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Evaluating Machine Learning Signal Validation in Bollinger Band Mean-Reversion Trading: A Strategy-Dependent Experimental Study

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ABSTRACT

Financial markets exhibit changing volatility and regime-dependent behavior, making the interaction between deterministic trading rules and machine-learning validation an important empirical question. This study evaluates a Bollinger Band Mean Reversion (BBMR) strategy and examines whether a generic machine-learning filtering layer improves the characteristics of its candidate signals. The supplied experimental registry contains 30 independent configurations: five unfiltered baseline configurations and 25 ML-assisted configurations formed by crossing five timeframes—1-minute, 3-minute, 5-minute, 15-minute and 1-hour—with five confidence settings of 0.50, 0.53, 0.55, 0.57 and 0.60. Across the registry, 99,807 recorded orders are reported. The five baseline configurations show a descriptive aggregate win percentage of 66.55% and a row-wise Net Realized sum of 316,612.56. The 25 ML-assisted configurations show a descriptive aggregate win percentage of 19.85% and a row-wise Net Realized sum of -135,285.70. Increasing the ML confidence setting reduces recorded activity from 15,278 orders at 0.50 to 2,373 at 0.60, but the reduction in activity is not accompanied by a corresponding improvement in win percentage or aggregate descriptive profitability. The ML-assisted win percentage remains below the baseline at every tested timeframe, and only the 1-hour ML group has a positive row-wise Net Realized sum. An implementation-level inspection further indicates that the validation feature layer is dominated by generic contextual variables such as moving-average slope, momentum, volatility and risk/reward measures rather than direct Bollinger mean-reversion descriptors. The findings therefore suggest a strategy-dependent limitation: the tested ML filter changes the trade population substantially, but does not improve the evaluated BBMR strategy and may be mismatched to the short-horizon mean-reversion mechanism. The result should not be generalized to all ML methods or all BBMR implementations; it is an empirical finding for the supplied configuration.

Keywords: Bollinger Bands, Mean Reversion, Machine Learning, Signal Validation, Algorithmic Trading, Feature Engineering, Multi-Timeframe Analysis, Backtesting, Strategy-Dependent Validation.

1. INTRODUCTION

Algorithmic trading systems increasingly combine deterministic technical-analysis rules with statistical and machine-learning components. A deterministic strategy can provide a transparent mechanism for generating candidate trades, while a validation layer can condition the acceptance of those candidates on additional market-context information. The usefulness of such a layered architecture depends on whether the validation model captures the mechanism that generates returns in the underlying strategy.

Bollinger Bands provide a volatility-sensitive representation consisting of a central moving average and upper and lower bands whose distance from the center changes with observed dispersion [1]. In a mean-reversion interpretation, price excursions away from the central tendency are treated as potential opportunities for movement back toward that tendency. Such strategies can generate relatively short-horizon opportunities in which the timing and magnitude of reversion may be more important than broad directional trend strength.

The present study examines a different role for machine learning. The ML component is not used to replace the BBMR signal generator. Instead, the rule-based strategy produces candidate signals and the ML layer evaluates whether those candidates should

be retained or filtered. The practical research question is not simply whether ML can predict prices, but whether a generic validation layer improves an already functioning mean-reversion strategy.

The supplied BBMR registry contains 30 independent configurations: five baseline runs and 25 ML-assisted runs. The experiments span five timeframes and five confidence settings. The results are particularly informative because the baseline strategy is consistently profitable in the supplied registry, whereas the ML-assisted configurations materially reduce trade frequency and show much lower win percentages. This creates an opportunity to study not only whether ML improves performance, but whether filtering changes the composition of the strategy's trade population in a way that can damage the original return-generating mechanism.

1.1 Bollinger Band Mean Reversion Signal Generation

The BBMR strategy is treated as the deterministic candidate-signal generator. In conceptual terms, Bollinger Bands describe price location relative to a moving-average center and volatility-adjusted outer boundaries. A mean-reversion strategy uses excursions from that central tendency as candidate opportunities and seeks subsequent movement back toward the mean. The supplied registry does not expose the complete code-level entry, exit, band-period, deviation, position-sizing or trade-management specification. Accordingly, this study does not reconstruct undocumented rules; it evaluates the recorded outputs of the supplied BBMR configurations.

The ML settings encoded in the experiment identifiers as ml50, ml53, ml55, ml57 and ml60 are treated as confidence thresholds of 0.50, 0.53, 0.55, 0.57 and 0.60, respectively. This mapping is used only for the experimental sensitivity analysis.

2. RESEARCH QUESTIONS AND OBJECTIVES

RQ1: Does ML-based signal validation improve the observed performance characteristics of the baseline BBMR strategy?

RQ2: How does the ML confidence setting affect trade frequency across 1m, 3m, 5m, 15m and 1h timeframes?

RQ3: How does observed win percentage vary across ML confidence settings and timeframes?

RQ4: Does ML filtering preserve or alter the economic characteristics of the baseline BBMR trade population?

RQ5: What evidence supports or challenges the hypothesis that generic ML validation is strategy-dependent rather than universally beneficial?

H0: The ML validation layer does not improve the evaluated BBMR strategy relative to the unfiltered baseline.

H1: The ML validation layer improves the evaluated BBMR strategy relative to the unfiltered baseline.

The study also treats strategy-feature alignment as an exploratory explanatory question: whether the validation feature set represents the short-horizon mean-reversion mechanism sufficiently to distinguish desirable BBMR signals from undesirable ones.

3. LITERATURE REVIEW

3.1 Bollinger Bands and Technical Analysis

Bollinger Bands were introduced as a volatility-aware technical-analysis representation in which the width of the outer bands responds to market dispersion [1]. Their algorithmic form provides a reproducible representation of price location relative to a moving average and recent volatility.

3.2 Computational Technical Analysis

Lo, Mamaysky and Wang proposed a computational framework for technical pattern recognition and empirical evaluation [2]. Their work supports the methodological principle that chart-derived rules can be translated into explicit computational procedures and tested systematically rather than evaluated only through subjective visual interpretation.

3.3 Mean Reversion and Algorithmic Trading

Mean-reversion strategies differ conceptually from directional trend-following strategies because their expected return mechanism is associated with the correction of temporary deviations from a reference level. Consequently, a validation model designed around generic trend, momentum or regime features may not necessarily preserve the information that determines whether a particular deviation will revert within the strategy's effective holding horizon.

3.4 Machine Learning in Financial Trading

Reviews of machine learning in financial forecasting document substantial variation in data sources, features, algorithms and evaluation procedures [3,4]. Financial machine-learning research also emphasizes non-stationarity, careful validation and the importance of aligning model design with the statistical characteristics of the task [5,6].

3.5 Data Snooping and Backtest Overfitting

Technical-rule research is exposed to data-snooping and multiple-comparison effects when many configurations are examined. Sullivan, Timmermann and White emphasized the need to account for data-snooping in technical trading-rule evaluation [7]. Bailey et al. discussed the probability of backtest overfitting when many configurations are explored [8]. These considerations motivate treating the 30 BBMR configurations as independent experiments rather than as one optimized portfolio.

3.6 Research Gap

The narrower empirical gap addressed here is the evaluation of machine learning as a post-signal validation layer around a deterministic mean-reversion strategy. The study extends a simple signal-frequency comparison by examining win percentage, profit factor, Net Realized and maximum drawdown, and by inspecting whether the implemented feature layer is aligned with the mechanism of Bollinger mean reversion.

4. RESEARCH METHODOLOGY

The study follows a computational experimental-evaluation approach. The BBMR strategy is treated as the deterministic candidate-signal generator, while ML-assisted configurations are evaluated as separate filtering experiments. Each configuration is analyzed independently. Row-wise aggregation is used only as a descriptive summary and is not interpreted as a pooled portfolio.

4.1 Methodological Pipeline

Table -1

Stage	Method
1. Market Data	Historical market observations represented through the supplied BBMR experiment registry.
2. Bollinger Representation	Bollinger Band structure used by the deterministic mean-reversion strategy.
3. Candidate Signal Generation	BBMR produces candidate trading signals.
4. Context / Feature Layer	Generic contextual features are constructed for the validation stage.
5. ML Validation	The candidate is evaluated using the configured ML confidence setting.
6. Signal Acceptance / Filtering	Candidates satisfying the validation criterion are retained; others are filtered.
7. Performance Evaluation	Orders, wins, losses, win percentage, profit, loss, Net Realized and maximum drawdown are evaluated at configuration level.

4.2 Data Partition and Experimental Registry

The broader research program is designed around development/training and unseen evaluation periods. However, the supplied BBMR experiment registry itself does not contain separate TRAIN rows. Therefore, this paper does not assign calendar boundaries or claim a training-period result that is absent from the BBMR registry. The empirical evidence reported here is the supplied baseline-versus-ML test-stage registry.

Table -2

Configuration Group	Runs	Experimental Role
Baseline	5	Unfiltered BBMR reference configurations across five timeframes
ML-Test	25	Five ML confidence settings crossed with five timeframes
Total	30	Independent configurations in the supplied BBMR registry

BBMR Experimental Design

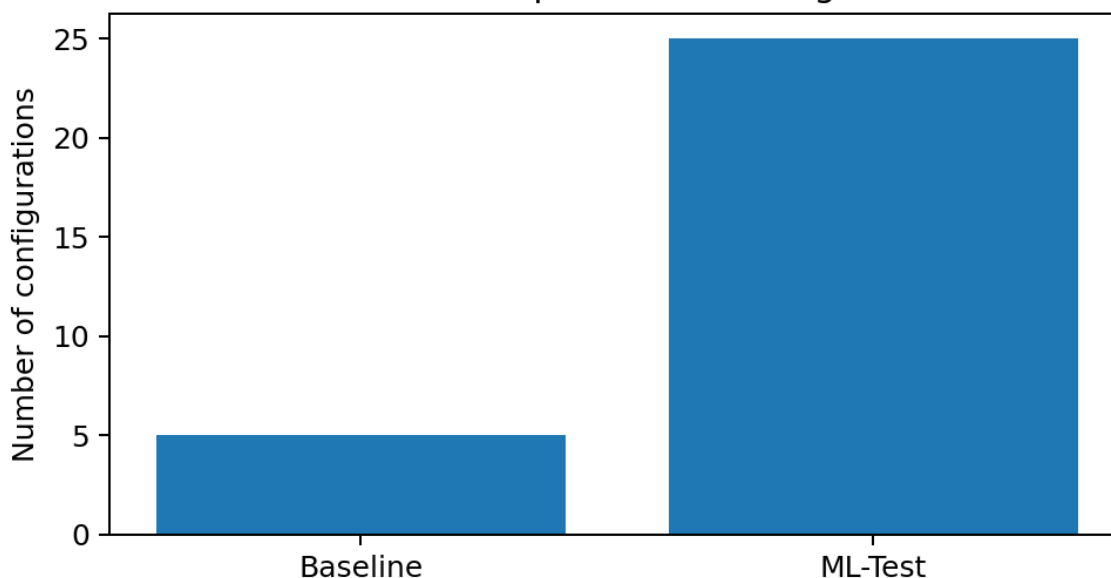


Figure -1: Source-defined BBMR experimental design: 5 baseline and 25 ML-assisted configurations.

4.3 Complete Experimental Design

Table -3

Dimension	Levels
Timeframe	1m, 3m, 5m, 15m, 1h
ML confidence	0.50, 0.53, 0.55, 0.57, 0.60
Baseline configurations	5
ML-assisted configurations	25
Total configurations	30

4.4 Evaluation Metrics

Table -4

Metric	Definition / Role
Total Orders	Number of recorded orders in a configuration.
Wins / Losses	Counts reported by the source registry.
Win Percentage	Wins divided by total orders, expressed as a percentage.
Total Profit	Reported aggregate profit within a configuration.
Total Loss	Reported aggregate loss within a configuration.
Net Realized	Reported difference between Total Profit and Total Loss.
Profit Factor	Total Profit divided by Total Loss.
Maximum Drawdown	Maximum reported drawdown for the individual configuration.

Where aggregate summaries are shown across several independent configurations, the paper reports row-wise descriptive sums. Such sums do not represent a single compounded account because different timeframes and confidence settings are separate experiments.

4.5 ML Validation and Feature Engineering

An implementation-level inspection of the feature-engineering layer provides additional context for interpreting the results. The common feature generator constructs strategy metadata and trade context, then computes moving-average slope, absolute moving-average slope, market regime, stop-loss points, take-profit points and risk/reward ratio. It further derives generic variables such as trend strength, momentum, volatility, risk pressure, reward pressure and signal quality. The feature layer permits runtime overrides of these values.

The feature set is therefore predominantly contextual and trend/risk oriented. For a non-Renko BBMR strategy, the implementation does not automatically add Renko-specific features, and the inspected feature generator does not directly represent several intuitive mean-reversion descriptors such as normalized distance from the Bollinger middle band, distance from the upper or lower band in volatility units, reversion velocity, time since mean contact, or short-horizon return-to-mean behavior. This observation is not treated as proof of causality, but it provides a plausible strategy-alignment hypothesis for the observed filtering effect.

4.6 ML Validation Architecture

Table -5

Stage	Function
BBMR Signal Generation	Generates candidate mean-reversion BUY/SELL signals.
Context / Feature Layer	Represents the candidate using generic market and risk context.
ML Validation	Evaluates the candidate using the configured confidence threshold.
Confidence Threshold	Controls validation selectivity and therefore trade population size.
Trade Management	Handles accepted candidates according to the underlying strategy implementation.

The architecture can therefore be represented as: BBMR SIGNAL GENERATION → FEATURE ENGINEERING → ML VALIDATION → SIGNAL ACCEPTANCE/REJECTION → TRADE MANAGEMENT. The important experimental distinction is that the ML component does not replace BBMR; it changes which BBMR candidates are allowed to reach trade management.

4.7 Evaluation Scope

The experiment is historical and computational. It is not a live execution study. The supplied registry provides sufficient information for configuration-level comparison but does not provide a reconstructed combined equity curve or order-level evidence for every individual filtered and rejected signal.

5. EXPERIMENTAL RESULTS

The supplied registry contains 99,807 recorded orders across 30 independent configurations: 56,324 baseline orders and 43,483 ML-assisted orders. Because configurations are independent, these totals are descriptive coverage measures rather than a pooled account.

5.1 Baseline BBMR Results

Table -6

TF	Orders	Wins	Losses	Win %	Profit	Loss	Net Realized	Max DD
1m	34,342	22,617	11,704	65.86%	1,471,645.78	1,306,621.24	165,024.54	24,991.88
3m	11,720	7,928	3,787	67.65%	835,420.13	781,015.07	54,405.06	19,616.23
5m	7,262	4,947	2,314	68.12%	677,629.47	614,035.00	63,594.47	17,507.11
15m	2,409	1,614	795	67.00%	410,585.79	391,557.37	19,028.42	28,325.32
1h	591	380	211	64.30%	205,782.76	191,222.69	14,560.07	44,305.05

The five baseline configurations report positive Net Realized values in every timeframe. The observed win percentage ranges from 64.30% at 1h to 68.12% at 5m. The row-wise descriptive Net Realized sum is 316,612.56.

5.2 ML-Test Confidence Sensitivity

Table -7

Conf.	Runs	Orders	Wins	Losses	Win %	Net	PF	Max DD
0.50	5	15,278	3,033	12,245	19.85%	-26,343.12	0.99	35,487.75
0.53	5	12,464	2,438	10,026	19.56%	-54,158.64	0.97	39,115.11
0.55	5	7,805	1,570	6,235	20.12%	-17,671.12	0.99	27,096.81
0.57	5	5,563	1,099	4,464	19.76%	-29,886.52	0.97	26,930.34
0.60	5	2,373	492	1,881	20.73%	-7,226.30	0.98	29,287.83

ML-Test Order Activity vs Confidence

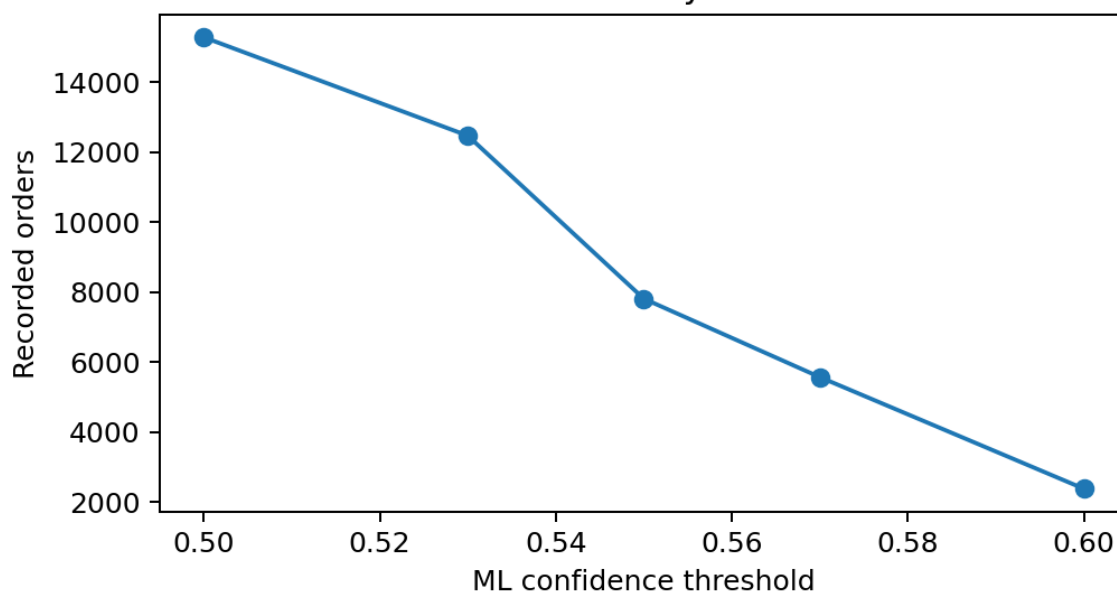


Figure -2: Recorded ML-Test order activity decreases as confidence increases.

ML-Test Win Percentage vs Confidence

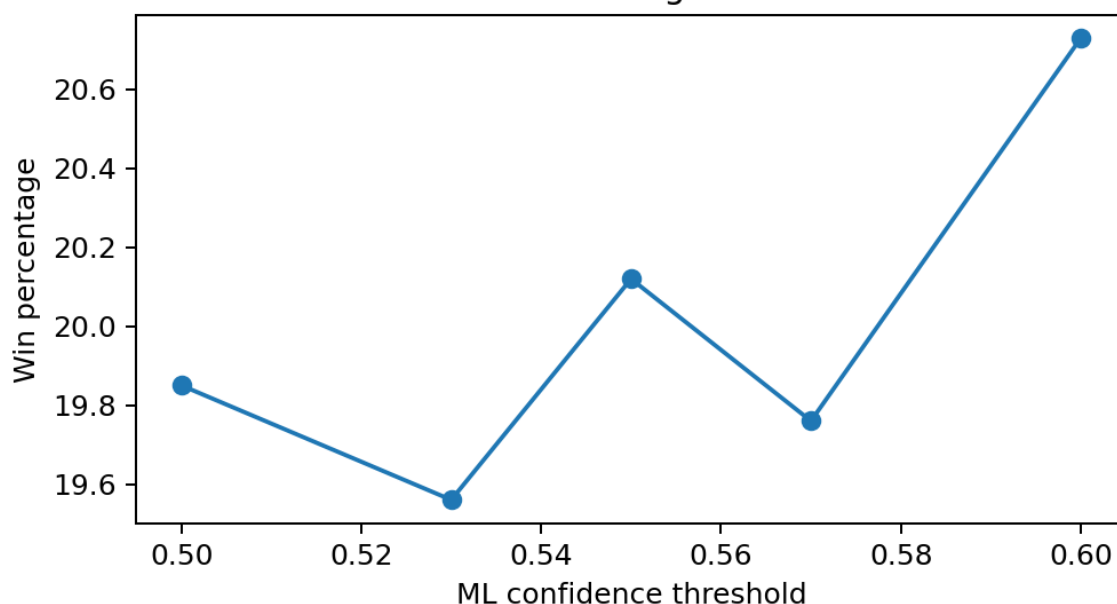


Figure -3: Aggregate ML-Test win percentage across confidence settings.

Increasing confidence from 0.50 to 0.60 reduces recorded ML-Test orders from 15,278 to 2,373, a reduction of approximately 84.5%. The win percentage does not increase monotonically: it moves from 19.85% to 19.56%, 20.12%, 19.76% and 20.73% across the five thresholds. All five threshold-level Net Realized sums remain negative.

5.3 Timeframe-Level ML-Test Results

Table -8

TF	Orders	Wins	Losses	Win %	PF	Net	Max DD
1m	28,934	5,802	23,132	20.05%	0.99	-21,624.71	30,050.74
3m	7,673	1,485	6,188	19.35%	0.94	-81,274.68	39,115.11
5m	5,062	993	4,069	19.62%	0.98	-25,546.44	28,356.43
15m	1,560	303	1,257	19.42%	0.96	-26,298.44	31,521.09
1h	254	49	205	19.29%	1.10	19,458.57	15,725.77

The ML-assisted group is highly selective at every timeframe. The 1m group contains the largest number of ML-assisted orders, while the 1h group contains the fewest. The observed ML win percentage is below the corresponding baseline in every timeframe. The 1h ML group is the only timeframe whose row-wise Net Realized sum is positive.

5.4 Baseline versus ML-Test Comparison

Table -9

TF	Base Orders	Base Win %	ML Orders	ML Win %	Order Reduction	Base Net	ML Net
1m	34,342	65.86%	28,934	20.05%	15.7%	165,024.54	-21,624.71
3m	11,720	67.65%	7,673	19.35%	34.5%	54,405.06	-81,274.68
5m	7,262	68.12%	5,062	19.62%	30.3%	63,594.47	-25,546.44
15m	2,409	67.00%	1,560	19.42%	35.2%	19,028.42	-26,298.44
1h	591	64.30%	254	19.29%	57.0%	14,560.07	19,458.57

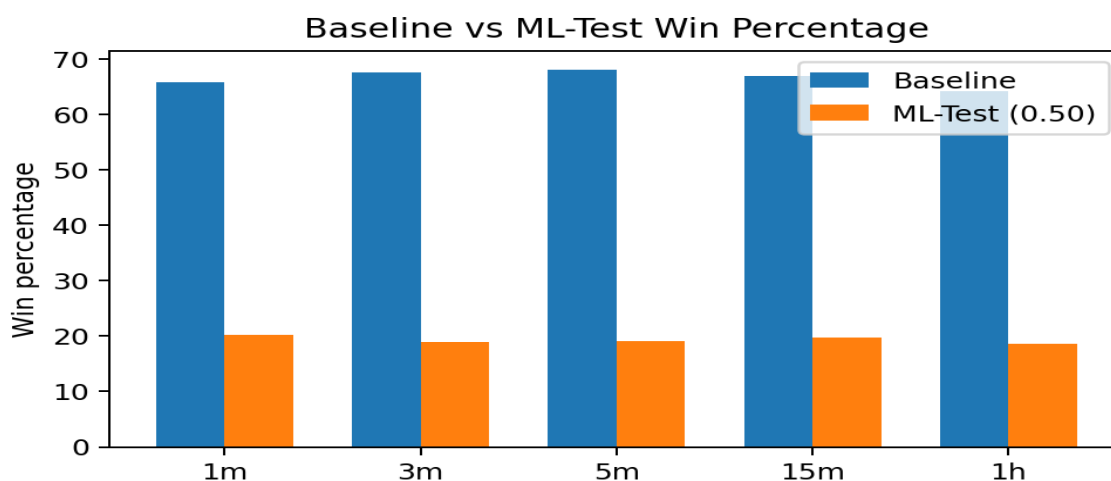


Figure -4: Baseline win percentage versus the 0.50 ML-assisted configuration by timeframe.

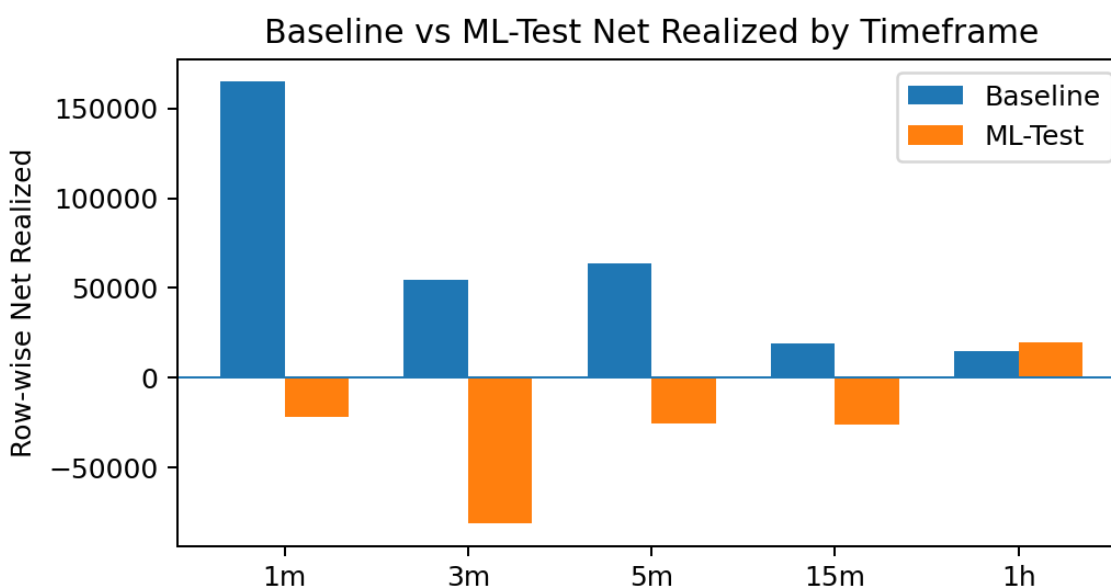


Figure -5: Baseline and aggregate ML-Test Net Realized by timeframe.

The comparison shows a consistent pattern: the ML layer reduces trade activity while also sharply reducing the observed win percentage. Order reduction ranges from 15.7% at 1m to 57.0% at 1h. Baseline Net Realized is positive in every timeframe, whereas ML Net Realized is negative at 1m, 3m, 5m and 15m and positive only at 1h.

5.5 Threshold-by-Timeframe Sensitivity

Table -10

Timeframe	0.50	0.53	0.55	0.57	0.60
1m	20.16%	19.82%	20.28%	19.72%	20.67%
3m	19.00%	18.69%	19.37%	19.96%	22.71%
5m	19.11%	19.37%	20.48%	19.63%	20.10%
15m	19.73%	19.18%	20.43%	19.38%	17.79%
1h	18.64%	19.30%	16.67%	22.22%	20.51%

The confidence response differs by timeframe. The 1m series reaches 20.67% at 0.60, the 3m series reaches 22.71% at 0.60, the 5m series peaks at 20.48% at 0.55, the 15m series peaks at 20.43% at 0.55, and the 1h series peaks at 22.22% at 0.57. These differences demonstrate sensitivity rather than a universal threshold relationship.

5.6 Economic Outcome Characteristics

The baseline configurations have a positive row-wise Net Realized sum of 316,612.56. The 25 ML-assisted configurations have a negative row-wise Net Realized sum of -135,285.70. The aggregate ML profit factor is below 1, while the 1h group is the only timeframe group with a positive Net Realized sum. These observations are descriptive and should not be interpreted as a single portfolio equity result.

6. DISCUSSION

The central empirical finding is that the tested ML validation layer does not improve the evaluated BBMR strategy. The baseline strategy records win percentages between 64.30% and 68.12% across the five timeframes, whereas the ML-assisted configurations remain between 19.29% and 20.05% at the aggregate timeframe level. At the same time, the ML filter substantially reduces trade frequency. Thus, the layer is clearly selective, but the selected population is not superior to the original BBMR candidate population under the tested configurations.

This result is important because it distinguishes selectivity from usefulness. A validation model can reduce the number of trades and even reduce some measures of activity without improving the economic characteristics of the remaining trades. In this experiment, the filtering process is associated with a large deterioration in observed win percentage and a negative aggregate descriptive Net Realized result.

A plausible explanation is strategy-feature misalignment. The inspected feature layer emphasizes moving-average slope, trend strength, momentum, volatility and risk/reward context. These variables may be useful for many directional or regime-sensitive strategies, but a BBMR opportunity is fundamentally associated with a deviation from a central tendency and the probability and speed of subsequent reversion. If the validator does not explicitly encode the magnitude of that deviation, its normalization by volatility, its distance from the mean, or its expected reversion horizon, the model may reject signals that appear weak from a generic trend perspective but are valuable under a mean-reversion mechanism.

The results should nevertheless not be interpreted as evidence that machine learning is inherently unsuitable for BBMR. The observed effect belongs to the tested implementation, feature representation, model configuration, confidence thresholds and experimental period. A strategy-specific validator using Bollinger-aware and mean-reversion-aware features could behave differently. The scientifically stronger conclusion is therefore that ML validation effectiveness is strategy-dependent and should be evaluated against the return-generation mechanism of the underlying strategy.

The finding also has a practical implication for algorithmic deployment. Based on the supplied experiments, the current generic ML filtering configuration should not be preferred over the baseline BBMR configuration for automated deployment. Before any deployment decision, paired order-level testing, realistic transaction-cost modelling and forward paper-trading validation would be required.

7. RESEARCH CONTRIBUTIONS

- A multi-timeframe empirical evaluation of an ML validation layer applied to a deterministic Bollinger Band Mean Reversion strategy.
- A 5 × 5 sensitivity design covering five ML confidence settings across five timeframes.
- Configuration-level comparison using trade activity, win percentage, profit factor, Net Realized and maximum drawdown.
- Evidence that increasing ML confidence produces strong selectivity but does not produce a monotonic improvement in economic outcomes.
- Identification of a strategy-feature alignment issue as a plausible explanation for why generic ML filtering can harm a short-horizon mean-reversion strategy.
- A strategy-dependent interpretation of ML validation effectiveness rather than a universal claim that ML improves or harms algorithmic trading.

8. THREATS TO VALIDITY AND LIMITATIONS

- Historical backtesting: the registry is historical and does not establish live-market execution performance.
- Multiple comparisons: 25 ML configurations create a configuration-selection problem if individual results are later selected for deployment.
- Single strategy family and asset scope: the current evidence concerns the supplied BBMR experiments and should not be generalized to all mean-reversion strategies, assets or ML models.

9. FUTURE RESEARCH

- Measure holding duration, MFE, MAE, expectancy and the distribution of quick profitable reversions for baseline, accepted and rejected signals.
- Add BBMR-specific features such as normalized distance from the middle band, distance to the upper/lower band, band-width normalization, deviation in volatility units, reversion velocity, consecutive moves away from the mean, time since mean contact and short-horizon return-to-mean measures.
- Define a strategy-specific ML target, such as whether a candidate achieves a predefined reversion objective within a specified number of bars before reaching an adverse threshold.
- Add transaction costs, slippage and latency and reconstruct configuration-level equity curves.
- Apply statistical resampling and multiple-testing controls to paired comparisons.
- Conduct forward paper-trading validation before any real-capital deployment.

10. CONCLUSION

This study evaluates machine-learning-assisted validation of a Bollinger Band Mean Reversion strategy across five timeframes and five confidence settings. The supplied registry contains 30 independent configurations and 99,807 recorded orders. The baseline configurations show strong and consistently positive reported outcomes, with win percentages from 64.30% to 68.12% and positive Net Realized values in all five timeframes.

The ML-assisted configurations materially reduce trade activity as confidence increases, but this selectivity is not accompanied by improved performance. The ML-assisted win percentage remains below the corresponding baseline in every timeframe, and the 25 ML configurations have a negative row-wise descriptive Net Realized sum of -135,285.70 compared with +316,612.56 for the five baseline configurations. Only the 1h ML group is positive at the timeframe aggregate level.

The principal conclusion is that the tested generic ML validation layer is not effective for the supplied BBMR implementation and should not be treated as an automatic improvement to the strategy. The evidence is consistent with a strategy-dependent filtering effect: a validator whose features do not explicitly represent the return-generation mechanism of mean reversion may remove candidate trades that are profitable under the original strategy. This is a conditional empirical finding, not a general rejection of machine learning. Future work should test BBMR-specific features, strategy-specific targets and paired order-level analysis to determine whether the observed degradation is caused by feature misalignment, target definition, model calibration or another component of the validation design.

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APPENDIX A. COMPLETE 30-CONFIGURATION BBMR REGISTRY

The following table reproduces the configuration-level results used in this study. Values are reported from the supplied BBMR experimental registry; no pooled portfolio interpretation is intended.

Table -11

#	Group	TF	Conf.	Orders	Wins	Losses	Win %	Net	Max DD
1	Baseline	1m	—	34,342	22,617	11,704	65.86%	165,024.54	24,991.88
2	Baseline	3m	—	11,720	7,928	3,787	67.65%	54,405.06	19,616.23
3	Baseline	5m	—	7,262	4,947	2,314	68.12%	63,594.47	17,507.11
4	Baseline	15m	—	2,409	1,614	795	67.00%	19,028.42	28,325.32
5	Baseline	1h	—	591	380	211	64.30%	14,560.07	44,305.05
6	ML-Test	1m	0.50	10,842	2,186	8,656	20.16%	16,702.10	23,619.45
7	ML-Test	1m	0.53	8,560	1,697	6,863	19.82%	-9,584.72	30,050.74
8	ML-Test	1m	0.55	4,922	998	3,924	20.28%	-6,600.80	19,563.50
9	ML-Test	1m	0.57	3,352	661	2,691	19.72%	-19,643.20	25,847.90
10	ML-Test	1m	0.60	1,258	260	998	20.67%	-2,498.09	12,015.74
11	ML-Test	3m	0.50	2,500	475	2,025	19.00%	-28,162.16	35,487.75
12	ML-Test	3m	0.53	2,145	401	1,744	18.69%	-33,191.66	39,115.11
13	ML-Test	3m	0.55	1,471	285	1,186	19.37%	-18,518.92	20,764.93
14	ML-Test	3m	0.57	1,077	215	862	19.96%	-9,127.60	18,169.63
15	ML-Test	3m	0.60	480	109	371	22.71%	7,725.66	4,766.66
16	ML-Test	5m	0.50	1,502	287	1,215	19.11%	-15,202.79	28,356.43
17	ML-Test	5m	0.53	1,337	259	1,078	19.37%	-8,870.93	24,022.67
18	ML-Test	5m	0.55	1,035	212	823	20.48%	7,333.02	17,084.01
19	ML-Test	5m	0.57	800	157	643	19.63%	-6,007.19	12,123.15
20	ML-Test	5m	0.60	388	78	310	20.10%	-2,798.55	14,651.45
21	ML-Test	15m	0.50	375	74	301	19.73%	-2,107.26	20,634.16
22	ML-Test	15m	0.53	365	70	295	19.18%	-7,976.32	31,521.09
23	ML-Test	15m	0.55	323	66	257	20.43%	2,238.06	27,096.81
24	ML-Test	15m	0.57	289	56	233	19.38%	-4,550.76	26,930.34
25	ML-Test	15m	0.60	208	37	171	17.79%	-13,902.16	29,287.83
26	ML-Test	1h	0.50	59	11	48	18.64%	2,426.99	15,725.77
27	ML-Test	1h	0.53	57	11	46	19.30%	5,464.99	13,975.97
28	ML-Test	1h	0.55	54	9	45	16.67%	-2,122.48	14,294.60
29	ML-Test	1h	0.57	45	10	35	22.22%	9,442.23	12,468.42
30	ML-Test	1h	0.60	39	8	31	20.51%	4,246.84	14,435.92