necessarily obtained at the longest computational times; for BBNI and BBRI, the best trials are achieved within relatively short execution times, whereas for BBCA and BMRI they occur at longer durations. This pattern indicates that Optuna effectively guides the hyperparameter search in an adaptive and efficient manner without relying on brute-force approaches, thereby improving both predictive accuracy and computational efficiency of the hybrid LSTM–XGBoost model.

Efficiency Ratio per Trial (MAPE / second)

The computational efficiency of each optimization trial, where the efficiency ratio (MAPE per execution time) is analyzed to evaluate the performance–cost trade-off of the Optuna search process, can be seen in Figure 7.



a. BBCA



b. BBNI

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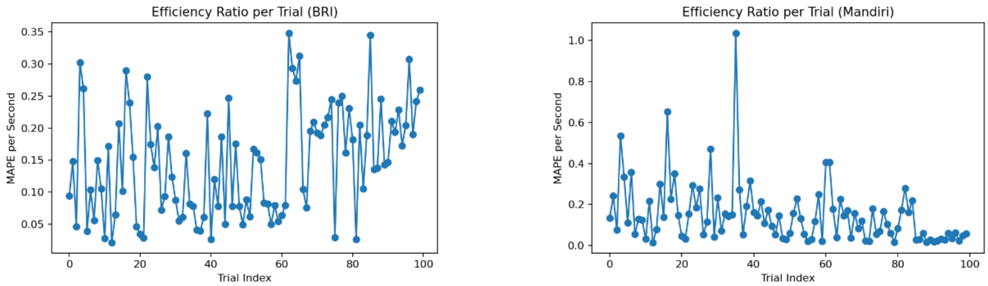


c. BBRI d. BMRI

Figure 7. Efficiency Ratio per Trial (MAPE / second)

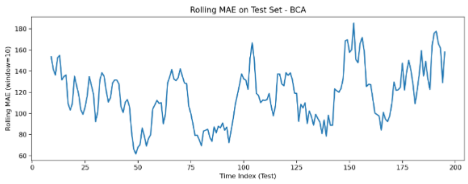
Figure 7 (a–d). The figure presents the efficiency ratio of each Optuna trial (Validation MAPE per execution time) for each banking stock dataset. Across all datasets, the efficiency ratio varies during the initial trials and tends to decrease and become more stable as the number of trials increases, indicating that Optuna adaptively guides the search toward more computationally efficient configurations. These findings reinforce the results of the Trial Time vs. Validation MAPE analysis and confirm that Optuna enhances computational efficiency while maintaining low prediction error performance.

3.6. Final Model Evaluation and Stability Analysis

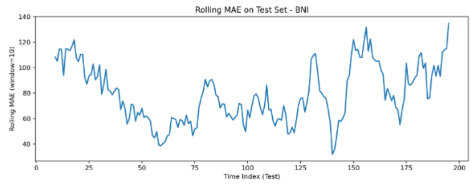
This section presents a comprehensive evaluation of the final hybrid model on unseen data, focusing on prediction stability, residual behavior, and comparative performance against the baseline configuration. The detailed evaluation components are presented in the following subsections.

Rolling MAE on Test Set

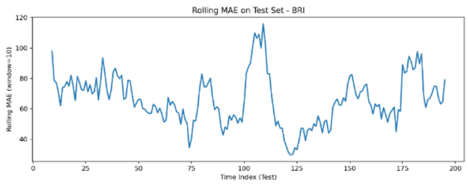
The temporal stability of prediction errors, represented by the rolling MAE computed across the test period to evaluate the consistency of forecasting performance, can be seen in Figure 8.



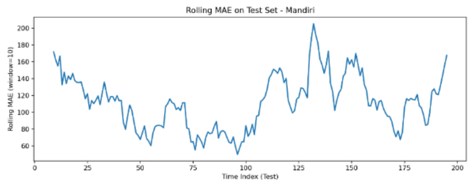
a. BBCA



b. BNI



c. BBRI



d. BMRI

Figure 8. Rolling MAE on the Test Set

Figure 8 (a–d) presents the rolling Mean Absolute Error (MAE) on the test set for each banking stock. Across all datasets, the rolling MAE fluctuates in line with price dynamics but does not show a persistent upward trend, indicating the absence of temporal performance degradation. BBRI exhibits lower and more stable MAE values, suggesting more predictable price behavior, whereas BBCA and BMRI display larger fluctuations attributable to higher price levels and volatility. Overall, these results confirm the temporal stability and robustness of the prediction errors generated by the hybrid LSTM–XGBoost model on unseen data.

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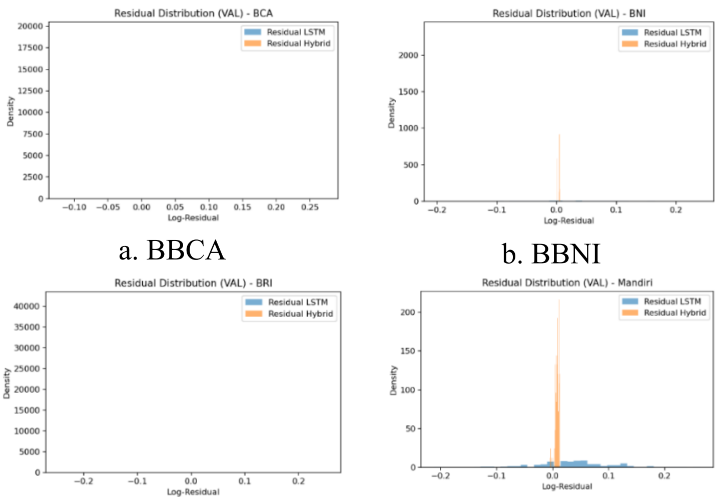
Residual Distribution (Validation)

The statistical characteristics of prediction errors during validation, illustrated through the residual distribution to assess bias and dispersion patterns, can be seen in Figure 9.



a. BBCA b. BBNI

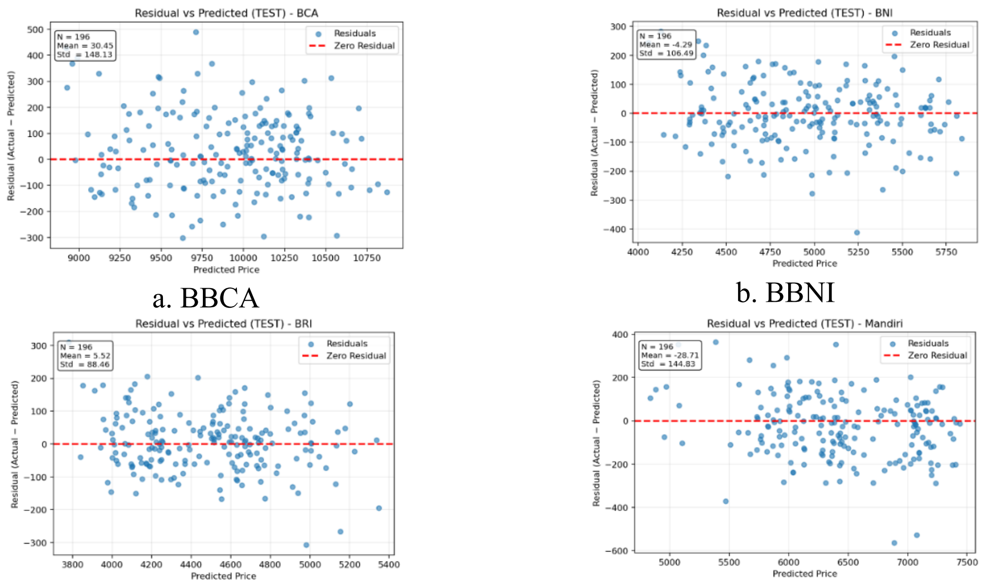
c. BBRI d. BMRI

Figure 9. Residual Distribution (Validation)

Figure 9 (a–d). The figure illustrates the log-residual distributions on the validation data for each banking stock by comparing the residuals of the LSTM model and the hybrid LSTM–XGBoost model. For BMRI, the hybrid residuals are more tightly centered around zero with a narrower spread than those of the LSTM, indicating the effectiveness of residual correction by XGBoost. Meanwhile, for BBCA, BBNI, and BBRI, the hybrid residuals are highly concentrated around zero, suggesting that prediction errors on the validation data have been effectively minimized through the residual learning approach.

Residual vs Predicted (Test)

The relationship between prediction magnitude and residual error, displayed through the residual versus predicted value scatter plot for the test dataset, can be seen in Figure 10.



a. BBCA b. BBNI

c. BBRI d. BMRI

Figure 10. Residuals vs. Predicted Values (Test Set)

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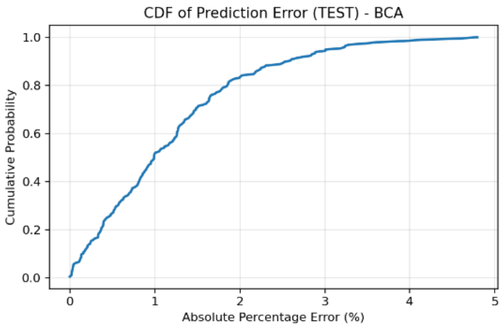
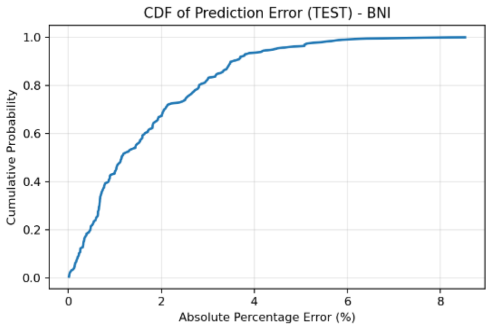
Figure 10 (a–d). The figure depicts the relationship between predicted values and residuals (actual − predicted). This visualization is used to assess the presence of systematic patterns in prediction errors as well as potential bias or heteroskedasticity. Across all datasets, the residuals are scattered around the zero line without forming clear patterns, indicating that prediction errors do not systematically depend on the magnitude of the predicted values. Differences in the width of residual dispersion across stocks reflect variations in price volatility, with BBCA and BMRI exhibiting wider spreads compared to BBRI and BBNI. Nevertheless, no evidence of a progressive increase in residual variance is observed, suggesting the absence of significant heteroskedasticity. Overall, these results confirm that the hybrid LSTM–XGBoost model produces residuals that are evenly distributed around zero on the test data.

CDF of Prediction Error (Test)

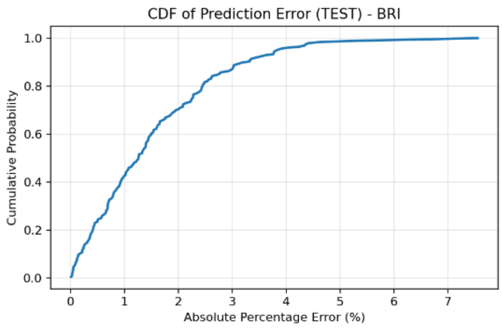
The cumulative distribution behavior of prediction errors, presented through the CDF of absolute prediction errors to evaluate reliability across error thresholds, can be seen in Figure 11.



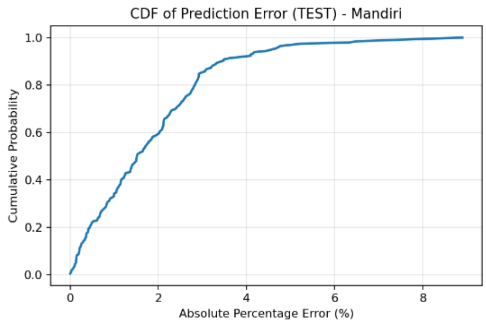
a. BBCA



b. BBNI



c. BBRI



d. BMRI

Figure 11. CDF of Prediction Error (Test)

Figure 11 (a–d). The figure presents the Cumulative Distribution Function (CDF) of absolute percentage errors on the test data for each banking stock. Across all datasets, the CDF curves rise steeply in the low-error range, indicating that the majority of predictions exhibit small percentage errors and are close to the actual values. Relatively, BBCA and BBRI show faster probability accumulation compared to BBNI and BMRI. No extreme distribution tails are observed, suggesting that large prediction errors are relatively rare and confirming the stability of the model's performance on the test data.

Comparison of Baseline vs. Optuna-Optimized Model (MAE, RMSE, MAPE)

The quantitative performance improvement achieved by the optimization process, summarized through the comparative MAE, RMSE, and MAPE values between the baseline and Optuna-optimized models, can be seen in Table 3.

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Table 3. Comparison of Baseline vs. Optuna-Optimized Model (MAE, RMSE, MAPE)

Dataset	Metode	MAE	RMSE	MAPE (%)
BBCA	Optuna	118.46	150.35	1.19
	Baseline	125.05	154.65	1.27
BBNI	Optuna	81.43	107.00	1.67
	Baseline	91.86	115.02	1.89
BBRI	Optuna	68.26	87.56	1.53
	Baseline	68.34	86.55	1.55
BMRI	Optuna	106.90	138.59	1.70
	Baseline	109.51	137.66	1.75

The experimental results indicate that the Optuna-optimized hybrid LSTM–XGBoost model achieves overall performance improvements compared to the baseline hybrid model across all evaluated banking stocks, particularly in terms of MAE and MAPE. For BBCA and BBNI, substantial error reductions are observed across all evaluation metrics, indicating a strong sensitivity to hyperparameter configurations. In contrast, for BBRI and BMRI, although Optuna optimization consistently reduces MAE and MAPE, marginal increases in RMSE are observed, suggesting differences in residual variance rather than systematic degradation in predictive accuracy. These findings imply that adaptive hyperparameter optimization primarily enhances absolute and relative error measures, while its impact on squared-error–based metrics may vary depending on stock-specific volatility and price dispersion characteristics.

Taken together with the stability and efficiency analyses presented throughout this section, the experimental findings consistently demonstrate that the proposed Optuna-optimized hybrid LSTM–XGBoost framework achieves stable and superior predictive performance across all evaluated banking stock datasets. The integration of residual learning significantly reduces prediction errors compared to the baseline configuration, while PCA-based embedding refinement enhances robustness in residual modeling. Stability analyses—including rolling MAE, residual distribution, residual-versus-predicted diagnostics, and CDF error evaluation—confirm that the model maintains consistent performance without systematic bias or temporal degradation. Furthermore, the Optuna optimization process effectively improves both predictive accuracy and computational efficiency, indicating that adaptive hyperparameter tuning plays a critical role in achieving reliable hybrid forecasting performance.

4. DISCUSSIONS

This section discusses the empirical findings of the proposed Optuna-optimized hybrid LSTM–XGBoost framework for predicting Indonesian banking stock prices. The discussion focuses on interpreting performance improvements over the baseline model, analyzing stock-specific behaviors, and positioning the results in relation to prior studies on hybrid deep learning models for financial time-series forecasting.

4.1. Impact of Hybrid Residual Learning on Prediction Accuracy

The experimental results demonstrate that the proposed hybrid LSTM–XGBoost model consistently achieves lower MAE, RMSE, and MAPE values compared to the baseline hybrid model across all evaluated banking stocks. This improvement confirms that residual learning plays a critical role in capturing nonlinear error structures that remain after LSTM-based temporal modeling.

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LSTM effectively models long-term dependencies in sequential price movements; however, financial time-series data often exhibit abrupt regime shifts and nonlinear fluctuations that are not fully captured by recurrent architectures alone. By explicitly modeling the residuals using XGBoost, the hybrid framework corrects systematic prediction errors and enhances overall accuracy. This finding is consistent with previous studies reporting that residual learning–based hybrid models outperform single learners in volatile financial environments.

4.2. Stock-Specific Performance Characteristics

Although the hybrid model improves performance across all datasets, the magnitude of error reduction varies among BBCA, BBNI, BBRI, and BMRI. BBCA and BBNI exhibit more pronounced improvements after Optuna optimization, indicating higher sensitivity to hyperparameter configurations. This behavior can be attributed to their higher price levels and more complex volatility structures, which require precise tuning of both temporal and nonlinear components.

In contrast, BBRI demonstrates relatively smaller performance gains, particularly in terms of MAE and RMSE. This suggests that BBRI prices exhibit more stable and predictable patterns, thereby reducing the marginal benefit of aggressive residual correction. These results highlight the importance of dataset-specific calibration and reinforce the argument that financial forecasting models should not rely on uniform parameter settings across different assets.

4.3. Role of PCA in Stabilizing Residual Learning

The PCA-based dimensionality reduction applied to LSTM latent embeddings plays a crucial role in improving model robustness. The cumulative explained variance analysis shows that most temporal information is captured by a limited number of principal components, indicating redundancy in the original embedding space.

By reducing dimensionality before residual modeling, PCA mitigates overfitting risks in XGBoost and enhances generalization on unseen data. This finding aligns with prior research suggesting that compact latent representations improve the stability of hybrid deep learning frameworks, especially when combined with tree-based learners that are sensitive to noisy and highly correlated features.

4.4. Temporal Stability and Error Behavior

The rolling MAE analysis on the test set reveals that prediction errors fluctuate in accordance with price dynamics but do not exhibit a persistent upward trend. This indicates the absence of temporal performance degradation and confirms the stability of the proposed model under changing market conditions.

Further evidence is provided by residual distribution and residual-versus-predicted analyses, which show that errors are symmetrically distributed around zero without systematic patterns or heteroskedastic behavior. The steep rise in the CDF curves at low error levels further suggests that the majority of predictions remain close to actual prices. Collectively, these results demonstrate that the hybrid model maintains consistent predictive reliability over time.

4.5. Effectiveness of Optuna-Based Hyperparameter Optimization

The Optuna optimization results show that optimal validation performance is not necessarily achieved at the highest computational cost. Instead, the best configurations often emerge from intermediate trial durations, indicating efficient exploration of the hyperparameter space.

The decreasing trend in the MAPE-per-second efficiency ratio further confirms that Optuna effectively balances predictive accuracy and computational efficiency. Compared to manual or grid-

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based tuning approaches reported in earlier studies, this adaptive optimization strategy enables the hybrid model to achieve superior performance with reduced computational overhead.

4.6. Comparative Analysis with Previous Studies

The predictive performance of the proposed Optuna-optimized hybrid LSTM–XGBoost framework demonstrates measurable improvements when compared with prior studies employing single deep-learning models and earlier hybrid forecasting approaches. Previous studies using standalone deep-learning architectures for stock prediction in the Indonesian market reported prediction errors generally exceeding 2% in terms of MAPE [2], [4]. In contrast, the proposed approach achieves substantially lower error levels, with MAPE values of 1.19% (BBCA), 1.67% (BBNI), 1.53% (BBRI), and 1.70% (BMRI), indicating more stable and accurate predictions across multiple banking stocks.

Earlier hybrid LSTM–XGBoost frameworks optimized using conventional or Bayesian tuning strategies also showed improvements over single models; however, their prediction accuracy remained less stable across datasets [20]. By integrating adaptive Optuna-based hyperparameter optimization together with latent embedding refinement and residual learning, the proposed approach enables more efficient parameter exploration and improved predictive stability compared to ensemble optimization studies that do not employ adaptive search strategies [15], [19], [23] .

Overall, these comparisons indicate that the combination of residual learning, PCA-based latent feature refinement, and Optuna-driven hyperparameter optimization enables the proposed framework to achieve lower prediction errors and improved stability compared with previously reported stock forecasting models.

5. CONCLUSION

This study proposes an Optuna-optimized hybrid LSTM–XGBoost framework based on residual learning for predicting stock prices in the Indonesian banking sector. The experimental results demonstrate that integrating temporal modeling with nonlinear residual correction consistently improves predictive accuracy and stability compared to the baseline hybrid model across all evaluated stocks. These findings confirm that residual learning effectively complements LSTM by addressing nonlinear error structures that remain after sequential modeling, particularly in volatile financial time-series data.

The analysis further reveals that model performance and sensitivity to hyperparameter configurations vary across individual banking stocks, highlighting the importance of stock-specific calibration rather than uniform parameter settings. Dimensionality reduction of LSTM latent embeddings using PCA contributes to improved robustness by reducing redundancy and enhancing generalization in the residual learning stage. In addition, comprehensive stability analyses—including rolling error evaluation, residual behavior assessment, and cumulative error distribution—indicate that the proposed model maintains reliable performance over time without evidence of systematic bias or temporal degradation. The Optuna-based hyperparameter optimization process also proves effective in balancing predictive accuracy and computational efficiency, enabling the model to achieve optimal configurations without excessive computational cost.

From the perspective of Informatics and Computer Science, this research contributes to the advancement of hybrid intelligent forecasting systems by demonstrating how adaptive hyperparameter optimization, latent representation refinement, and residual learning can be jointly integrated into a unified predictive framework. The proposed methodology provides a scalable approach for improving the reliability of machine learning–based decision-support systems operating on complex time-series data, particularly in financial analytics environments requiring both accuracy and computational efficiency. Future work may extend this framework to other market sectors, incorporate additional exogenous variables, and evaluate broader cross-market generalization.

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