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A Comparative Study of Multi-Factor Trading Architectures and Walk-Forward Machine Learning Filtering for Cryptocurrency Markets

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Abstract: The architectural diversity of algorithmic trading methods within cryptocurrency trading is extensive; however, there is little known about the connection between the density of indicators used and the performance of such algorithms. This study rigorously compares two rule-based trading algorithms for Ethereum (ETH-USD) and Bitcoin (BTC-USD) over a four-year market cycle from 2022 to 2025. The first method uses a weight-based approach that includes more than 50 different technical indicators. The second one uses a simple unweighted voting algorithm. To test whether machine learning can selectively improve trade entry quality, researchers introduce the Technical Indicator State Vector (TISV) framework and use an XGBoost classifier in a strict walk-forward setting. Empirical results demonstrate that the simpler, high-frequency strategy outperformed the complex composite model by a factor of 4.27 over four years, driven by geometric compounding and superior capital utilization. Furthermore, TISV-based ML filtering improved the composite strategy's out-of-sample Sharpe ratio by 739% and its win rate from 35% to 63.76%. However, it provided no measurable benefit to the high-frequency scalping strategy. These findings establish a diagnostic criterion: machine learning-based trade filtering works only when a strategy's outcomes measurably depend on market entry conditions (defined as an Area Under the Curve > 0.60).

Keywords: Algorithmic Trading; Cryptocurrency Markets; Exponential Moving Averages; Bollinger Bands; Technical Indicators; Technical Indicator State Vector; Walk-Forward Optimization; High-Frequency Trading.

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1. Introduction

The fast-growing financial market has attracted many investors because of its huge profit-making potential. But accurately predicting asset prices is difficult in financial markets because of their dynamic nature [2]. It becomes even tougher in the cryptocurrency market because of its volatility, making it difficult for investors to make smart decisions. Analyzing blockchain-based cryptocurrency markets is challenging because of their inherent volatility [3]. For years, technical analysts have tried to

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tame this volatility by combining trend, momentum, and volatility indicators [4]. A persistent question in quantitative design is whether aggregating a high density of technical indicators into a single composite signal yields superior risk-adjusted returns compared to deploying a minimal set of indicators at high frequency [5].

Some literature that constructs a multi-factor stock selection model has adopted a weighted-scoring approach despite its shortcomings, such as its inability to effectively identify the connection between the weights of stock-picking concepts and portfolio performance [16]. To address these limitations, this paper proposes a comprehensive empirical comparison between a heavily weighted composite framework (Strategy 1) and a nimble Unweighted Voting Framework (Strategy 2) [6]. Furthermore, recognizing that traditional price-prediction models often struggle with the binary trade-execution problem in these markets, researchers introduce the Technical Indicator State Vector (TISV) [7]. The TISV serves as a machine-learning extension layer, using Chen and Guestrin's XGBoost algorithm [1] to predict future development [15]. By establishing a strictly causal walk-forward optimization protocol, researchers aim to determine if an ML model can identify, at the exact moment of trade entry, which market conditions historically produce winning trades [8].

2. Literature Review

2.1. Technical Analysis and Strategy Architecture

Technical analysis is prevalent among algorithmic traders in the crypto market [9]. It involves implementing strategies based on technical indicators that generate BUY and SELL signals to support investment decisions [10]. But rather than relying on popular market myths, empirical analysis can drive profitable cryptocurrency ventures [11]. Several researchers have affirmed the effectiveness of hierarchical strategies [14]. For example, studies using Exponential Moving Averages (EMA), Bollinger Bands (BB), and the Relative Strength Index (RSI) found that hierarchical strategies based on trend indicators outperformed those based on momentum indicators [13]. However, traditional approaches such as technical analysis (which uses historical market data) and fundamental analysis face challenges such as data noise and data delays [12].

2.2. Machine Learning in Cryptocurrency Forecasting

However, because static, rule-based systems have limitations, researchers are increasingly turning to machine learning [17]. Research on multi-class machine learning frameworks for generating daily Bitcoin trading signals (Buy, Sell, and Hold) has compared XGBoost, LightGBM, and Random Forest. Ensemble learning methods for forecasting cryptocurrency volatility are also gaining popularity. Notably, recent research shows that XGBoost provides the most accurate forecasts. Method comparisons show that Gradient Boosting and XGBoost outperform SVR and LSTM for cryptocurrencies. For predicting bullish and bearish trends in Ethereum, experimental research shows XGBoost's best performance at 84.58%, far above LSTM at 50.45%. This performance gap suggests that XGBoost better captures nonlinear relationships between input variables and market trends. Despite XGBoost’s dominance, hybrid models have also shown promise. Research proposing a hybrid deep learning and machine learning model that integrates LSTM networks and XGBoost found that the LSTM component captures temporal dependencies while XGBoost models nonlinear relationships. Similarly, researchers have developed stacking ensembles that integrate econometric models (GARCH) with XGBoost meta-learning to produce improved variance forecasts [18].

2.3. Advanced Filtering and Feature Engineering

Besides simple prediction, the literature now places significant emphasis on signal filtering. One study investigated Shannon entropy as a filtering technique to improve trading signals, finding it effective at selecting trades by reducing noise and detecting trends [4]. Confidence-based classification systems have also been proposed, which distinguish between directional prediction and decision-making. Using prediction confidence as a criterion for trading decisions, while training only on directional moves, can enhance risk-adjusted returns. Feature engineering also cannot be neglected [5]. Techniques that systematically combine time series and recalibrated technical analysis have proven highly effective, achieving up to 73% better-than-benchmark performance.

3. Strategy Architecture and Methodology

3.1. Strategy 1: Weighted Composite Framework

Figure 1 shows the general structure of the suggested Strategy 1. The strategy is implemented as an advanced market analysis engine. The strategy assumes the market state is defined by aggregating data from many technical indicators across different analysis areas.

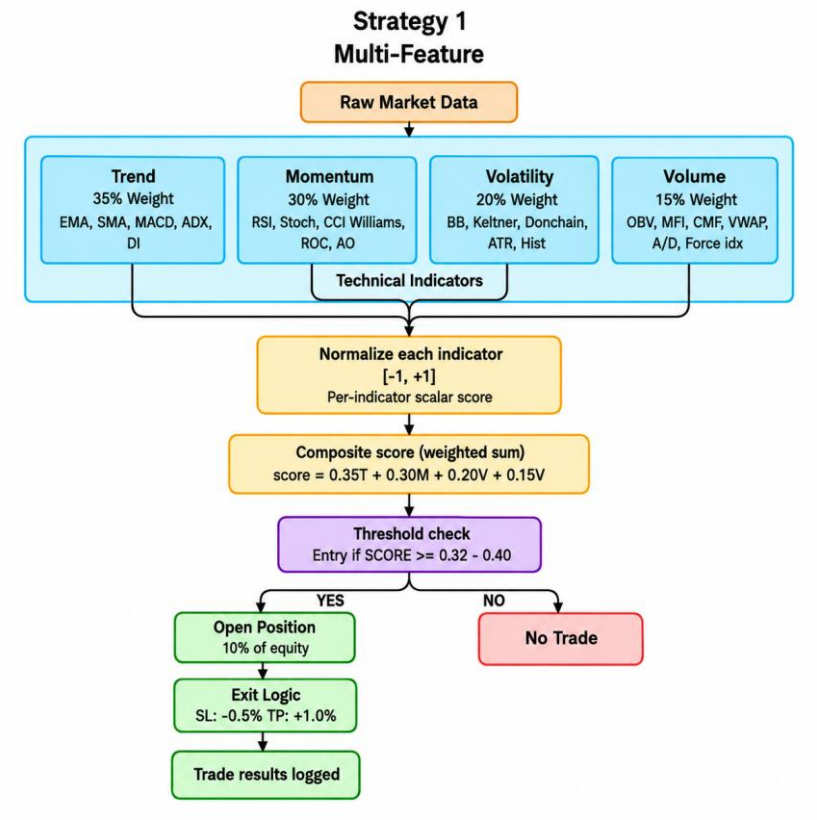


Figure 1: Architecture diagram for strategy 1: multi-feature framework

3.1.1. Indicator Spectrum

The strategy processes 52 distinct technical indicators divided into four weighted buckets:

- **Trend Factors** (wT = 0.35): Includes Simple and Exponential Moving Averages (10, 20, 50, 100, 200 periods), MACD, and Average Directional Index (ADX).
- **Momentum Factors** (wM = 0.30): Includes RSI (7, 14, 21), Stochastic Oscillator (%K, %D), Commodity Channel Index (CCI), and the Awesome Oscillator (AO).
- **Volatility Factors** (wV = 0.20): Includes Average True Range (ATR), Bollinger Bands width expansion, and Donchian Channels.
- **Volume Factors** (wV ol = 0.15): Includes On-Balance Volume (OBV), Money Flow Index (MFI), and Volume Weighted Average Price (VWAP) deviations.

3.1.2. Composite Scoring and Execution

The *i*-th indicator is mapped to a single real number si in the range [−1, 1]. The overall composite value Scomp is computed as:

$$S_{comp} = w_T \left(\frac{1}{N_T}\sum_{i=1}^{N_T} s_i\right) + w_M \left(\frac{1}{N_M}\sum_{j=1}^{N_M} s_j\right) + w_V \left(\frac{1}{N_V}\sum_{k=1}^{N_V} s_k\right) + w_{Vol} \left(\frac{1}{N_{Vol}}\sum_{l=1}^{N_{Vol}} s_l\right) \quad (1)$$

A position is entered when |Scomp| ≥ τentry, which was optimized to 0.40. The first strategy applies the conservative dollar-based approach to manage the number of positions (10%).

3.2. Strategy 2: Unweighted Voting Framework

Figure 2 presents the overall architecture of the proposed Strategy 2. It relies on the principle that cryptocurrency markets contain brief, explosive imbalances. Rather than quantifying a macro regime, it targets micro-dislocations using a highly reactive, unweighted voting mechanism, as illustrated in Algorithm 1.

3.2.1. Core Indicator Logic

Strategy 2 utilizes only 8 core indicators:

- **Momentum Triggers:** Identifies extremes using RSI (< 30 or > 70) and MACD zero-lag expansion.
- **Mean Reversion:** Detects Bollinger Band touches conjoined with short-term SMA differentials.
- **Volume Traps:** Filters out low-liquidity fakeouts by mandating current volume > 1.5 × SMAvolume(20).
- **VWAP Deviation:** Triggers when the price deviates > 0.2% from the intraday VWAP.

3.2.2. Execution Algorithm

The strategy counts independent BUY and SELL signals. If Count (Signals) ≥ 2, a trade is executed utilizing an aggressive 50% of rolling equity.

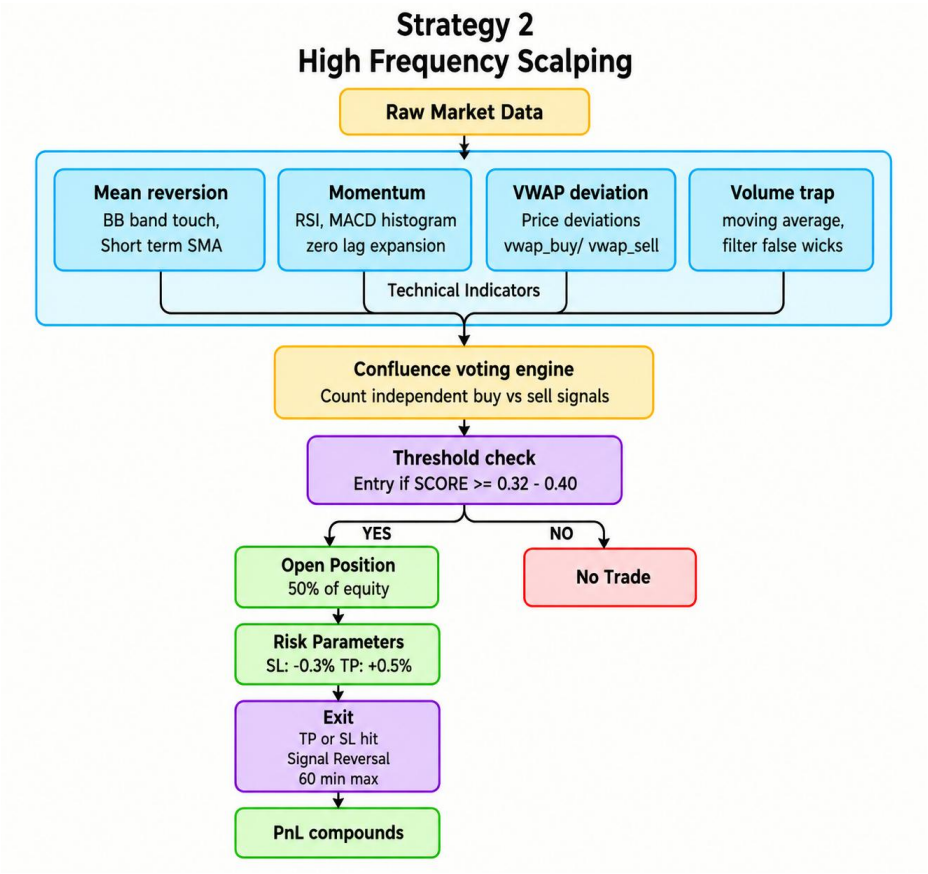


Figure 2: Architecture diagram for strategy 2: high-frequency scalping

3.3. Technical Indicator State Vector (TISV) Framework

Figure 3 presents the architecture of the proposed TISV framework. To address the binary trade execution problem, researchers introduce the TISV framework. TISV captures a 12-dimensional snapshot of market conditions at the exact bar when the underlying rule-based strategy initiates a trade.

3.3.1. Feature Space Definition

The 12 features extracted for the XGBoost model include:

- **RSI_{14}:** Overbought/Oversold baseline
- **$MACD_{Hist}$:** Momentum strength
- **$BB_{\%B}$:** Price normalization within volatility bands

- **BBW $_{idth}$:** Volatility squeeze/expansion metric
- **Vol$_{Ratio}$:** Liquidity anomaly detection

Algorithm 1 Strategy 2: High-Frequency Scalping Execution Logic

Require: OHLCV data array D, Equity E

```
Pos ← None
for each bar b ∈ D do
    Signals ← 0
    if RSI(b) < 30 then
        Signals ← Signals + 1
    end if
    if Price(b) < BBlower(b) then
        Signals ← Signals + 1
    end if
    if Price(b) < V WAP (b) × 0.998 then
        Signals ← Signals + 1
    end if
    if Pos = None and Signals ≥ 2 and V ol(b) > 1.5 × V olSMA then
        Size ← E × 0.5
        Pos ← OpenLong(Price(b), Size)
        Pos.TP ← Price(b) × 1.005
        Pos.SL ← Price(b) × 0.997
        Pos.HoldTime ← 0
    end if
    if Pos ≠ None then
        Pos.HoldTime ← Pos.HoldTime + 1
        if High(b) ≥ Pos.TP or Low(b) ≤ Pos.SL or Pos.HoldTime ≥ 12 then
            E ← E + ClosePosition(Pos, Price(b))
            Pos ← None
        end if
    end if
end for
```

- **ATR$_{\%}$:** Per-bar percentage volatility
- **V WAP$_{Dev}$:** Distance from fair intraday value
- **Mom$_{12}$:** 1-hour price velocity
- **Mom$_{48}$:** 4-hour price velocity
- **EMA$_{Cross}$:** Short vs. long spread metric
- **Price$_{Rank}$:** 20-bar positional percentile
- **Stoch$_{\%K}$:** Fast momentum oscillator

3.3.2. Walk-Forward Optimization Protocol

To avoid look-ahead bias, researchers use a walk-forward design. Researchers use IS (2022-2023) training data with 5-fold temporal cross-validation. Label y is defined by the formula:

$$y_i = \begin{cases} 1, & \text{if } NetPnL_i > 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The model learns P (y = 1 | TISV). Researchers calibrate an optimal probability threshold.

τ using a Regularized Composite Score function:

$$\text{Score}(\tau) = \text{Sharpe}(\tau)0.6 \times \text{Coverage}(\tau)0.4 \quad (3)$$

Researchers use the optimal τ to screen the OOS (2024-2025) data without refitting.

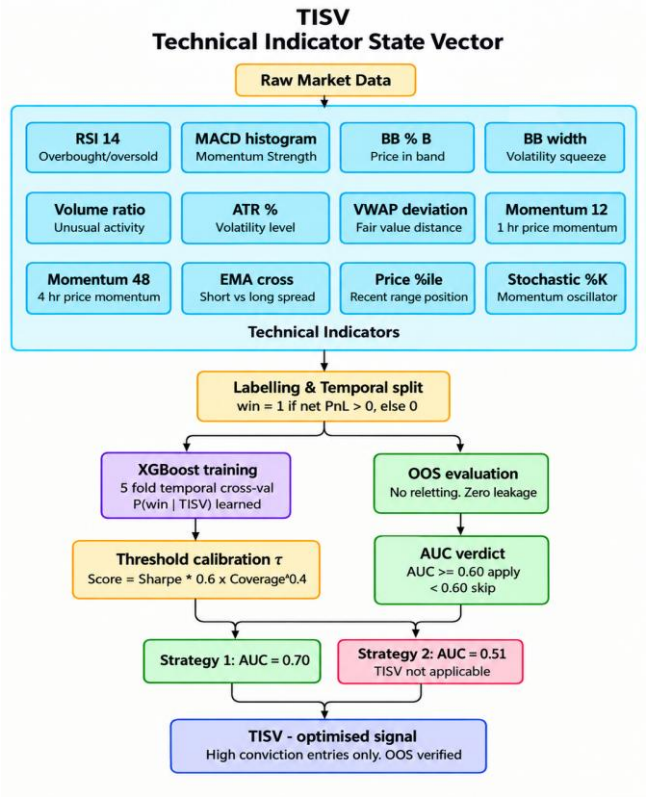


Figure 3: Architecture diagram for the tisv framework

3.4. Experimental Setup

Researchers' backtested on historical OHLCV data for ETH-USD and BTC-USD from various exchanges. Strategy 1 was executed on the 5-min aggregation (420,508 bars). Strategy 2 was executed on the 1-hour aggregation (for the long-term strategy test for sustainable high-frequency turnover ∼, 35,040 bars). The backtest includes $10,000 initial capital, standard maker/taker fees (0.01% each side), and simulated slippage between bid/ask prices. Performance is measured by Total Return, Win Rate, Maximum Drawdown, Sharpe Ratio, and Profit Factor.

4. Results Analysis and Discussions

4.1. 4-Year Baseline Performance Comparison

The empirical results across the full market cycle for 2022-2025 show a significant performance difference.

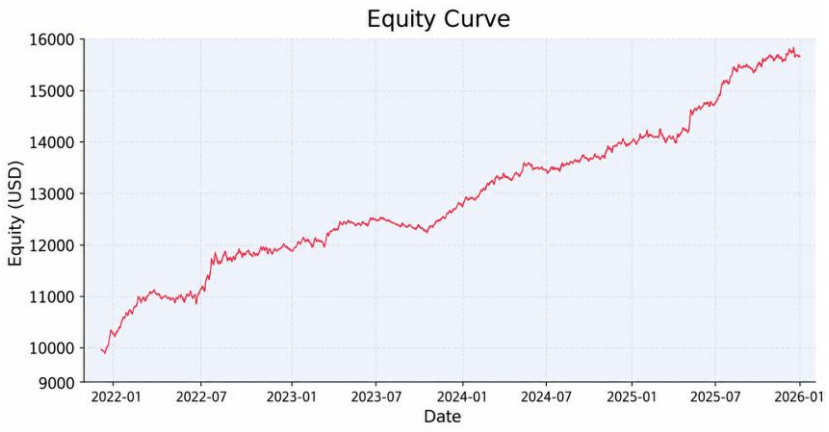


Figure 4: Strategy 1 equity curve over the 4-year testing period (2022–2025)

Figure 4 and Figure 5 show the equity curves for Strategy 1 and Strategy 2, respectively, while Table 1 presents the quantitative performance assessment.Strategy 1 shows consistent but somewhat restrained growth over the four-year test period because of its cautious capital deployment. In contrast, Figure 5 shows a much steeper equity chart for Strategy 2, indicating much greater portfolio growth over the same period. The performance parameters in Table 1 further confirm that Strategy 2 performed much better, generating 4.27 times Strategy 1's total gain and a higher win rate (38.89% vs 34.05%). While Strategy 1 generated a smaller maximum drawdown, Strategy 2 almost doubled the initial capital from $10,000 to $29,311.

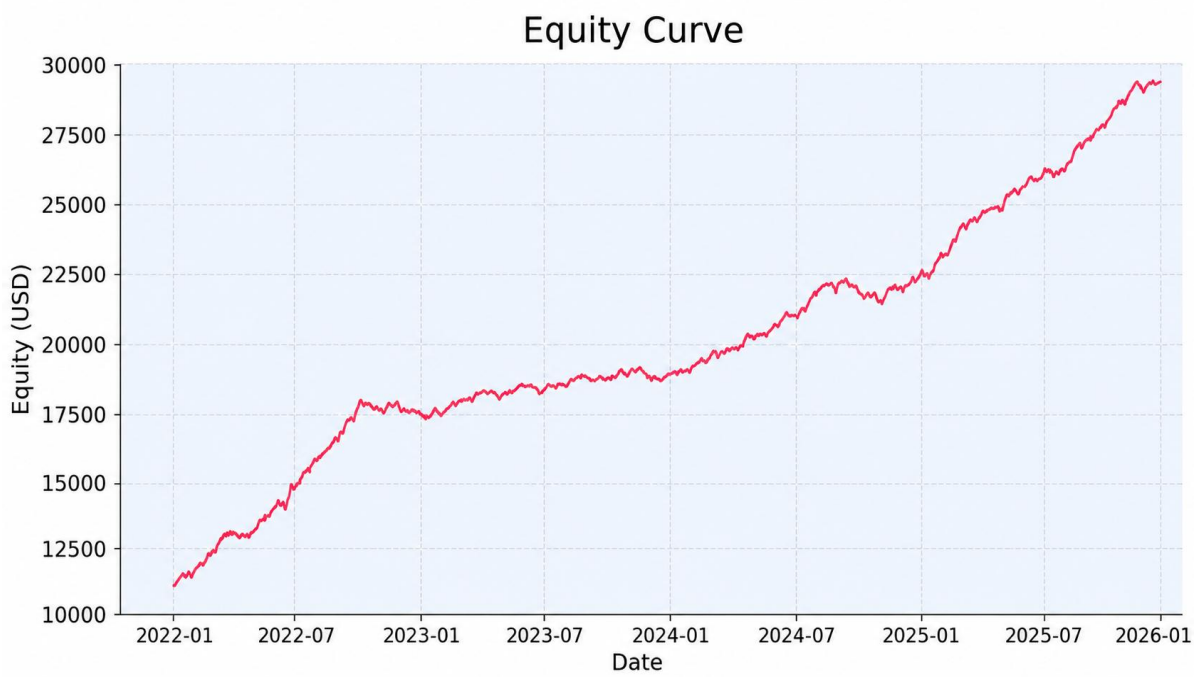


Figure 5: Strategy 2 equity curve over the 4-year testing period (2022–2025)

The growing performance gap is largely explained by geometric compounding. Strategy 1's constant $1,000 deployment drove linear growth and strong cash drag. By contrast, Strategy 2's 50% rolling equity meant gains were constantly reinvested, creating exponential growth from a small per-trade edge. Moreover, Strategy 2 avoided capital immobilization during the extended 2023 consolidation by using the strict 60-min time-based exit rule, as shown by the steady upward equity trend in Figure 5.

Table 1: Side-by-side 4-year performance summary (ETH-USD)

Metric	Strategy 1	Strategy 2	Winner
Total Return	+45.20%	+193.11%	Strategy 2
Total Trades	11,860	19,163	N/A
Win Rate	34.05%	38.89%	Strategy 2
Max Drawdown	-3.18%	-4.88%	Strategy 1
Metric	Strategy 1	Strategy 2	Winner

4.2. Walk-Forward TISV Optimization Results

Implementing the TISV XGBoost filter produced contrasting results that highlight the structural differences between the two approaches. Figure 6 and Figure 7 show the OOS equity charts for the two optimized strategies, while the quantitative results are presented in Strategy 1.

4.2.1. Strategy 1: High Entry-State Dependence

As shown in Figure 6, the equity curve of the TISV-optimized Strategy 1 is persistently more successful in its out-of-sample performance than the basic strategy. The additional numerical results in Table 2 show that eliminating 87.7% of the lowest-probability trades greatly improved strategy performance. The optimization improved 10 of 11 performance criteria by increasing win rate, net profit, and Sharpe ratio, while minimizing maximum drawdown.

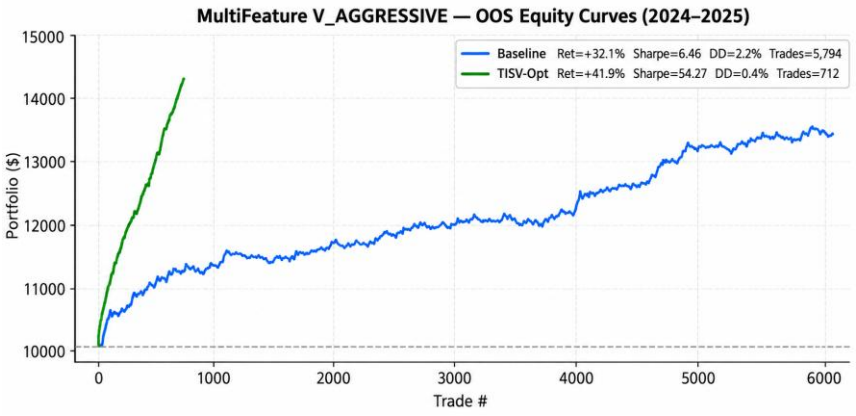


Figure 6: TISV-optimized out-of-sample equity curve for strategy 1

This shows that the XGBoost classifier found the composite score predictive in specific high-conviction market conditions, namely high VWAP deviation and momentum confirmation.

Table 2: TISV out-of-sample results for strategy 1 (2024–2025)

Metric	Baseline OOS	TISV-Optimized (τ = 0.69)	Delta
Trades	5,794	712	-5,082
Win Rate	35.02%	63.76%	+28.74%
Net PnL	$3,212.59	$4,188.37	+$975.78
Max DD	-2.19%	-0.40%	+1.79%
Sharpe	6.46	54.27	+739%

4.2.2. Strategy 2: Structural Inapplicability

Conversely, applying TISV to Strategy 2 yielded a CV AUC of 0.5073 ± 0.0072, a result statistically indistinguishable from random guessing. As shown in Figure 7, TISV optimization did not improve equity growth in Strategy 2. The usage of the calibrated threshold (τ = 0.57) filtered out 1,464 trades from the initial number of 10,015 out-of-sample trades. Although the percentage of winning trades remained about the same at 39.00%, the strategy's return fell sharply from +108.75% to +15.70%. This significant drop in portfolio growth shows the inefficacy of filtering 85% of trading signals, as Strategy 2 relies on compounding effects that work at high frequencies. The flat line in the equity plot in Figure 7 illustrates clearly that the entry.

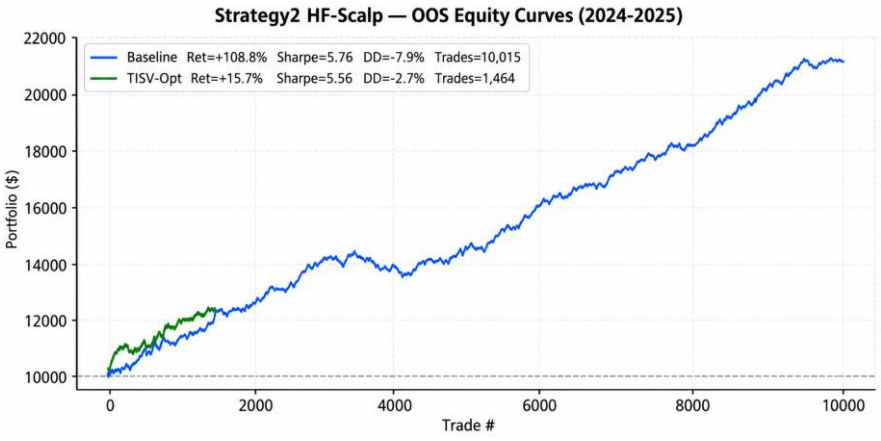


Figure 7: TISV-optimized out-of-sample equity curve for Strategy 2

The results imply that adding more technical indicators does not necessarily improve the trade strategy's performance. Strategy 1 combined data from 52 technical indicators, so the resulting signal likely contained redundant features and multicollinearity, since many indicators are calculated from the same price data. As a result, the signal became less adaptive to changes in market conditions. In turn, Strategy 2 showed that localizing the micro-dislocations in the market environment, along with the correct

risk–reward balance (0.5% take-profit and 0.3% stop-loss), led to better trading performance. In addition, based on the experimental evidence, the researchers suggest a criterion for the empirical applicability of machine learning trade filters. The evidence shows that machine learning trade filters work best for trading algorithms that depend on the market environment, yielding performance much higher than purely random (approximately AUC < 0.60 in our case). In contrast, high-frequency trading algorithms derive most of their expected profit from accumulating many independent trades. Over-filtering reduces the number of trades, destroying the geometric compounding effect.

5. Conclusion

Over four years of ETH-USD testing, this study shows that the frequency-based strategy architecture, combined with geometric compounding, beat the precision-based multivariate composite approach. More specifically, the straightforward scalping method with eight indicators yielded an annualised return of 193.11%, while the more complex strategy with fifty-two indicators yielded a profit of 45.20%. As a result, generating lucrative strategies requires not only complex indicators but also effective fund allocation and management, as well as regular execution. In addition, the Technical Indicator State Vector (TISV) technique proved beneficial for walk-forward optimisation of regime-based trading strategies. In light of this, the Sharpe ratio was dramatically enhanced by more than 700% for Strategy 1, while drawdown was decreased due to the implementation of XGBoost-based filtering. In contrast, using the same filter did not improve performance for the regime-independent scalping approach. In conclusion, the findings provide evidence that it is essential to ensure that the efficiency of trade filtering through machine learning is aligned with the strategy that is utilised during the trading process. In subsequent studies, the authors intend to investigate the efficacy of adaptive deep learning structures, especially LSTM-based sequence modelling, for dynamically predicting TISV. Additionally, they intend to implement Strategy 2 in other cryptocurrency markets that are characterised by high levels of volatility, such as Solana cryptocurrency (SOL-USD).

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Ethics and Consent Statement: This research adheres to ethical guidelines and obtains informed consent from all participants. Confidentiality measures were implemented to safeguard participant privacy.

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