Zelta Automations

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TRADING STRATEGY DEVELOPMENT ON BTC & ETH

Inter IIT Tech Meet 13.0

Final Submission Report

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INTER IIT TECH MEET 13.0

Contents

1 Introduction

In the highly volatile and rapidly evolving cryptocurrency markets, algorithmic trading has become essential for effectively managing risks and maximizing returns. The BTC/USDT and ETH/USDT markets, two of the most prominent and active cryptocurrency trading pairings, provide a challenging yet rewarding setting for developing intricate trading strategies.

This research aims to create and apply algorithmic trading strategies tailored to these markets to surpass benchmark returns and effectively control risks. The techniques use trustworthy mathematical and statistical models for optimization and decision-making, utilizing historical price and trading volume data from January 1, 2020, to December 31, 2023. The study also incorporates risk management and thorough backtesting to guarantee resilience and flexibility in various market circumstances

2 Background and Problem Description

The task entails developing algorithmic trading plans specifically for the BTC/USDT and ETH/USDT trading pairs to minimize risk and generate steady returns. This entails gathering and preprocessing historical data to guarantee its quality and dependability, creating strategies based on statistical models like mean-reversion and trend-following, and backtesting to assess performance in actual market conditions while considering transaction costs and slippage.

Furthermore, the techniques use the substantial correlation and interdependence between the price movements of Bitcoin and Ethereum and Reinforcement Learning techniques to maximize returns while preserving acceptable risk levels.

3 Market Dynamics of BTC and ETH

The markets for Bitcoin (BTC) and Ethereum (ETH) are among the most active and liquid in the cryptocurrency business, and they often exhibit a high level of interconnection. Being the largest and most well-known cryptocurrency, Bitcoin frequently influences shifts in the value of other assets, like Ethereum, by acting as an indicator for the market. This relationship is demonstrated by their positive correlation.

The markets for Ethereum and Bitcoin each have distinctive characteristics despite their similarities. Bitcoin is primarily regarded as a store of value, but Ethereum serves as a framework for smart contracts and decentralized applications. Bitcoin and Ethereum are crucial instruments for understanding and controlling the dynamics of the cryptocurrency market because of their unique uses and high trade volumes, volatility, and susceptibility to global events.

4 Trading Strategy for the ETH/USDT Market

4.1 Strategy Hypothesis

The hourly price movements of Bitcoin (BTC) exhibit a strong positive correlation with those of Ethereum (ETH), indicating a significant co-movement between the two cryptocurrencies. Furthermore Bitcoin (BTC) exerts a notable influence on the subsequent price movements of Ethereum (ETH), highlighting its dominant role in shaping the dynamics of correlated cryptocurrency markets. This relationship underscores the potential for leveraging BTC's price trends to forecast ETH's short-term market behavior.

4.2 Hypothesis Testing: BTC and ETH Correlation

Hypotheses:

- **Null Hypothesis (H)**: BTC and ETH prices hourly data have a weak correlation ($r \leq 0.5$).
- **Alternative Hypothesis (H)**: BTC and ETH hourly data have a significant correlation ($r > 0.5$).

Methodology: We calculated the **cross-correlation** of the log return series for BTC and ETH. The correlation between ETH's log returns and lag-1 BTC returns was found to be **0.0551**, with a **statistical significance level** of **0.0367** at a **5%** significance level.

Additionally, the **Pearson correlation coefficient (r)** was calculated as **0.7851**, indicating a strong positive correlation between BTC and ETH. The **p-value** was extremely small (0.00), well below the 5% threshold.

Conclusion: Given the **Pearson correlation** ($r = 0.7851$) and the extremely low **p-value**, we **reject the null hypothesis**. Therefore, there is strong evidence that BTC and ETH are significantly correlated, meaning past BTC movements impact ETH prices.

4.3 Key Aspects of This Hypothesis

- **Strong Positive Correlation:** This implies a strong linear relationship between the two assets' price movements.
- **Lead-Lag Relationship:** The hypothesis explicitly states that past changes in Bitcoin price has a significant effect on Ethereum's price changes, implying that BTC might predict ETH's price movement.

4.4 Experimented Approaches

4.4.1 Markov Regime-Switching Models

The Markov Regime-Switching Model is a statistical framework designed to analyze time series data characterized by distinct "**regimes**" or states, each exhibiting unique behavioral patterns. Transitions between these regimes are modeled as a Markov process, where

the probability of transitioning is solely dependent on the current state, independent of prior states.
The time series is modeled with a first-order auto regression:

$$y_t = c_{st} + \phi y_{t-1} + \epsilon_t \tag{1}$$

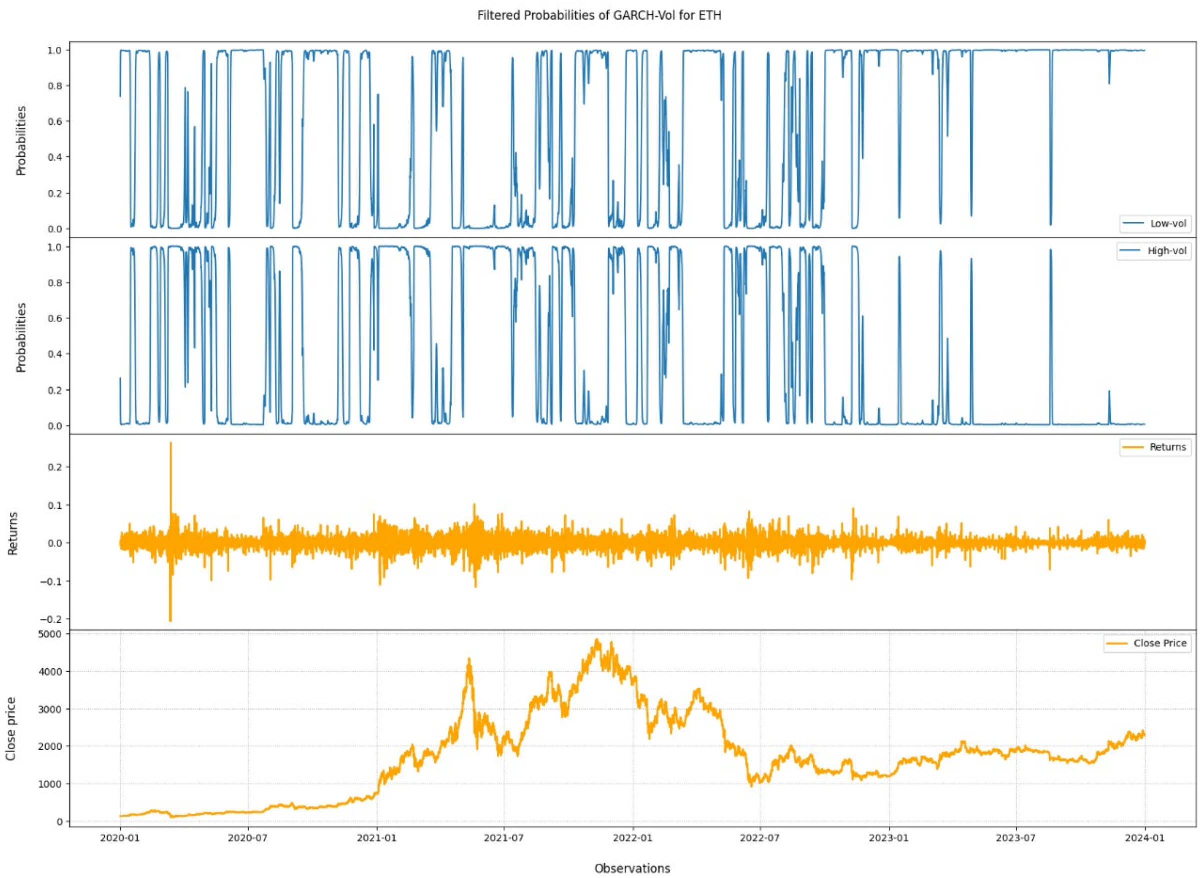
The Markov Switching Generalized Auto regressive Conditional Heteroskedasticity **(MSGARCH)** model is a statistical approach used to analyze and model financial time series with changing volatility regimes. It combines the GARCH framework for modeling volatility with the Markov regime-switching mechanism, enabling it to capture regime-dependent volatility dynamics more flexibly and realistically.

GARCH Model Mathematical Description: Consider here a GARCH(1,1) model in which the coefficients are subject to changes in regime,

$$y_t = h_t v_t, \quad \text{where} \quad v_t \sim N(0, 1) \tag{2}$$

GARCH model is typically modeling the conditional variance:

$$h_t^2 = \gamma_{st} + \alpha_{st} y_{t-1}^2 + \beta_{st} h_{t-1}^2 \tag{3}$$



4.4.2 Volatility Clustering using PCA and K-Means

We tried to use PCA and K-means clustering to generate different volatility clusters, in order to enhance the trading strategy by reducing dimensionality and grouping similar trading periods.

K-Means clustering was applied to **PCA-transformed training** and testing datasets, with the model fitted on training data to predict test cluster labels. Interactive plots visualized price clusters over time, and key statistics like size, average close price, and volatility provided insights into cluster characteristics.

4.4.3 ATR Based Volatility Modeling

ATR (Average True Range) measures market volatility by averaging true ranges, which account for gaps between the current close and previous close or the high-low range over a specified period.

Calculation: The True Range (TR) is the greatest of the following three values:

Mathematically:

$$TR_t = \max(\text{High}_t - \text{Low}_t, |\text{High}_t - \text{Close}_{t-1}|, |\text{Low}_t - \text{Close}_{t-1}|) \tag{4}$$

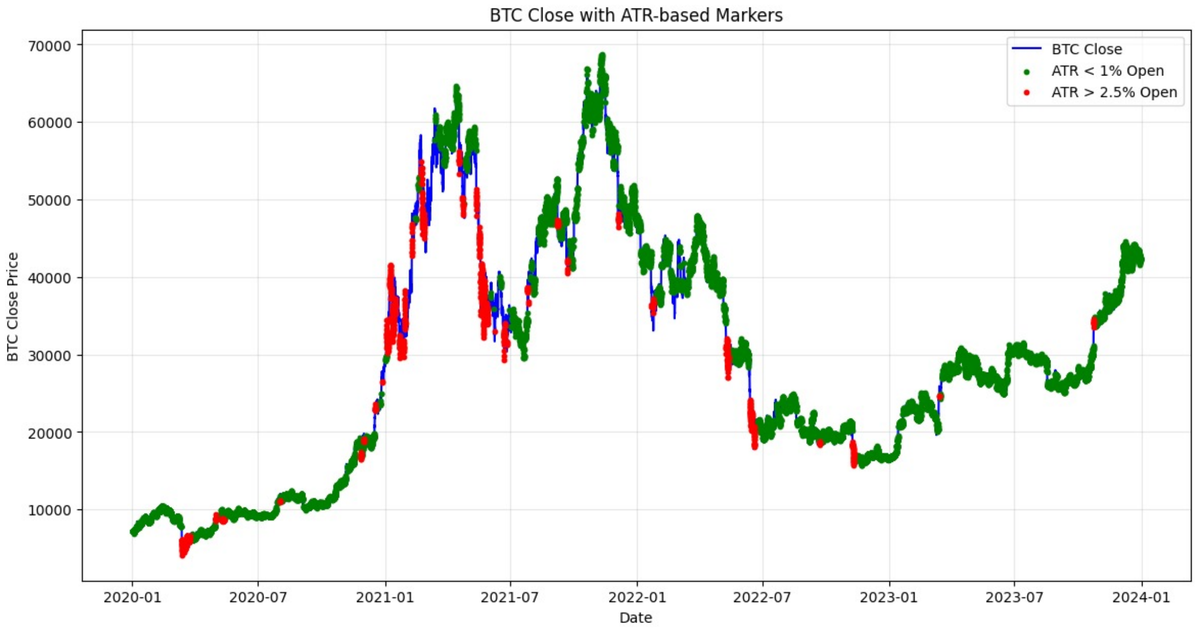
The Average True Range (ATR) is calculated as:

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

1% Threshold: The strategy focuses on low-volatility conditions by setting the ATR value less than 1% of the BTC opening price. This ensures:

- **Low-volatility conditions,** where price movements are smaller and trends are more predictable.
- **Avoidance of high-volatility periods,** marked by erratic movements and reversals, making trades more reliable.

Low-volatility periods increase the likelihood of sustained trends, ideal for profitable trading.



4.5 Key Features and Unique Approaches of the Strategy

4.5.1 CUSUM

CUSUM (Cumulative Sum) is a statistical method used to detect shifts in the mean of a process over time. It tracks cumulative deviations from a reference value, where consistent positive or negative deviations indicate potential market shifts. The deviation between each observed value x_i (e.g., price) and the reference value μ_0 (mean of the process) is calculated as:

$$d_i = x_i - \mu_0$$

The cumulative sum at time i is computed by summing these deviations up to that point:

$$S_m = \sum_{i=1}^{m} (x_i - \mu_0)$$

This method helps to identify significant shifts in market conditions when the deviations consistently move in one direction.

4.5.2 Filtering Techniques to Use as Reference Value

To enhance the accuracy and robustness of CUSUM, various **filtering techniques** are employed to refine the reference value μ_0, making it more reliable for trend detection:

- **Kalman Filtering**: A technique that estimates the system's state from noisy data by predicting future states and adjusting based on new observations. This provides a more accurate and stable reference value for CUSUM.

- **Gaussian Filtering**: This method smooths the data using a Gaussian function, reducing high-frequency noise while preserving underlying trends and structure in the data.
- **Heikin Ashi Candles**: A charting technique that averages price data to smooth out erratic movements. By reducing noise, Heikin Ashi candles make it easier to identify market trends and reversals.

These filters were applied to generate the reference value for CUSUM. Based on our observations, the Kalman Filter performed the best, enhancing its ability to detect market shifts and deviations.

4.5.3 V-mask Technique and Dynamic Volatility Threshold

The **V-mask** and **dynamic volatility threshold** are critical enhancements to the CUSUM method, improving its ability to detect regime shifts while adapting to changing market conditions.

- **V-mask**: The V-mask is a tool used with the CUSUM chart to identify significant deviations from expected behavior. The V-mask is a V-shaped overlay on the CUSUM chart, moving forward with each new data point. If the CUSUM values stay within the arms of the V-mask, the process is considered "in-control." If any values exceed the arms, the process is flagged as "out-of-control," indicating a potential shift in market behavior.
- **Dynamic Volatility Threshold**: The threshold k for CUSUM is dynamically adjusted based on the market's **volatility**, ensuring that the method remains sensitive to market fluctuations. This threshold is calculated using the rolling standard deviation (σ_i) of the asset's price over a defined window:

$$k_i = \delta \times \sigma_i$$

Where:

- δ is a constant factor that adjusts the threshold sensitivity,
- σ_i is the rolling standard deviation of the price over recent data points.

This dynamic threshold ensures that CUSUM responds appropriately to both high and low volatility periods, detecting genuine shifts in the market while avoiding false signals during stable periods.

4.5.4 Final Application in Regime Detection

In the **ETH trading strategy**, **CUSUM** is applied to **BTC price data** to detect **bullish** and **bearish** market regimes. The process involves:

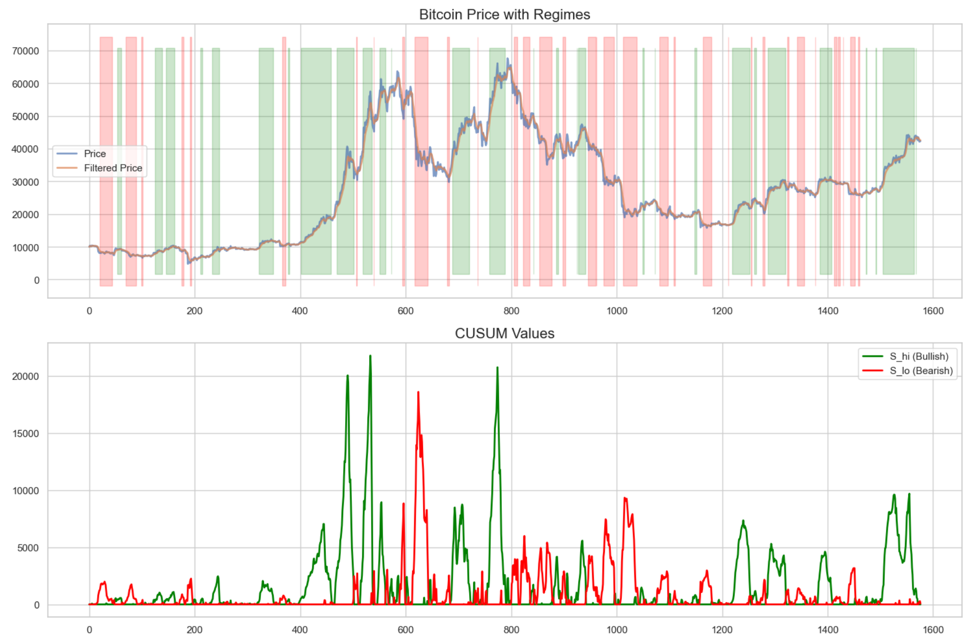
- Calculating the deviation between observed BTC prices and the **filtered reference value**.
- Computing **upward (S_{hi})** and **downward (S_{lo})** CUSUM values to track market deviations.
- Identifying market regimes:
  - **Bullish**: When S_{hi} exceeds a threshold.
  - **Bearish**: When S_{lo} exceeds a threshold.

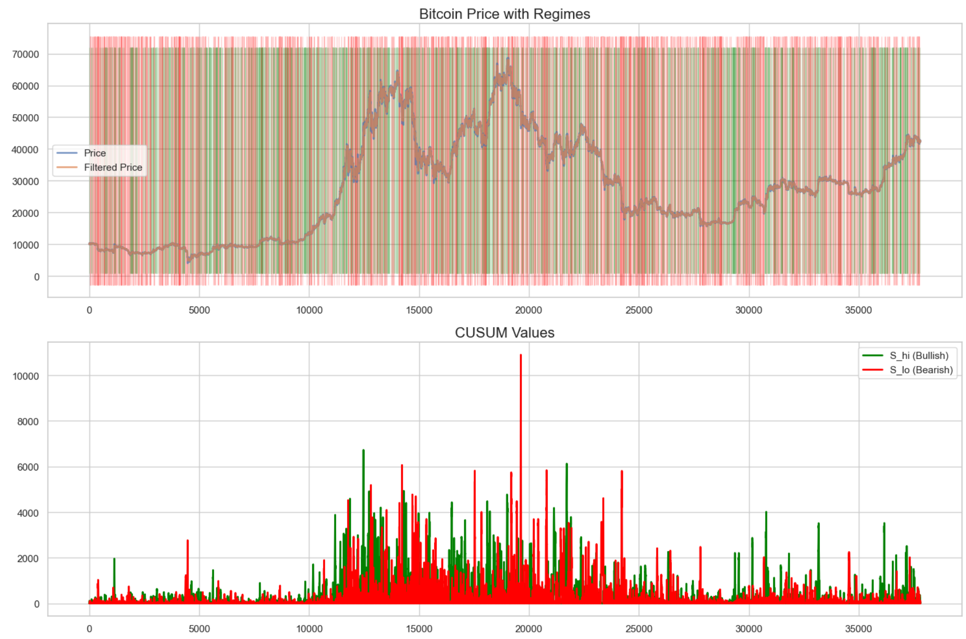
The upward and downward CUSUM statistics are calculated as:

$$S_{\text{hi}}(i) = \max(0, S_{\text{hi}}(i-1) + (x_i - \mu_0 - k))$$

$$S_{\text{lo}}(i) = \max(0, S_{\text{lo}}(i-1) + (\mu_0 - x_i - k))$$

These methods detect BTC market regime shifts, align ETH trades, and use the V-mask technique to confirm significant deviations with a dynamic volatility threshold for adaptability.





4.5.5 Hurst Exponent

The Hurst exponent (H) is a statistical measure that quantifies the long-term memory of a time series and helps determine the underlying trend behavior. By analyzing the rate of return of a time series over various time intervals, it identifies whether the series exhibits mean reversion, a random walk, or persistent trending behavior. The Hurst exponent (H) ranges from 0 to 1 with the following interpretations:

- **H < 0.5:** Indicates a **mean-reverting** series where past deviations from the mean are likely to be corrected.
- **H = 0.5:** The series behaves as a **random walk**, with no significant trending or mean reversion.
- **H > 0.5:** Indicates a **persistent trending** series where upward or downward movements tend to persist over time.

In our ETH/USDT strategy, the Hurst exponent was used as a filter, focusing on the trending region ($H > 0.5$) to align with market conditions favoring sustained trends. Trending markets were prioritized for momentum-based strategies, as they are more likely to yield profitable trades.

4.5.6 Correlation Analysis

The strategy begins by calculating a **rolling correlation** between BTC and ETH closing prices, typically using a window of 7 hours. This rolling approach allows for real-time updates on the relationship between the two assets.

- **Signal Interpretation:**

- **High correlation (> 0.6):** Indicates BTC and ETH are moving together, and trades should align with the broader market trend.
- **Low or diverging correlation:** Signals uncertainty in ETH's movement with respect to the BTC market.

4.6 Rationale Behind the Combination of Indicators

4.6.1 Indicators on BTC to confirm ETH's Trend

CUSUM (Cumulative Sum)

1. Tracks cumulative deviations from a reference price to identify persistent trends.
2. **Strategy Use:**
   - Bullish Regime: Detected when upward CUSUM (S_{hi}) exceeds a threshold.
   - Bearish Regime: Detected when downward CUSUM (S_{lo}) exceeds a threshold.
   - These signals guide ETH trades to align with BTC's market trends, focusing on sustained momentum while avoiding noise.

Relative Strength Index (RSI)

- A momentum oscillator ranging from 0 to 100, identifying overbought (RSI > 70) or oversold (RSI < 30) conditions.
- **Strategy Use:** Confirms entry signals in trending markets ($H > 0.5$). For example:
  - **Overbought:** RSI > 70 indicates strong bullish momentum.
  - **Oversold:** RSI < 30 signals a strong bearish trend.

Bollinger Bands (BB)

- A volatility indicator consisting of a moving average with upper and lower bands at a set number of standard deviations.
- **Strategy Use:** Confirms bearish trends during downtrends ($H > 0.5$). Price below the lower band indicates an oversold condition, supporting the continuation of the bearish trend.

4.6.2 Indicators of ETH for Entry and Exit

Hurst Exponent

- **Trending Market ($H > 0.5$):** Trades are initiated in the direction of the trend, enhancing momentum strategy effectiveness.
- **Mean-Reverting Market ($H \leq 0.5$):** Avoids trades or exits early to minimize losses during non-trending conditions.

Supertrend Direction

- A trend-following indicator combining price and volatility, calculated by adding/subtracting a multiple of the ATR to/from a moving average.
- **Strategy Use:**
  - **Bullish Phase (Supertrend > 0):** Indicates an upward trend; suitable for long trades.
  - **Bearish Phase (Supertrend < 0):** Indicates a downward trend; signals short trades.

4.7 Entry and Exit Conditions

Common Trading Conditions

1. **Dynamic ATR:** Execute trades only when BTC's ATR is less than 1% of BTC's closing price.
2. **Correlation:** Execute trades only when the BTC-ETH correlation exceeds 0.6.
3. **Hurst Exponent:** Execute trades only when the Hurst exponent is above 0.5.

Long Trades

- **Entry Conditions:**
  - BTC RSI is above 70 (indicating strength).
  - BTC's closing price is higher than the middle Bollinger Band.
  - **BTC** regime is identified as bullish by CUSUM.
  - ETH Supertrend Direction is 1 (indicating a bullish phase).
- **Exit Conditions:**
  - BTC RSI drops below 30 (indicating weakness).
  - ETH RSI (current) is less than ETH RSI (previous).
  - **BTC** regime is identified as bearish by CUSUM.
  - ETH Supertrend Direction is -1 (indicating a bearish phase).
  - BTC's closing price falls below the lower Bollinger Band.

Short Trades

- **Entry Conditions:**
  - BTC RSI is below 30 (indicating weakness).
  - **BTC** regime is identified as bearish by CUSUM.

  - ETH Supertrend Direction is -1 (indicating a bearish phase).
  - BTC's closing price is lower than the lower Bollinger Band.

- **Exit Conditions:**
  - BTC RSI (current and previous) exceeds 70.
  - ETH RSI (current) exceeds ETH RSI (previous).
  - BTC's closing price is higher than the middle Bollinger Band.
  - **BTC** regime is identified as bullish by CUSUM.
  - ETH Supertrend Direction is 1 (indicating a bullish phase).

4.8 Risk Management Techniques

Trailing Stop-Loss Mechanism:

- **For Long Positions:**
  - The stop-loss follows the highest price reached since entry. It moves up as the price rises, calculated as a percentage below the peak price. Additionally, it is compared with the lowest price over the last 24 hours.
  - The final stop price is set as either this 24-hour low or the average between the trailing stop and the 24-hour low.
- **For Short Positions:**
  - The stop-loss trails the lowest price reached since entry, adjusting upward as prices fall. This helps limit losses if the market rebounds unexpectedly.

Volatility-Based Exit:

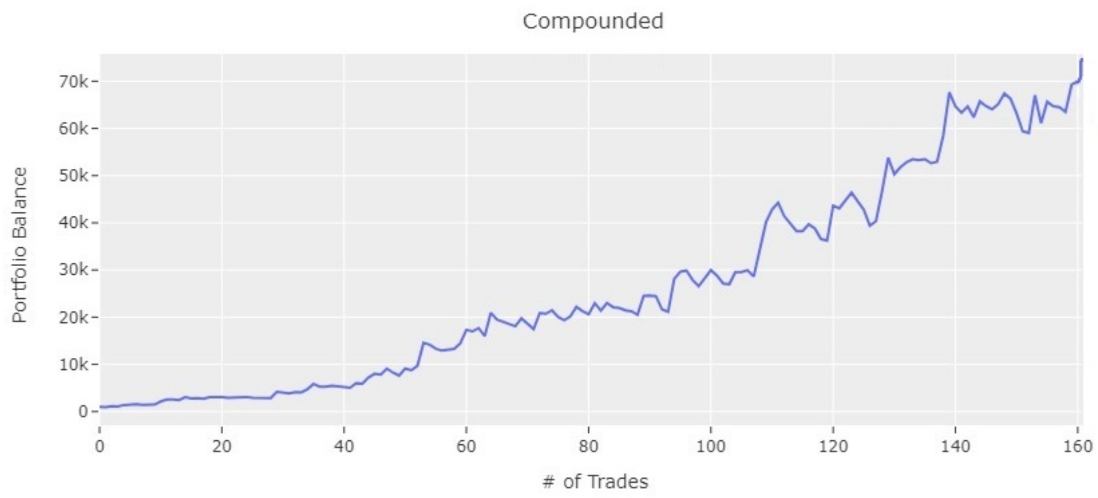
- **Condition:** If Bitcoin's Average True Range (ATR) exceeds 2.5% of its opening price, the position is closed immediately.
- **Purpose:** High volatility can cause unpredictable price swings. Exiting trades during such conditions mitigates unnecessary risks and potential losses.

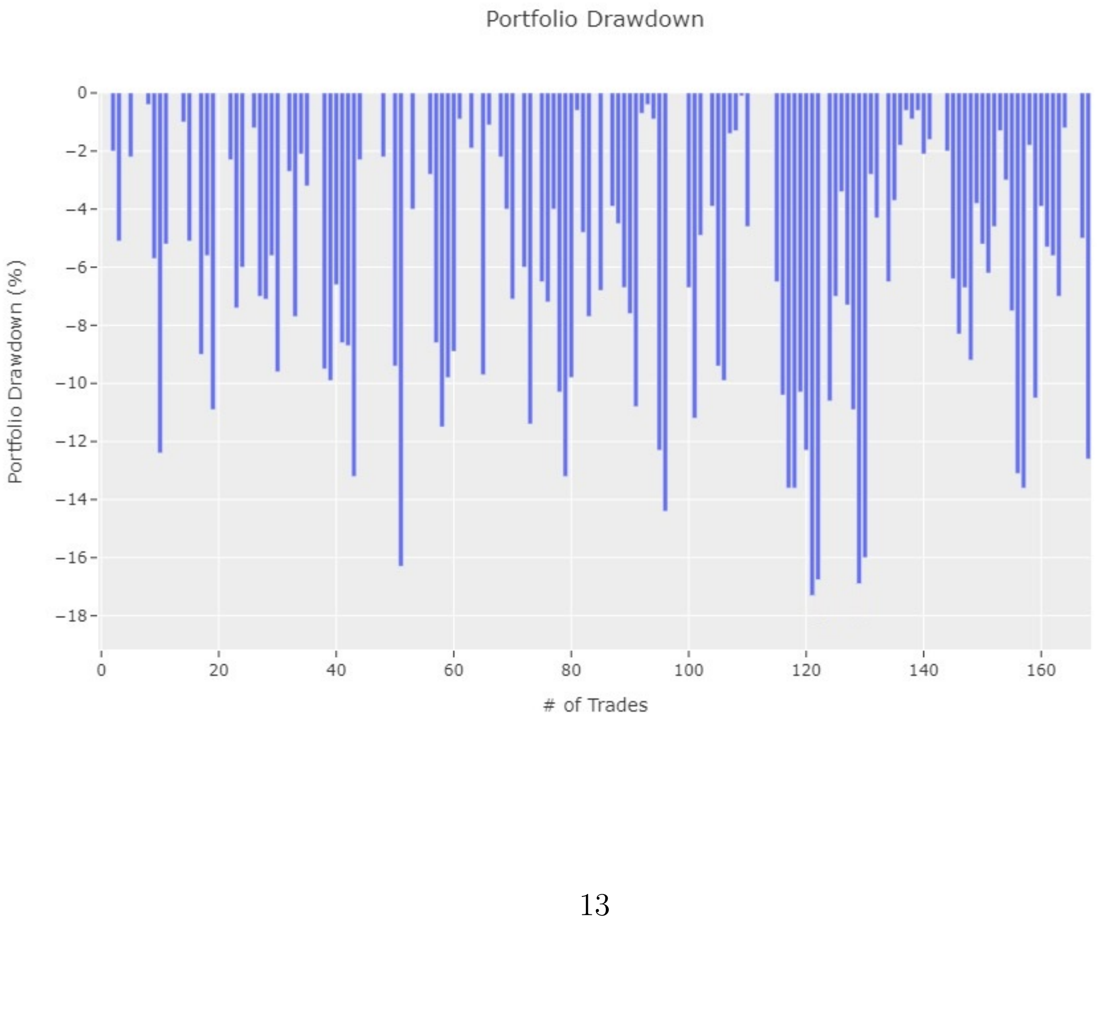
Time-Based Exit:

- **Condition:** All trades, both long and short, are held for a maximum of 4 weeks (28 days). Once the holding period expires, the position is automatically closed, irrespective of profit or loss.
- **Purpose:** Ensures trades are not left open indefinitely, reducing prolonged exposure to market risks and encouraging regular market reassessment.

Cool down Period:

- **Condition:** After a stop-loss is triggered, a 1-day cooldown period is enforced before initiating a new trade.
- **Purpose:** Prevents immediate re-entry, reducing the likelihood of false signals during turbulent market conditions. This disciplined approach ensures trades are entered only when conditions stabilize.

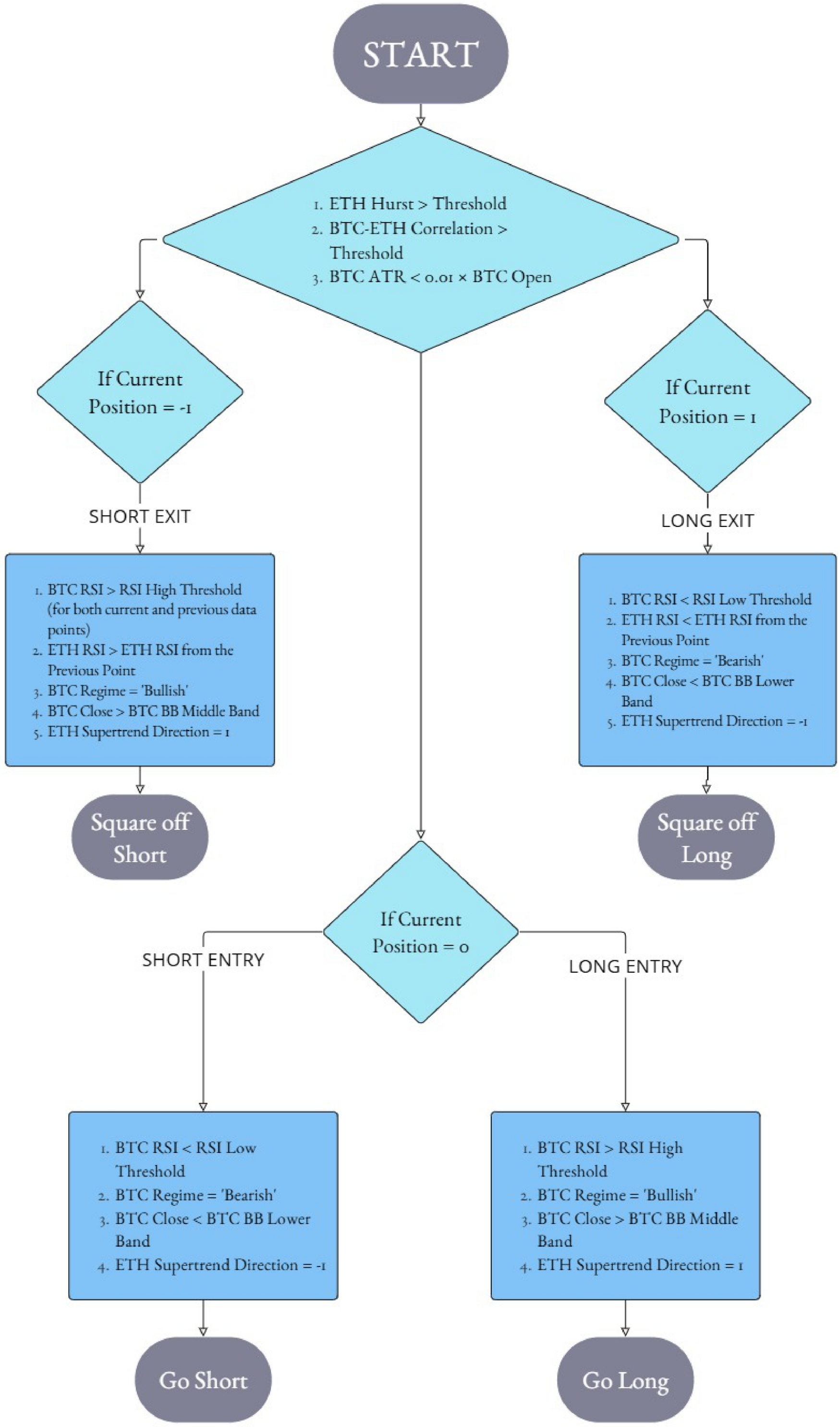




4.9 Key Metrics

Category	Metric	Value
Static Statistics	From	2020-01-01 00:00:00
	To	2023-12-31 00:00:00
	Total Trades	162
	Leverage Applied	1.0
	Winning Trades	77
	Losing Trades	85
	No. of Long Trades	91
	No. of Short Trades	71
	Benchmark Return (%)	1687.59
	Benchmark Return ($1000)	16,875.87
Performance Metrics	Win Rate (%)	47.53
	Winning Streak	4
	Losing Streak	5
	Gross Profit	5,485.45
	Net Profit	5,242.45
	Average Profit	32.36
	Maximum Drawdown (%)	8.16
	Average Drawdown (%)	1.15
	Largest Win	502.67
	Average Win	110.67
Drawdown and Loss Metrics	Largest Loss	-113.54
	Average Loss	-38.57
	Maximum Holding Time	28 days
	Average Holding Time	6 days 02:47:02
	Maximum Adverse Excursion	14.69
	Average Adverse Excursion	3.70
Ratios	Sharpe Ratio	5.966
	Sortino Ratio	19.67
Compound Statistics	Trades Executed	166
	Initial Balance	1,000.00
	Profit Percentage	7684.52
	Final Balance	77,845.15
	Maximum Drawdown (%)	17.14
	Average Drawdown (%)	4.48
	Time to Recovery (TTR)	44 days
TTR Metrics	Average TTR	17.64 days
	Maximum PNL	11,434.42
	Minimum PNL	-7,292.17
	Max Portfolio Balance	88,817.63
	Minimum Portfolio Balance	935.92
	Total Fee	7,684.92

Table 1: Key Metrics


START
1. ETH Hurst > Threshold
2. BTC-ETH Correlation > Threshold
3. BTC ATR < 0.01 × BTC Open
If Current Position = -1
SHORT EXIT
1. BTC RSI > RSI High Threshold (for both current and previous data points)
2. ETH RSI > ETH RSI from the Previous Point
3. BTC Regime = 'Bullish'
4. BTC Close > BTC BB Middle Band
5. ETH Supertrend Direction = 1
Square off Short
If Current Position = 1
LONG EXIT
1. BTC RSI < RSI Low Threshold
2. ETH RSI < ETH RSI from the Previous Point
3. BTC Regime = 'Bearish'
4. BTC Close < BTC BB Lower Band
5. ETH Supertrend Direction = -1
Square off Long
If Current Position = 0
SHORT ENTRY
LONG ENTRY
1. BTC RSI < RSI Low Threshold
2. BTC Regime = 'Bearish'
3. BTC Close < BTC BB Lower Band
4. ETH Supertrend Direction = -1
Go Short
1. BTC RSI > RSI High Threshold
2. BTC Regime = 'Bullish'
3. BTC Close > BTC BB Middle Band
4. ETH Supertrend Direction = 1
Go Long

5 Trading Strategy for the BTC/USDT Market

5.1 Reinforcement Learning Approach

Reinforcement learning allows the strategy to learn optimal actions (such as holding, buying, or shorting) through exploration and exploitation during training. This **continuous learning** is valuable in **dynamic markets**, as the strategy can adapt to changing conditions, rewarding actions that lead to gains and penalizing losses.
Unlike static systems, RL models can adjust their approach based on historical performance, making them more resilient to the unpredictable nature of cryptocurrency markets.

5.2 Key Aspects

- **Leverage:** The RL agent strongly emphasizes on minimizing drawdowns while achieving superior risk-adjusted returns. By effectively containing drawdowns, the portfolio can capitalize on leverage to enhance overall returns.
- **Exploration-Exploitation:** The strategy allows the agent to make the most of the training data. It strikes a balance between exploring diverse trading actions and exploiting learned strategies, enabling the agent to identify and refine the most effective approaches for optimal performance.

5.3 Training Testing Split

To evaluate the model's performance, the dataset spanning 2020 to 2023 was divided into an initial training period of 3 years. After this model is tested for each quarter, and after each quarter the data of this quarter is added to the training data. This can be illustrated as:

Training Data Range - 01-01-2020 to 31-12-2022
Testing Data Range - 01-01-2023 to 01-01-2024

After completing all quarterly evaluations and updates, the model is finalized using the complete dataset (2020–2023).

5.4 State Space

The state space is constructed using various indicators, the current position, and the percentage change in price. The state space signals are carefully crafted to ensure the agent can efficiently identify and respond to market trends.
The components of the state space are defined as follows:

- **Percentage Change in Price - 20 bins :** The percentage change in price is divided into 20 distinct bins from -5 to 5 percent, while clipping the outliers in the outermost bin, allowing for a more granular representation of the price movements. This approach helps to capture similar details of the market's behavior.
- **Current Position :** Represents the current trading position:
  - **0: No position**
  - **1: Long position**
  - **-1: Short position**
- **RSI Signal :** The Relative Strength Index (RSI) is calculated based on the previous 14 candles. In this strategy, RSI signals are utilized to identify potential trends, providing valuable insights for evaluating the agent's performance. The RSI signals are classified as:
  - **1: If RSI $>$ 75**
  - **-1: If RSI $<$ 35**
  - **0: Otherwise**
- **Exponential Moving Averages (EMA)**
  The strategy incorporates three Exponential Moving Averages (EMAs) calculated over different periods: EMA(7), EMA(14), and EMA(28). These EMAs are used to analyze short-term, medium-term, and long-term trends. If these EMAs follow an increasing or decreasing order, then it suggest a bullish or bearish trend respectively. The relationship between the EMAs as follows:
  - **1: If EMA(7) $>$ EMA(14) $>$ EMA(28) (bullish trend)**
  - **-1: If EMA(7) $<$ EMA(14) $<$ EMA(28) (bearish trend)**
  - **0: Otherwise**
- **Aroon Indicator**
  The Aroon Indicator is a technical analysis tool used to determine whether the market is trending toward its highs or lows. It helps to assess the strength and direction of a trend, providing insights into potential reversals or continuation of the current market movement. It is calculated as:
  - **1: Bullish signal**
  - **-1: Bearish signal**

This comprehensive state space captures the market dynamics and provides a robust foundation for decision-making in the trading strategy.

5.5 Action Space:

An action space of size 4 has been defined, with each action representing a specific trading operation. The details of the actions are as follows:

- **Action 1: Enter Long**
  - If no position is currently held: Enter a long position.
  - If a short position is currently held: Exit the short position and enter a long position (long reversal).
- **Action 2: Exit Long**
  - If a long position is currently held: Exit the position.
- **Action 3: Enter Short**
  - If no position is currently held: Enter a short position.
  - If a long position is currently held: Exit the long position and enter a short position (short reversal).
- **Action 4: Exit Short**
  - If a short position is currently held: Exit the position.

5.6 Reward Structure:

The reward structure for each action is as follows:

- **Entering Long Position (Action 1):**
  - A commission is subtracted as a penalty upon entering a long position.
  - If switching from a short position, the reward includes the realized profit or loss from closing the short position minus the associated commission.
- **Exiting Long Position (Action 2):**
  - Reward includes the realized profit or loss from closing the long position minus the associated commission.
- **Entering Short Position (Action 3):**
  - A commission is subtracted as a penalty upon entering a short position.
  - If switching from a long position, the reward includes the realized profit or loss from closing the long position minus the associated commission.
- **Exiting Short Position (Action 4):**
  - Reward includes the realized profit or loss from closing the short position minus the associated commission.

Large Negative Rewards: Large negative rewards are given in case the agent discovers a path that leads to bankruptcy.

- **Stop Loss Mechanism:**
  - If a long position incurs a loss that exceeds `STOP_LOSS_PERCENT = 5%`, the position is closed, and the reward reflects the realized loss after deducting the commission.
  - Similarly, if a short position incurs a loss exceeding `STOP_LOSS_PERCENT = 5%`, the position is closed with the reward reflecting the realized loss and commission.
- **No Trade Case:**
  - For open positions, the reward reflects the change in net worth due to market price movements.
  - For no open positions, a penalty proportional to the absolute price difference from the previous step is applied to discourage inactivity.

In summary, for open positions, the reward is dynamically adjusted based on unrealized gains or losses, calculated as the change in portfolio value (net worth) compared to the previous step.

5.7 Training Process:

- **Epsilon-Greedy Policy:** Balances exploration and exploitation.
  Epsilon Decay: Reduces exploration over time to focus on exploiting learned policies.
- **Q-Table Update:** Uses the Bellman equation to update the Q-values:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right)$$

  Where:
  - α: Learning rate.
  - γ: Discount factor.
  - r: Immediate reward.
  - (s, s'): Current and next states.
  - (a, a'): Current and next actions.

5.8 Risk Management

- **Stop-loss mechanism:** Automatically exits positions if the price moves adversely beyond the stop-loss threshold set at 5%.
- **Position Sizing:** Limits the size of short positions to 75% of available balance to manage leverage and risk in the trading environment.

5.9 Key Metrics(Annualised 23)

Category	Metric	Value
Static Statistics	From	2023-01-01 00:00:00
	To	2024-01-01 00:00:00
	Total Trades	31
	Leverage Applied	1
	Winning Trades	20
	Losing Trades	11
	No. of Long Trades	30
	No. of Short Trades	1
	Benchmark Return (%)	157.08
	Benchmark Return ($1000)	1571.76
Performance Metrics	Win Rate (%)	64.52
	Winning Streak	5
	Losing Streak	2
	Gross Profit	1368.99
	Net Profit	1322.49
	Average Profit	42.66
	Maximum Drawdown (%)	7.75
	Average Drawdown (%)	1.71
	Largest Win	275.92
	Average Win	95.45
Drawdown and Loss Metrics	Largest Loss	-68
	Average Loss	-53
	Maximum Holding Time	47 days
	Average Holding Time	11 days 06:03:52
	Maximum Adverse Excursion	8.73
	Average Adverse Excursion	3.68
Ratios	Sharpe Ratio	9.15
	Sortino Ratio	26.95

Category	Metric	Value
Compound Statistics	Trades Executed	31
	Initial Balance	1,000.00
	Profit Percentage	224.90
	Final Balance	3249.01
	Maximum Drawdown (%)	13.50
	Average Drawdown (%)	2.97
	Time to Recovery (TTR)	53.12 days
TTR Metrics	Average TTR	20.57 days
	Maximum PNL	562.89
	Minimum PNL	-175.45
	Max Portfolio Balance	3350.24
	Minimum Portfolio Balance	1000
	Total Fee	94.22

Table 2: Key Metrics