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Random Forest Classification for Indonesian Blue-Chip Banking Stock Trend Prediction

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ABSTRACT

This study applies a Random Forest classification approach to predict stock price trend direction for Indonesian blue-chip banking stocks specifically BBRI, BBCA, BMRI, and BBNI as the analytical core of a Decision Support System (DSS) for retail investors. The rapid development of fintech and digital investment platforms in Indonesia has intensified the need for intelligent, data-driven tools to assist retail investors in making informed decisions. Despite growing research on stock prediction, studies that simultaneously evaluate multiple Indonesian banking blue-chip stocks using ensemble machine learning methods remain limited. This study uses one year of historical Open-High-Low-Close-Volume (OHLCV) data from May 2025 to May 2026, comprising 234 clean observations per stock after feature engineering. Sixteen technical indicators were extracted as input features, including Moving Averages (MA5, MA10, MA20), Relative Strength Index (RSI), MACD, Volatility, and Volume Ratio. A binary classification label was assigned based on next-day closing price direction. The Random Forest model was trained on 80% of the data (187 samples) and tested on the remaining 20% (47 samples). Experimental results demonstrate that BBNI achieved the highest F1-score of 0.5965, while BBCA and BBNI both reached an accuracy of 51.06%. The study concludes that Volatility and MACD are the most influential features across all four stocks. This DSS framework provides a practical and reproducible foundation for intelligent investment decision support in the Indonesian banking sector.

Keywords: Blue-Chip Banking; Decision Support System; Random Forest; Stock Price Prediction; Technical Indicators.

ABSTRAK

Penelitian ini menerapkan pendekatan klasifikasi Random Forest untuk memprediksi arah tren harga saham perbankan blue-chip Indonesia, yaitu BBRI, BBCA, BMRI, dan BBNI, sebagai inti analitis dari Sistem Pendukung Keputusan (SPK) bagi investor ritel. Pesatnya perkembangan fintech dan platform investasi digital di Indonesia meningkatkan kebutuhan akan alat berbasis data yang cerdas untuk membantu investor ritel mengambil keputusan yang tepat. Meskipun penelitian tentang prediksi saham terus berkembang, studi yang secara bersamaan mengevaluasi beberapa saham blue-chip perbankan Indonesia menggunakan metode ensemble machine learning masih terbatas. Penelitian ini menggunakan data historis Open-High-Low-Close-Volume (OHLCV) selama satu tahun dari Mei 2025 hingga Mei 2026, terdiri atas 234 observasi bersih per saham setelah proses rekayasa fitur. Sebanyak enam belas indikator teknikal diekstraksi sebagai fitur masukan, meliputi Moving Average (MA5, MA10, MA20), Relative Strength Index (RSI), MACD, Volatilitas, dan Rasio Volume. Label klasifikasi biner ditentukan berdasarkan arah harga penutupan hari berikutnya. Model Random Forest dilatih menggunakan 80% data (187 sampel) dan diuji pada 20% sisanya (47 sampel). Hasil eksperimen menunjukkan bahwa BBNI memperoleh F1-score tertinggi sebesar 0,5965, sementara BBCA dan BBNI sama-sama mencapai akurasi 51,06%. Penelitian ini menyimpulkan bahwa Volatilitas dan MACD merupakan fitur paling berpengaruh pada keempat saham tersebut. Kerangka SPK ini memberikan fondasi yang praktis dan reproducible untuk mendukung keputusan investasi cerdas di sektor perbankan Indonesia.

Kata Kunci: *Indikator Teknikal; Perbankan Blue-Chip; Prediksi Harga Saham; Random Forest; Sistem Pendukung Keputusan.*

INTRODUCTION

The Indonesian capital market, particularly the banking sector, plays a pivotal role in the national economy. As of 2025, the Indonesia Stock Exchange (IDX) lists over 900 companies, with banking stocks classified as blue-chip consistently representing the highest market capitalization. Stocks such as Bank Rakyat Indonesia (BBRI), Bank Central Asia (BBCA), Bank Mandiri (BMRI), and Bank Negara Indonesia (BBNI) are among the most actively traded securities, attracting both institutional and retail investors.

The proliferation of financial technology (fintech) platforms in Indonesia has democratized stock market participation. Applications such as Ajaib, Stockbit, and Bibit have lowered barriers to entry, resulting in a significant increase in retail investor accounts, which reached 14.81 million by the end of 2024 (OJK, 2024). However, retail investors frequently lack the analytical tools and expertise to make well-informed trading decisions, making them susceptible to behavioral biases and market volatility (Nguyen et al., 2015).

Decision Support Systems (DSS) have been proposed as a means of bridging the analytical gap for non-expert investors. In the context of financial markets, a DSS integrates historical data, technical indicators, and predictive models to generate actionable signals (Kara et al., 2011). Machine learning-based DSS, particularly those using ensemble methods, have demonstrated superior performance over single classifiers in capturing complex non-linear patterns in time-series financial data (Zhang et al., 2016).

Among ensemble methods, Random Forest (RF) has received considerable attention in financial forecasting due to its robustness against overfitting, ability to handle high-dimensional feature spaces, and built-in feature importance estimation (Liaw & Wiener, 2002; Gu et al., 2020). Previous studies have applied RF to predict stock price movements in various markets, including the Chinese A-share market (Tan et al., 2019), the US S&P 500 (Patel et al., 2015), and Southeast Asian emerging markets (Tran et al., 2024). However, studies specifically targeting Indonesian banking blue-chip stocks using a multi-stock comparative RF-DSS framework remain scarce.

The primary research gap addressed in this study is the absence of a comparative RF-based DSS that simultaneously evaluates prediction performance across multiple Indonesian blue-chip banking stocks using a standardized technical indicator feature set. Existing Indonesian studies have largely focused on single-stock prediction (Utomo, 2023) or applied simpler models such as SVM or LSTM without ensemble comparison. This study fills that gap by constructing a unified DSS pipeline, evaluating it across BBRI, BBCA, BMRI, and BBNI, and identifying the most discriminative technical features.

The objectives of this study are: (1) to engineer a set of 16 technical indicators from OHLCV data as RF model input features; (2) to train and evaluate a Random Forest classifier for next-day stock price trend direction prediction; (3) to compare classification performance across four blue-chip banking stocks; and (4) to identify the most influential features driving prediction accuracy. This research contributes a reproducible, data-driven DSS framework applicable to the Indonesian banking equity context. It should be noted that the primary contribution of this study lies in its comparative, application-level novelty, namely the systematic cross-stock evaluation of an established Random Forest framework on Indonesian banking blue-chip equities, rather than in proposing a new algorithmic or methodological innovation.

METHOD

This section presents both the theoretical foundation and the operational research design underlying the proposed Random Forest-based Decision Support System (DSS). To ensure the scientific validity of the study and permit precise replication by future researchers, the discussion first establishes the conceptual basis such as the role of DSS in financial markets, the mechanics of the Random Forest algorithm, and the rationale for the selected technical indicators before detailing the concrete, reproducible, multi-stage quantitative workflow used to collect data, engineer features, configure the model, and evaluate its performance.

Decision Support Systems in Financial Markets

A Decision Support System is an information system that supports business or organizational decision-making activities. In the context of financial markets, a DSS integrates data acquisition, feature extraction, predictive modeling, and result interpretation into a cohesive framework (Delen & Ram, 2018). The output of a financial DSS is typically a trading signal buy, hold, or sell derived from quantitative model predictions rather than human judgment alone. This study operationalizes the DSS as a binary classification pipeline that outputs an upward (1) or downward (0) trend prediction for the next trading day.

Random Forest Algorithm

Random Forest is an ensemble learning method introduced by Breiman (2001) that constructs multiple decision trees during training and outputs the class that is the mode of the individual tree predictions. Each tree is trained on a bootstrapped sample of the training data (bagging), and at each node split, a random subset of features is considered, reducing variance and correlation among trees. The prediction of the ensemble is given by:

$$F(x) = mode\ \{ h_1(x), h_2(x), \ldots, h_n(x) \}$$

Where $h_i(x)$ denotes the prediction of the i-th tree and n is the number of trees. Random Forest also provides a natural feature importance measure based on the mean decrease in impurity (Gini importance) across all trees, which is leveraged in this study to identify the most informative technical indicators (Liaw & Wiener, 2002).

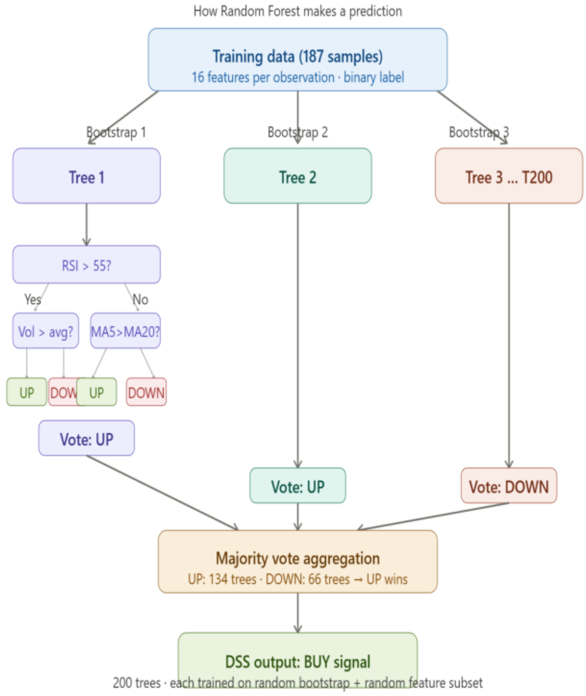


Figure 1. Random forest mechanism

Technical Indicators as Features

Technical analysis assumes that historical price and volume data reflect all available market information and can be used to forecast future price movements (Murphy, 1999). This study employs 16 features derived from OHLCV data: three Moving Averages (MA5, MA10, MA20), the Relative Strength Index (RSI-14), Moving Average Convergence Divergence (MACD), short-term price Volatility, High-Low ratio (HL_ratio), Open-Close ratio (OC_ratio), daily Return, Volume Ratio, 5-day Momentum, and the raw OHLCV values. These indicators capture trend, momentum, volatility, and volume dimensions of market behavior (Achelis, 2001).

Research Design

This study applies a quantitative experimental research design to evaluate the performance of the Random Forest algorithm in predicting stock market trends as part of a Decision Support System (DSS). The research focuses on analyzing historical stock market data from the Indonesian banking sector to support investment decision-making processes through machine learning approaches. The overall research workflow was carried out systematically through several interconnected stages consisting of data collection, preprocessing, feature engineering, model training, performance evaluation, and feature importance analysis as illustrated in Figure 2. Each stage was designed to ensure that the resulting prediction model can produce stable and reliable classification outcomes when applied to financial time-series data.

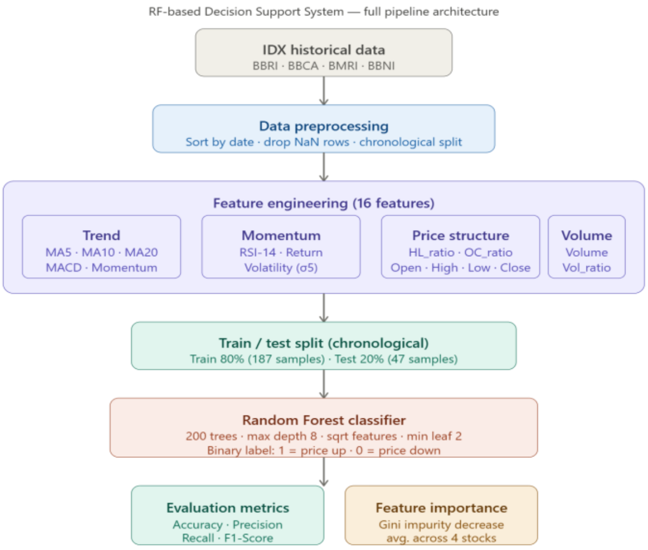


Figure 2. System architecture

Figure 2 illustrates the overall research methodology used in developing the Random Forest-based Decision Support System for stock trend prediction. The process begins with problem identification and literature review, followed by data collection from Indonesian banking stocks listed on the IDX. The collected data are then processed through preprocessing and feature engineering stages before being used for model training. Finally, the model performance is evaluated using classification metrics and feature importance analysis to generate investment decision insights.

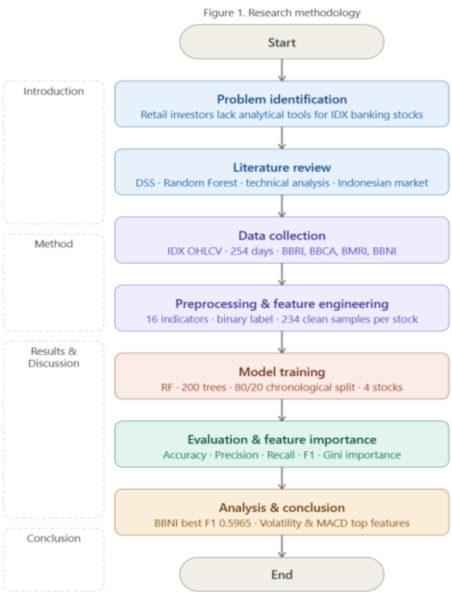


Figure 3. Research methodology flowchart

The flowchart depicts the sequential research stages adopted in this study, mapped against the corresponding IMRaD sections, commencing from problem identification and literature review, progressing through data collection, preprocessing, and model development, and terminating in performance evaluation and conclusion formulation, ensuring a systematic and reproducible research workflow.

Data and Descriptive Statistics

Historical Open, High, Low, Close, and Volume (OHLCV) data for BBRI, BBCA, BMRI, and BBNI were retrieved from the Indonesia Stock Exchange (IDX) via the source files BBRI.xls, BBCA.xls, BMRI.xls, and BBNI.xls. The temporal scope spans from 2 May 2025 to 27 May 2026, capturing a total of 254 raw trading observations per emiten. To mitigate computational bias introduced by indicator initialization windows, a rolling-window truncation was executed. Following the removal of rows containing lookback-induced missing values, each asset yielded a uniform matrix of 234 clean, continuous daily observations. This structural dataset encompasses a complete annual market cycle, effectively encapsulating the seasonal, macroeconomic, and event-driven market dynamics inherent to the Indonesian tier-1 banking sector.

Table 1 Descriptive Statistics of Closing Prices (IDR)

Stock	N (days)	Min (IDR)	Max (IDR)	Mean (IDR)	Std Dev
BBRI	234	2,990	4,450	3,762	386.4
BBCA	234	5,850	9,700	7,866	1,024.7
BMRI	234	4,050	5,525	4,771	328.2
BBNI	234	3,510	4,630	4,212	293.1

Source: Authors' computation from OHLCV data (IDX, 2025-2026).

Feature Engineering and Class Labeling

A multidimensional feature engineering process was conducted to construct predictive indicators from the raw OHLCV dataset. A total of sixteen predictive variables were generated to capture trend movement, momentum behavior, volatility, and trading activity within the stock market. Trend indicators were represented using Moving Averages (MA5, MA10, and MA20), calculated as rolling arithmetic means over 5-day, 10-day, and 20-day trading windows. Market momentum and overbought or oversold conditions were modeled using the Relative Strength Index (RSI) with a 14-period calculation based on the formulation proposed by Wilder (1978). Trend divergence characteristics were represented using the Moving Average Convergence Divergence (MACD), formulated as the difference between the 12-period Exponential Moving Average (EMA12) and the 26-period Exponential Moving Average (EMA26):

$$MACD = EMA12 - EMA26$$

Stock price volatility was measured using the rolling standard deviation of logarithmic daily returns over a 5-day period. In addition, price-range dynamics were represented using normalized High-Low ratios (HL ratio) and Open-Close ratios (OC ratio). Trading activity indicators such as daily volume ratio and momentum indicators were also embedded into the final feature matrix. The binary target variable representing stock directional trends was formulated using a forward-shifted closing price comparison:

$$Yt = 1, \text{ if } Close\ (t+1) > Close\ (t)$$
$$Yt = 0, \text{ otherwise}$$

This labeling mechanism categorizes stock movement into upward and downward trends. To prevent data leakage and look-ahead bias during the training process, the final row of each time-series dataset was excluded because the future target value (t+1) was unavailable.

Model Configuration and Evaluation

To preserve temporal consistency and avoid information leakage, the dataset partitioning process was conducted chronologically without random shuffling. The first 80% of observations (187 sequential samples) were allocated as training data, while the remaining 20% (47 sequential samples) were reserved as out-of-sample testing data. The Random Forest classifier was configured using hyperparameters selected based on common practice in prior financial forecasting studies to mitigate overfitting risk, rather than through an exhaustive hyperparameter optimization procedure. The model architecture employed 200 estimators (n_estimators = 200), a maximum tree depth of 8, a minimum split requirement of 5 samples, and a minimum leaf node size of 2 samples.

$$max\_features = \sqrt{m}$$

The performance of the proposed Decision Support System was evaluated using multiple classification metrics derived from the confusion matrix, including Accuracy, Precision, Recall, and F1-Score. These metrics were selected to comprehensively evaluate the predictive consistency, classification stability, and robustness of the Random Forest model in forecasting stock market directional trends.

RESULTS AND DISCUSSION

The Results and Discussion section presents the performance evaluation of the proposed Random Forest-based Decision Support System in predicting the directional movement of Indonesian banking stocks. This section discusses the classification performance obtained from each stock model, followed by an analysis of feature importance to identify the most influential technical indicators affecting prediction outcomes.

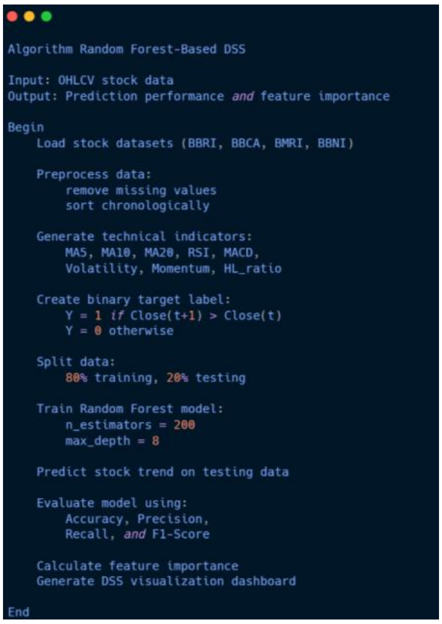
Classification Performance

Table 2 summarizes the Random Forest classification results for each stock. All models were trained on 187 samples and tested on 47 samples from the chronological test window (approximately the final two months of the observation period).

Table 2 Random Forest Classification Results per Stock

Stock	N	Test	Accuracy	Precision	Recall	F1-Score
BBRI	234	47	38.30%	36.96%	100.00%	0.5397
BBCA	234	47	51.06%	40.62%	76.47%	0.5306
BMRI	234	47	38.30%	29.03%	56.25%	0.3830
BBNI	234	47	51.06%	44.74%	89.47%	0.5965

Source: Random Forest model evaluation results (out-of-sample test set, n = 47 per stock).



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Algorithm Random Forest-Based DSS

Input: OHLCV stock data
Output: Prediction performance and feature importance

Begin
    Load stock datasets (BBRI, BBCA, BMRI, BBNI)

    Preprocess data:
        remove missing values
        sort chronologically

    Generate technical indicators:
        MA5, MA10, MA20, RSI, MACD,
        Volatility, Momentum, HL_ratio

    Create binary target label:
        Y = 1 if Close(t+1) > Close(t)
        Y = 0 otherwise

    Split data:
        80% training, 20% testing

    Train Random Forest model:
        n_estimators = 200
        max_depth = 8

    Predict stock trend on testing data

    Evaluate model using:
        Accuracy, Precision,
        Recall, and F1-Score

    Calculate feature importance
    Generate DSS visualization dashboard

End
```

Figure 4. Pseudocode of the Random Forest-based DSS for stock trend classification.

The pseudocode above illustrates the main workflow of the proposed Decision Support System (DSS) using the Random Forest algorithm for stock market trend prediction. The process begins with loading and preprocessing OHLCV stock data, followed by the generation of technical indicators such as Moving Average, RSI, MACD, and Volatility. The dataset is then transformed into binary trend labels and divided into training and testing data using a chronological split. Next, the Random Forest model is trained and used to predict stock trends. Finally, the system evaluates classification performance using Accuracy, Precision, Recall, and F1-Score, followed by feature importance analysis and dashboard visualization generation.

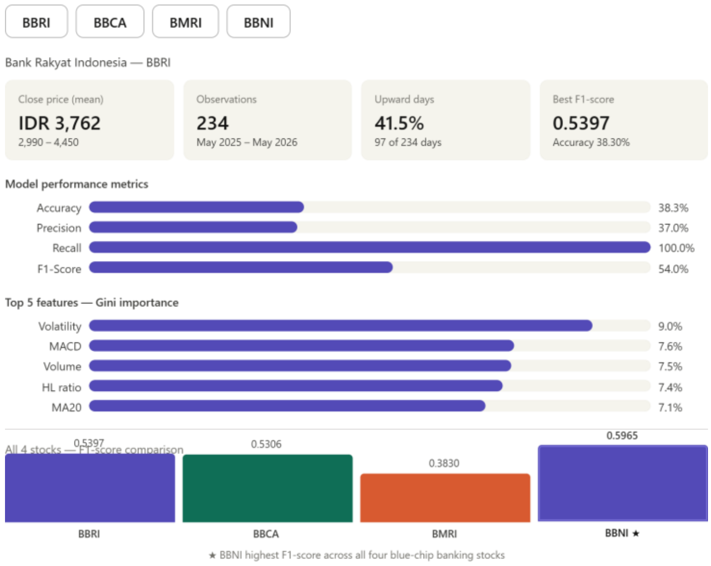

Figure 5. Classification performance comparison

The figure presents a comparative visualization of Random Forest classification performance metrics Accuracy, Precision, Recall, and F1-Score across the four Indonesian blue-chip banking stocks, wherein BBNI recorded the highest F1-Score of 0.5965 with a Recall of 89.47%, while BMRI yielded the lowest overall performance at an F1-Score of 0.3830, reflecting differential predictability among the observed banking equities.

BBNI achieved the highest F1-score of 0.5965, followed by BBRI (0.5397), BBCA (0.5306), and BMRI (0.3830). Notably, BBRI and BBNI exhibited exceptionally high Recall values (100% and 89.47%, respectively), indicating that the model correctly identified almost all upward price movements in the test period. This characteristic is particularly relevant for a DSS in a retail investment context, where missing a genuine upward signal (false negative) may be more costly than a false alarm (false positive).

The accuracy values ranging from 38.30% to 51.06% are consistent with findings in the literature for short-term daily direction prediction. Tan et al. (2019) reported comparable predictive performance for Random Forest-based stock selection in the Chinese A-share market, while Tran et al. (2024) reported similarly modest directional accuracy for machine-learning-based stock trend prediction in the Vietnamese market. The relatively lower accuracy observed in this study may reflect the elevated uncertainty in the Indonesian banking market during the observation window (May 2025-May 2026), which coincided with heightened macroeconomic uncertainty in the Indonesian banking sector during the observation period.

BMRI exhibited the lowest performance across all metrics. This may be attributed to its higher price volatility (Std = 328 IDR) and structural behavioral patterns in BMRI trading, which may not be fully captured by the 16 technical features employed. BBCA, despite having the largest absolute price range (5,850-9,700 IDR), maintained competitive performance, suggesting that normalized technical indicators effectively standardize cross-stock feature scales.

Feature Importance Analysis

Table 3 presents the average Gini-based feature importance across the four Random Forest models. Volatility (σ = 0.0896) and MACD (0.0756) emerge as the top two most informative features, collectively explaining approximately 16.5% of the model's decision-making weight.

Table 3 Average Feature Importance

Rank	Feature	Importance
1	Volatility	0.0896
2	MACD	0.0756
3	Volume	0.0752
4	HL_ratio	0.0737

Rank	Feature	Importance
5	MA20	0.0706
6	Vol_ratio	0.0689
7	Return	0.0687
8	RSI	0.0626
9	MA10	0.0613
10	Momentum	0.0612

Source: Random Forest feature importance output (Gini importance, averaged across four stock models).

The dominance of Volatility as the top feature aligns with theoretical expectations from market microstructure theory: periods of elevated volatility signal uncertainty in price discovery, creating predictable mean-reversion or momentum effects that decision trees can exploit (Baur et al., 2012). The high ranking of MACD confirms prior findings by Patel et al. (2015) and Zhang et al. (2016), who identified MACD as one of the most effective trend-following indicators in ensemble models. This finding contrasts with evidence from high-frequency trading contexts, where Deep et al. (2025) reported that raw price-based features dominate Random Forest predictions while classical technical indicators such as RSI and Bollinger Bands contribute only marginally, suggesting that the relative value of technical indicators versus price-level features may depend on the prediction horizon and market microstructure.

Volume-related features (Volume raw and Vol_ratio) ranked 3rd and 6th, collectively suggesting that trading volume dynamics carry substantial signal for the Indonesian banking stocks. This is consistent with the volume-price relationship documented by recent studies in emerging markets (Nguyen et al., 2015; Tan et al., 2019). In contrast, individual price-level features (Open, High, Low, Close) ranked in the bottom four, suggesting that normalized indicators are more informative than absolute price levels for binary trend classification.

These findings have direct implications for the DSS design: a streamlined feature set comprising Volatility, MACD, Volume, HL_ratio, and MA20 may achieve comparable performance to the full 16-feature set, reducing computational overhead and improving model interpretability for end-users of the decision support system.

Study Limitations

This study has several limitations that should be acknowledged. First, the analysis relies on a single one-year observation window (May 2025-May 2026), which may not capture longer-term market cycles or structural regime changes. Second, the feature set is restricted to price- and volume-derived technical indicators and does not incorporate macroeconomic variables such as interest rates or exchange rates that may also influence banking stock trends. Third, the Random Forest hyperparameters were fixed rather than exhaustively tuned, and no comparison was made against alternative ensemble or deep learning baselines such as XGBoost or LSTM. These constraints suggest that the reported performance should be interpreted as a reproducible baseline rather than an upper bound, and they motivate the directions for future research outlined below. Fourth, given the relatively small out-of-sample test set (n = 47 per stock), formal statistical significance testing (e.g., McNemar's test) and confidence intervals were not computed; the reported performance differences across stocks should therefore be interpreted descriptively rather than as statistically confirmed differences.

CONCLUSION

This study developed a Random Forest-based Decision Support System for predicting next-day stock price trend direction for four Indonesian blue-chip banking stocks (BBRI, BBCA, BMRI, BBNI). Using 234 observations per stock, 16 technical features derived from OHLCV data, and a chronological 80/20 train-test split, the RF model achieved F1-scores ranging from 0.3830 (BMRI) to 0.5965 (BBNI). Volatility and MACD were identified as the most informative features across all models, while absolute price-level features contributed the least discriminative power. This DSS framework provides a practical and reproducible foundation for intelligent investment decision support in the Indonesian banking equity market, particularly for retail investors on fintech platforms. The high Recall achieved for BBRI and BBNI makes the system especially suitable for upward-trend detection, which is the primary objective for long-position retail investors. Future research should explore the integration of macroeconomic features such as Bank Indonesia benchmark rates and USD/IDR exchange rates, comparison with LSTM and XGBoost baselines, a multi-class formulation that adds a "neutral" class for sideways-trending days, and real-time deployment testing within an actual fintech DSS interface.

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