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MODELING PRICE REVERSALS IN THE INDONESIAN EQUITY MARKET USING SUPERVISED MACHINE LEARNING

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Abstract

This study aims to develop a classification model using the random forest approach to identify mean reversion events in stock prices within the Indonesian capital market, which applies a long-only trading system and prohibits short selling. A mean reversion event is defined as a condition in which the price deviates from the average—specifically, the 50-period Simple Moving Average (SMA)—and subsequently moves back toward the average within a certain timeframe. The model is trained on historical data from three of the most liquid stocks in the financial sector: BBCA, BMRI, and BBNI. The features used include technical indicators such as SMA, Relative Strength Index (RSI), oscillators, and price autocorrelation. Two models were developed with variations in parameters including the reversal window, number of estimators, maximum depth, class weight, threshold, and classification probability. Evaluation was conducted using the Receiver Operating Characteristic (ROC) curve and precision-recall metrics, and further tested on out-of-sample data from cross-sector stocks to assess the model's generalization capability across various market conditions. In addition, the buy-sell strategy was tested through simulations and validated using Monte Carlo methods to evaluate the model's robustness in actual trading conditions and under random data variations. The results indicate that mean reversion events can be effectively modeled, yielding high reliability—particularly in models that are more selective or less responsive to short-term price fluctuations. The model also demonstrated strong simulation performance, especially when implemented with appropriate filtering methods.

Keyword: *Mean Reversion; Random Forest; Technical Indicators; Stock Market.*

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INTRODUCTION

The Indonesian stock market operates under specific regulatory rules that prohibit short selling, requiring investors to engage only in long positions (Antara, 2025). This regulatory environment limits the potential for profit to periods of rising stock prices. Consequently, Stock purchase opportunities become constrained, particularly during market pullbacks following a bull run or during phases of price consolidation. In such conditions, the ability to accurately time market entries and exits becomes essential, making the identification of reversal points critically important.

Machine learning has become widespread in financial markets, with most research focusing on two primary applications: price direction forecasting and short term trend or sentiment analysis (Rouf et al., 2021; Khan et al., 2022) . The main goal of these prediction efforts is to forecast stock price movements between specific time points to generate profits from market positions. However, despite the growing interest in machine learning applications, limited research has been conducted on its use for identifying potential reversal conditions in the Indonesian market.

Identifying potential reversal points enables market participants to anticipate future price action based on recognized historical patterns. This capability aids in risk management while pursuing profit opportunities. Although reversal detection is not entirely novel within the broader field of financial machine learning, its specific application to the Indonesian stock market remains relatively underexplored. .

This study fills the gap by formulating reversal detection as a supervised classification problem, focusing exclusively on long-only trading positions. Rather than predicting future price direction in a general sense, we train models to learn the historical conditions under which reversals are more likely to happen. To leverage a potentially diverse set of technical indicators and autocorrelated delta features, a Random Forest classifier is chosen with the rationale that it can adequately learn complex non linear interactions inherent in the data. Random Forests are widely used in financial classification problems due to their robustness in handling high-dimensional, non-linear feature spaces. Autoregressive models have been used for time series forecasting for a while to forecast temporal trend moves or finding when price trend transitions (Box et al., 2016; Ma et al., 2020). More recently hybrid approaches have emerged that incorporate autoregressive modeling of technical indicators commonly used by traders such as SMA, RSI, and momentum oscillators to enhance predictive accuracy in financial time series analysis (Almeida & Vieira, 2023).

Although much work has been published, the amount of research is still relatively low when taking into account emerging markets like Indonesia, and the attempt to use machine learning not to predict a direction, but rather to detect reversal patterns that lead to resumption of a trend. Prior work with machine learning has focused more on directional prediction or momentum classification, and less of a focus on identifying pattern recognition for reversal conditions when constrained to long only positions (Jiang, 2021).

RESEARCH METHOD

This study employed a quantitative methodology based on time series analysis using supervised machine learning to create a probabilistic reversal engine for identifying mean reversion events in financial markets. The Random Forest model was selected due to its capability to manage complex financial data and nonlinear patterns, predict mean reversion and highlight the relative importance of various indicators. As a binary classifier, it effectively estimates the probability of a price reverting to its mean. Historical intraday market data were obtained from a TradingView Premium account, followed by a

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comprehensive preprocessing phase. The stocks selected for reversal pattern recognition were three large-cap companies from the financial sector—BBCA, BMRI, and BBNI. These stocks were chosen because they exhibit high liquidity, broad investor participation, and strong leadership in sectoral price movement within the Indonesian market. Training the model on such representative instruments helps ensure that the machine learning algorithm learns generalized and stable reversal patterns that may be transferable to other assets with similar structural characteristics. All processes related to data handling, feature engineering, model training, and performance evaluation were conducted in a Python-based environment.

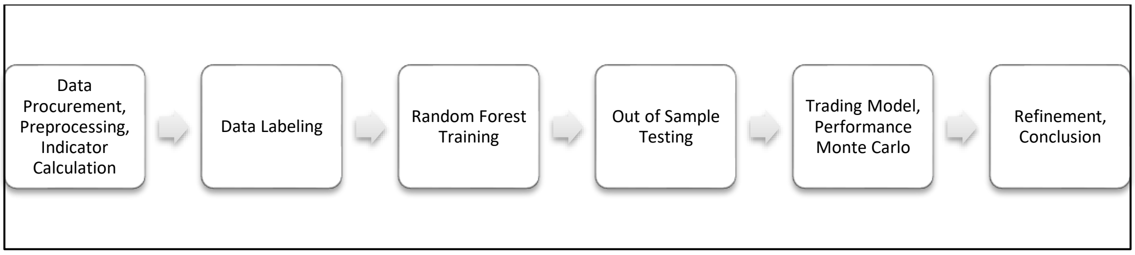

Figure 1. Research Flow

A variety of technical indicators were calculated to construct the feature set used for capturing momentum, volatility, cyclical structures, and behavioral signals associated with mean reversion (Almeida & Vieira, 2023). These indicators include the Simple Moving Average (SMA), standard deviation from the mean, Relative Strength Index (RSI), Awesome Oscillator, Squeeze Momentum, and recent price movement autocorrelation delta. For example The indicators in the feature set are designed to work synergistically. For instance, the Awesome Oscillator—defined as the difference between the 5-period and 34-period SMA of the median price—is a valuable tool for detecting cyclical momentum shifts. Local minima in the oscillator typically reflect momentum exhaustion or potential price reversals. Complementing this, the RSI is included to assess overbought or oversold conditions, the standard deviation captures the magnitude of deviation from the mean, and the autocorrelation delta measures trend weakening or behavioral shifts indicative of a reversal. Combined, these indicators form a multidimensional stack of features that enhance the model's ability to identify mean reversion setups.

The SMA used as a reference mean is a 50 period, fitted based on visual inspection of historical price patterns commonly referenced by market participants. This mid term mean reflects a popular equilibrium level used in discretionary trading, making it an intuitive anchor for defining reversion.

The labeling of a reversal was defined as a point where price deviates pass a specified amount of points from the mean (50 period SMA), and after that deviation, price travels back towards the mean. The anchor reversal point is defined at the local minimum value of the awesome oscillator and squeeze momentum, where the point indicates a likely inflection in momentum. This anchor point marks the end of a confirmed mean reversion event and was labeled with r_start = 1.

For model training, rows with missing indicator values were removed to ensure data quality. Binary target labels were then assigned by looking back 5, 10, or 15 days from each r_start = 1 point, with these preceding days labeled as 1, representing the lead up to a mean reversion. All other days remained labeled as 0. This setup enables the model to learn the technical conditions that typically precede a mean reversion event. A Random Forest

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classifier (Breiman, 2001) was subsequently trained on the labeled dataset, using the set of technical indicator features as input variables. .

Once trained, the model is evaluated on a fully out-of-sample dataset consisting of one stock from the financial sector and three stocks from different industries , none of which were included in the training phase. . This testing setup is designed to assess the model's ability to generalize across market contexts, ensuring that detected reversal patterns are not specific to a single industry. The model's probabilistic output is then integrated into a rule based, long only trading strategy, where trade entries are triggered based on the model's confidence in an impending mean reversion event. To optimize performance, a grid search is applied to evaluate different configurations of key trade parameters —particularly risk reward thresholds— enabling the strategy to dynamically adjust based on out of sample results. The complete strategy is evaluated using a rolling window validation framework, which preserves temporal causality and mitigates look-ahead bias , ensuring evaluation under realistic market conditions. To further examine the robustness and risk characteristics of the strategy, a Monte Carlo simulation is conducted by bootstrapping trade outcomes to analyze performance metrics such as the Sharpe ratio, drawdown, and downside risk across varying trade sequences

Finally , this study draws on the Efficient Market Hypothesis (EMH) as its theoretical fondation. The weak form of EMH posits that asset prices fully reflect all historical information, implying that past prices and volume data should have no predictive power for future returns. By training a machine learning model on historical technical indicators to predict future mean reversion behavior, this study implicitly tests the validity of the weak-form EMH. . If the model demonstrates significant out of sample predictive accuracy and trading profitability, it would suggests the existence of systematic inefficiencies in price formation—challenging the core assumptions of weak-form market efficiency. .

RESULTS AND DISCUSSION

In total, 15,819 data points were processed, spanning the period from 2004 to early 2025. . A total of 33 columns of technical indicators were constructed and a correlation matrix heatmap (figure 2) was generated to visualize the relationships among all variables. . The correlation analysis reveals that, while technical indicators exhibit moderate correlation with fundamental price variables, they contribute distinct layers of information beyond mere price data. This aligns with their intended function—to capture underlying market dynamics. . Lagged windows and delta-based variables display strong autocorrelation within their respective structures but maintain lower correlations with raw price levels. This suggests that such indicators are effective in representing temporal dependencies and behavioral shifts over time. While each indicator reflects unique patterns, the full set provides a diversified yet balanced input structure for modeling.

Subsequently, a labeling process was conducted. A new binary label column, **r_start**, was created to identify the initiation points of mean-reversion reversals, as illustrated in Figure 3. The upper panel displays the full set of labeled reversal points, while the lower panel provides a magnified view for greater clarity. After the labeling process was complete, models was trained via a random forest classifier and hyper parameter tuning is conducted using grid search. The search space contained the following parameter combinations: number of estimators: (50, 100), maximum depth of tree (None, 5, 10), and weighted class weight ({0: 0.3, 1: 0.7}, {0: 0.5, 1: 0.5} and 'balanced'). Prediction thresholds of 0.3, 0.5, and 0.7. Days prior to the start of reversal (main activity where the model learns from indicators) were also included in grid search with windows of 5, 10, and 15 days. From the grid search, the best 20 performance are listed in table 1 below.

Two distinct parameter configurations were chosen with the purpose of determining which model will perform better in out of sample testing set. The first configuration consist of a pre reversal window of 15 days, 50 estimators, maximum tree depth of 5, a class weight of 50:50 and a threshold of 0.3. The second configuration are pre-reversal window of 10 days, 100 estimators, maximum tree depth of 10, a class weight of 50:50, and threshold of 0.3.

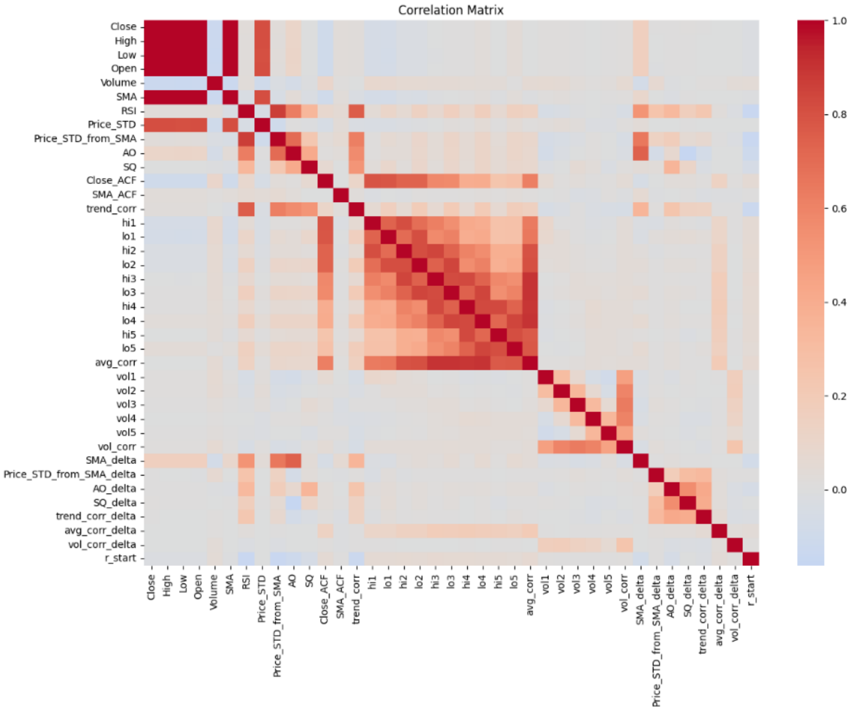

Figure 2. Indicators Correlational Heat Map

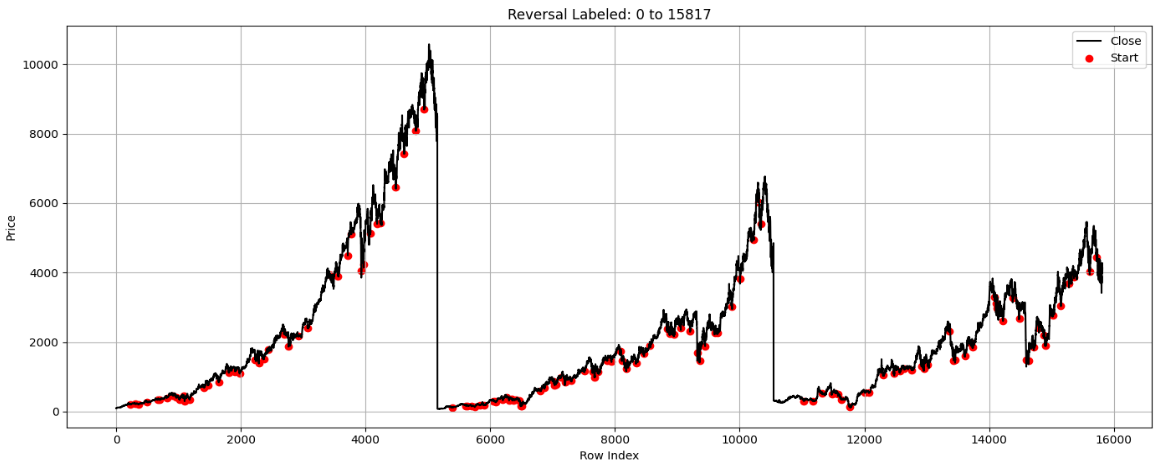

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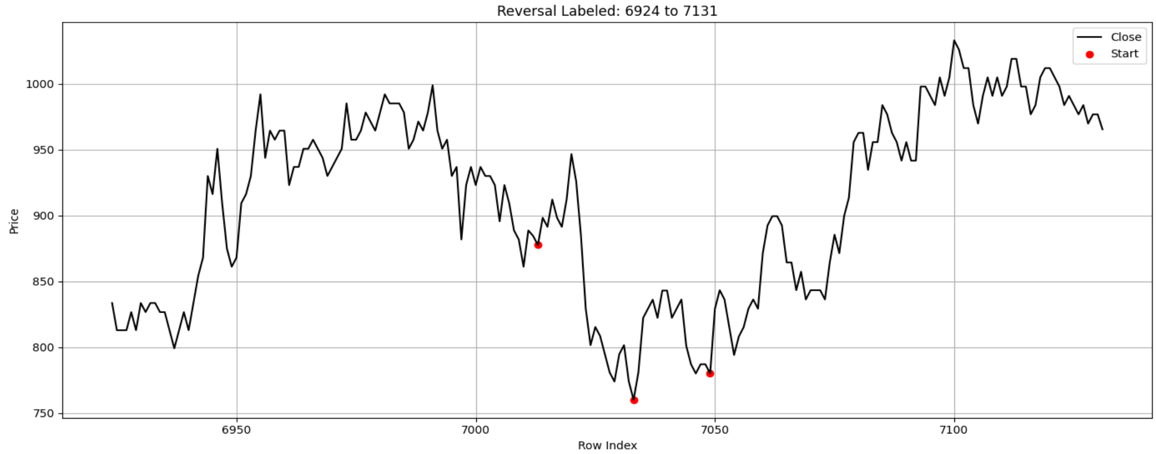
Figure 3. Labelled Data



The performance of both models was evaluated using the confusion matrix, precision recall curve, and receiver operating characteristic (ROC) curve. These metrics provide general accuracy of the classification, the trade off between precision and recall, and the model's discriminative power. Model 1 shows a rapid decline in precision with increasing recall, notably beyond recall threshold of 0.4. This pattern suggests limited robustness across varying classification thresholds, and experienced loss of precision as the model produced more true positives. In other words, the model becomes more sensitive but less reliable, suggesting an imbalance between detection rate and prediction confidence.

Model 2 exhibited a flatter, less oscillatory precision recall (PR) curve, indicating more stable performance and better trade-off between precision and recall across various thresholds. This stability suggests greater reliability and flexibility in threshold selection. For both models, the area under the ROC curve (AUC) was 0.89, reflecting comparable discriminatory power between classes. However, it is important to note that ROC curves are generally less sensitive to threshold variation than PR curves. The ROC curve for Model 2 appears slightly more convex at lower false positive rates, indicating a potential performance advantage in scenarios where minimizing false positives is critical.

Table 1. Grid Searched Model Parameters

days	est	depth	Class weight	Thd	f1	prec	recall	TP	FN	FP	TN
15	100	10	balanced	0.5	0.569	0.482	0.694	497	219	535	3810
15	100	10	{0: 0.5, 1: 0.5}	0.3	0.561	0.528	0.598	428	288	382	3963
15	50	5	{0: 0.5, 1: 0.5}	0.3	0.561	0.531	0.594	425	291	375	3970
15	100	5	{0: 0.3, 1: 0.7}	0.5	0.561	0.542	0.581	416	300	352	3993
15	50	10	balanced	0.5	0.561	0.473	0.689	493	223	550	3795
15	100	5	{0: 0.5, 1: 0.5}	0.3	0.560	0.534	0.588	421	295	367	3978
15	100	5	balanced	0.7	0.560	0.525	0.599	429	287	388	3957
15	50	5	balanced	0.7	0.559	0.528	0.594	425	291	380	3965
15	50	10	{0: 0.5, 1: 0.5}	0.3	0.558	0.527	0.594	425	291	381	3964
15	50	10	{0: 0.3, 1: 0.7}	0.5	0.556	0.572	0.541	387	329	289	4056
15	50	5	{0: 0.3, 1: 0.7}	0.5	0.555	0.531	0.581	416	300	367	3978
15	100	0	balanced	0.3	0.555	0.537	0.574	411	305	355	3990
15	50	10	{0: 0.3, 1: 0.7}	0.3	0.554	0.445	0.735	526	190	656	3689
15	100	10	{0: 0.3, 1: 0.7}	0.3	0.553	0.443	0.737	528	188	665	3680
15	50	0	{0: 0.3, 1: 0.7}	0.3	0.551	0.514	0.595	426	290	403	3942
15	100	10	{0: 0.3, 1: 0.7}	0.5	0.551	0.567	0.535	383	333	292	4053
15	100	0	{0: 0.5, 1: 0.5}	0.3	0.549	0.498	0.612	438	278	441	3904
15	100	0	{0: 0.3, 1: 0.7}	0.3	0.549	0.521	0.580	415	301	381	3964
15	50	0	balanced	0.3	0.549	0.517	0.585	419	297	392	3953
10	100	10	{0: 0.5, 1: 0.5}	0.3	0.546	0.511	0.588	291	204	279	4287

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In general, model 1 shows a priority towards recall at the expense of precision, producing a more aggressive identification of mean reversion cases, resulting in a higher amount of false positives, which could prove beneficial in situations where false negatives cause worse problems than acting on false signals.

Model 2 allows for a lower recall rate but much greater precision, meaning better performance for the situations where false positives carry large consequences. Despite the same AUC score, Model 2 exhibited better calibration stability and more reliable comprehensive model performance, meaning it is the better model in a situation optimizing for conservative strategy.

When comparing feature importance between model 1 and model 2, there are large and distinct differences in underlying predictive strategy and prioritization of signal, which produces performance differences in each model. Model 1 reflects a heavy momentum orientation, with the Relative Strength Index (RSI) accounting for 30 per cent of total feature importance, significantly higher than its contribution of 19 per cent in Model 2. Given the disproportionate importance assigned to the RSI feature in Model 1, it seems fair to assert that it is very momentum oriented, which probably includes a greater number of mean reversion predictions, and its high usage of features associated with price deviation from the SMA and the Awesome Oscillator (AO), which both indicate short, structurally sustained dislocations in price, attenuation patterns, or oscillatory behavior. In contrast, features associated with market structure, including volatility and correlation metrics, are relatively underweighted, reflecting a more reactive and less structurally informed approach.

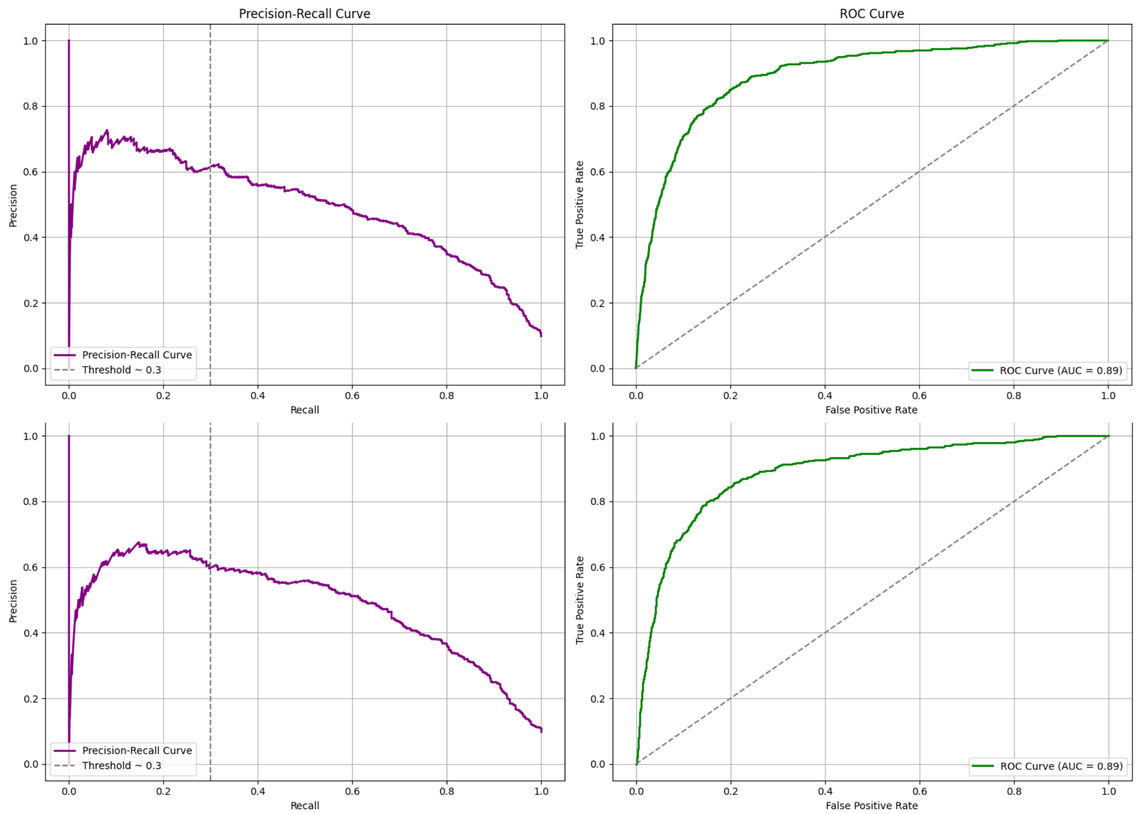

Figure 4. Model Precision and ROC Curve

Table 2. Model Indicator Weights

Model 1		Model 2	
RSI	0.30	RSI	0.19
Price_STD_from_SMA	0.20	Price_STD_from_SMA	0.14
AO	0.13	AO	0.10
trend_corr	0.11	trend_corr	0.08
SMA_delta	0.07	AO_delta	0.08
AO_delta	0.07	SMA_delta	0.07
SQ	0.03	SQ	0.06
trend_corr_delta	0.03	trend_corr_delta	0.05
SQ_delta	0.02	SQ_delta	0.05
avg_corr	0.02	avg_corr	0.04
Price_STD_from_SMA_delta	0.01	avg_corr_delta	0.04
avg_corr_delta	0.01	vol_corr	0.04
vol_corr_delta	0.01	Price_STD_from_SMA_delta	0.04
vol_corr	0.00	vol_corr_delta	0.03

Model 2 is more evenly weighted with respect to feature importance, and incorporated more complementary indicators. While RSI remains its most influential feature, its relative importance is reduced, and a greater share of importance is allocated to other indicators such as the Squeeze (SQ), trend correlation changes (trend_corr_delta), and various delta from auto correlation metrics. This distribution marks Model 2 sensitivity to more varied market dynamics, including volatility compression, trend price shifts, and inter feature dependencies. Such configuration aligns with Model 2 conservative prediction profile, marked by higher precision and improved threshold stability, and flatter PR curve.

Model 1 is a momentum based statistical model that is optimized for recall under an event based specification to maximize the capture of all of the potential mean reversion events even at the potential expense of some degree of false positives. In contrast, Model 2 has a structurally diverse and calibrated design, it is well balanced in terms of overall performance, more structured, conditioned on precision and reliability in the face of varying market conditions. The models embody both different strategies and confidently reframes trade contextually with varying potential risk profiles and tolerances.

Figure 5. Model 1 Probability 50%

Figure 6. Model 2 Probability 50%

Next step is the testing phase where initially, the two models were tested in one stock (BBRI) from same industry as trained model. The tested results are illustrated in Figure 5, where at a 50% probability threshold, Model 1 produced many more signals than Model 2, indicated more sensitivity to possible reversal trade opportunities, probably at the cost of accuracy. However, at the probability threshold of 70%, Model 1 produced no trade signals, indicating limited ability to identify high confidence opportunities. While Model 2 was able to maintain trade signals even at high probability thresholds, indicating greater robustness or consistency in identifying high confidence reversal trades.

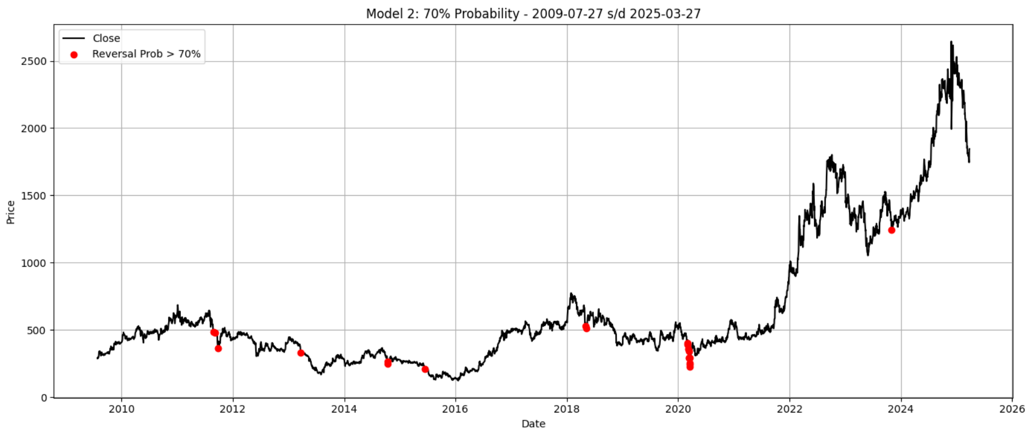

Figure 7. Predicted Reversals

The initial test results suggest that Model 1 is more aggressive, as indicated by the higher number of trade signals generated at lower probability thresholds , While this leads to more frequent trades, the marginal improvement in returns implies increased trading activity with limited performance gain, resulting in greater management overhead. In contrast, Model 2 demonstrates consistently reliable performance even at stricter confidence thresholds (e.g., 70% probability). This supports the use of Model 2 in strategies aimed at improving accuracy and reducing noise. Model 2 provides strong evidence of its ability to identify high-confidence reversal points.

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Following training, both models were tested on stocks within the same industry group. To further assess generalizability, the models were also evaluated on three out-of-sample stocks from different industry sectors—ADRO, PGAS, and TLKM. These stocks were randomly selected, and a visual inspection was conducted beforehand to confirm the presence of mean-reverting patterns suitable for testing. Model effectiveness on these new stocks was evaluated based on the number of reversal signals generated and the corresponding probability threshold levels at which these signals occurred. .

For each predicted reversal point, a long only trading strategy was simulated by applying a range of predefined stop loss (SL) and take profit (TP) levels, constrained by a maximum risk to reward ratio of 1:2. Specifically, SL thresholds ranged from 50 to 1,000 points and TP thresholds from 50 to 2,000 points, both varied in increments of 25 points. A comprehensive grid search was then conducted to evaluate all possible SL-TP combinations and identify the most effective configurations for each stock, based on predicted mean reversal points. To evaluate the robustness and generalizability of these optimized strategies beyond conventional backtesting, Monte Carlo simulations were next employed. Two separate simulations were performed for each stock, one based on the top 100 highest Sharpe ratio, and another by complete set of grid searched strategies (table 3).

In each simulation, 1000 synthetic equity curves were generated by randomly resampling trade level profit and loss (PnL) values with replacement, while maintaining the original number of trades per strategy. This approach models alternative trade sequences under the assumption of independent trade outcomes, which will produce a probabilistic framework to assess the stability of strategy performance.

The distribution of final PnLs was summarized using the median, 5th and 95th percentiles, providing a good view of the expected performance range and tail risk. This analysis enabled the identification of configurations that demonstrate resilience across randomized conditions, helping to differentiate between robust strategies and those potentially overfit to historical data.

For ADRO, both models demonstrated strong and consistent profitability. The narrow spread between the 5th and 95th percentile profit and loss (PnL) distributions, combined with high median final PnLs, confirmed reliable performance. Model 2 outperformed Model 1, where it yield higher returns across both the top 100 SL TP combination and the full parameter grid. These results align with recent findings (He et al., 2023), which demonstrated that parameter optimization can significantly enhance returns when properly tailored to specific securities. The model's performance remained stable across a broad range of stop loss (SL) and take profit (TP) configurations, indicating adaptability and resilience, a phenomenon also observed in research on optimal trade execution with mean reverting signals (Kolm & Ritter, 2019).

Table 3 Monte Carle Simulated Model Strategy Results (in price points)

Stock	Strategy	Model	Trades	Median PnL	5th Perc PnL	95th Perc PnL
ADRO	Top 100	Model 1	300	128,462.50	111,718.75	143,878.75
		Model 2	285	140,987.50	122,275.00	158,557.50
	All Strategies	Model 1	9,259	2,362,050.00	2,277,367.50	2,448,078.75
		Model 2	8,711	2,488,450.00	2,403,107.50	2,574,777.50
PGAS	Top 100	Model 1	412	97,850.00	66,531.25	127,153.75
		Model 2	1,984	98,400.00	70,962.50	126,432.50
	All Strategies	Model 1	44,165	-342,937.50	-538,300.00	-152,198.75
		Model 2	34,265	-1,279,662.50	-1,418,885.00	-1,118,168.75
TLKM	Top 100	Model 1	245	169,775.00	144,023.75	195,058.75
		Model 2	290	148,112.50	122,846.25	172,413.75
	All Strategies	Model 1	29,201	3,142,462.50	2,984,838.75	3,296,725.00

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Model 2	28,048	2,408,137.50	2,254,483.75	2,570,653.75

PGAS produced a contrast different profile. Even though top 100 strategies for both models achieved positive returns, the aggregate performance across the entire grid was negative, especially for Model 2. This outcome suggests that certain stock has high sensitivity to parameter selection, with a significant proportion of configurations resulting in substantial losses. Such condition supports concerns raised in recent literature (Lim & Zohren, 2021), which demonstrates cases where apparent mean reversion is actually due to other market mechanisms. While Model 2's top 100 strategy also showed an increased trade count, it did not translate into improved robustness, highlighting the need for caution in applying same models specifically to PGAS.

For TLKM, both models performed equally well, with Model 1 slightly outperforming Model 2. The consistency and magnitude of positive returns across the full grid search for Model 1, alongside tight confidence intervals, pointed to a reliable and stable model for this asset. This is consistent with recent research (Wang et al., 2019), which validates that certain stocks consistently show stronger mean reverting properties due to specific market microstructure factors. Although Model 2's performance was marginally lower, it remained statistically sound, confirming the viability of the mean reversion approach in TLKM's market context.

These findings emphasize the critical importance of asset specific validation, a conclusion strongly supported by studies showing that models work well for specific stocks but will fail for others (Krauss et al., 2017). While the mean reversion models demonstrated strong statistical viability and robust performance in stocks such as ADRO and TLKM, their generalizability did not fully extend across all assets, evidenced by underperformance in PGAS.

In conclusion, the Monte Carlo simulation results confirm that the proposed mean reversion models are both viable and statistically robust within favorable market environments, particularly for stocks like ADRO and TLKM. The consistent generation of positive expectancy across a wide parameter space validates the models practical potential when aligned with suitable market dynamics. However, the marked underperformance in PGAS highlights a key limitation: mean reversion models success is contingent upon asset specific characteristics, necessitating tailored implementation strategies, as demonstrated by research on the robustness of mean reversion strategies under different market conditions (Dixon, 2018).

These results underscore the imperative of context aware modeling and emphasize the need for careful optimization of risk reward parameters. As recent studies argue (Zhang et al., 2020), pure price based mean reversion may require supplementation with additional data sources for maximum effectiveness. Although the models exhibit strong foundational structure, effective deployment in live trading scenarios requires additional layers of filtering, adaptive stop loss / take profit calibration, and potentially discretionary overlays or dynamic mechanisms. The empirical evidence, supported by recent academic literature, suggests that quantitative models can outperform market efficiency assumptions, but only when reinforced with rigorous validation, domain expertise, and robust risk management frameworks.

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CONCLUSION

This study demonstrates it is possible to use Random Forest classifiers to recognize mean reversal events in the Indonesian stock market, which has rules preventing traders from short selling. By focusing on the identification of reversal patterns rather than direct price direction forecasting, the study offers a novel approach tailored to conditions of the Indonesian market.

A number of disparate technical indicators, captured diverse aspects of market reversal dynamics including momentum, volatility and cyclical behavior. The comparative analysis of two Random Forest models reveals that a balanced feature importance distribution, as seen in Model 2, leads to higher precision and more reliable performance across different market conditions. While model 1 offers more trading opportunities, simulated results proves that less frequent but reliable signals are preferable in real world trading.

Out of sample testing on stocks from various industries confirms the generalizability of the models, with Model 2 maintaining robust performance even under stricter probability thresholds. Monte Carlo simulations further substantiate the model effectiveness, particularly in stocks like ADRO and TLKM, while also highlighting the need for custom tailored strategy for certain stocks, as evidenced by the models' underperformance in PGAS.

The integration of machine learning techniques, specifically Random Forest classifiers, into trading strategies offers potentially profitable scenarios for trading and enhancing decision making in the Indonesian stock market. Especially in anticipating reversals with emphasizing the need of context specific approaches and rigorous validation in financial modeling.

Future research could focus on enhancing reversal point prediction by integrating a more data driven approach, incorporating sentiment analysis derived from qualitative sources or developing additional data augmented modeling frameworks.

REFERENCES

Almeida, L., & Vieira, E. (2023). Technical Analysis, Fundamental Analysis, and Ichimoku Dynamics: A Bibliometric Analysis. *Risks*, *11*(8).

Antara. (2025). *OJK tunda implementasi short selling dan kaji buyback saham tanpa RUPS*. https://www.antaranews.com/berita/4685601/ojk-tunda-implementasi-short-selling-dan-kaji-buyback-saham-tanpa-rups

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time Series Analysis: Forecasting and control* (5th ed.). Wiley.

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5–32.

Dixon, M. (2018). Sequence classification of the limit order book using recurrent neural networks. *Journal of Computational Science*, *24*, 277–286.

He, C., Wang, T., Liu, X., & Huang, K. (2023). An Innovative High Frequency Statistical Artbitrage in Chinese Futures Market. *Journal of Innovation & Knowledge*, *8*(3), 100369.

Jiang, W. (2021). Applications of deep learning in stock market prediction: Recent progress. *Expert Systems with Applications*, *184*(July), 115537.

Khan, W., Ghazanfar, M. A., Azam, M. A., Karami, A., Alyoubi, K. H., & Alfakeeh, A. S. (2022). Stock market prediction using machine learning classifiers and social media, news. *Journal of Ambient Intelligence and Humanized Computing*, *13*(7), 3433–3456.

Kolm, P. N., & Ritter, G. (2019). Dynamic Replication and Hedging: *The Journal of Financial Data Science*, *1*, 159–171.

E-ISSN : 3032-2480
https://journal.feb.uniku.ac.id/digibe

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. *European Journal of Operational Research*, *259*(2), 689–702.

Lim, B., & Zohren, S. (2021). Time-series forecasting with deep learning: A survey. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2194).

Ma, L., Grant, A. J., & Sofronov, G. (2020). Multiple change point detection and validation in autoregressive time series data. *Statistical Papers*, *61*(4), 1507–1528.

Rouf, N., Malik, M. B., Arif, T., Sharma, S., Singh, S., Aich, S., & Kim, H. C. (2021). Stock market prediction using machine learning techniques: A decade survey on methodologies, recent developments, and future directions. *Electronics (Switzerland)*, *10*(21).

Wang, J., Zhang, Y., Tang, K., Wu, J., & Xiong, Z. (2019). AlphaStock: A buying-winners-and-selling-losers investment strategy using interpretable deep reinforcement attention networks. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1900–1908.

Zhang, Z., Zohren, S., & Roberts, S. (2020). Deep Reinforcement Learning for Trading. *Journal of Financial Data Science*, *2*(2), 25–40.