End Term report

Inter-IIT Tech. meet 13.0

Zelta Automations

Curating Alphas on BTC and ETH USDT Crypto Market

Submitted By:

Team - 91

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1 Approach Outline

1.1 Problem Understanding

Our ongoing project for Inter-IIT 13.0 focuses on developing algorithmic trading strategies for BTC/USDT and ETH/USDT markets. Our goal is to outperform benchmark returns by designing responsive, risk-managed models that adapt to market volatility, leveraging trend-following and momentum-based approaches.

We Observed Key Differences between BTC/USDT and ETH/USDT:

- **Volatility:** ETH/USDT is typically more volatile than BTC/USDT, exhibiting larger and more frequent price fluctuations. This volatility presents higher potential returns but also increased risk. BTC, on the other hand, tends to have more stable movements with fewer extreme fluctuations, resulting in a slightly lower overall volatility.
- **Liquidity:** In the cryptocurrency market, Bitcoin (BTC) exhibits the highest liquidity, resulting in narrower bid-ask spreads and more fluid price movements. Ethereum (ETH), while also highly liquid, generally has lower trading volume compared to BTC. Consequently, ETH/USDT typically experiences slightly wider spreads, particularly during periods of heightened market activity.
- **Price Behavior:** Bitcoin generally exhibits a more predictable, trend-driven movement, characterized by extended uptrends or downtrends. Consequently, it is well-suited for trend-following trading strategies. Ethereum, on the other hand, tends to experience shorter, high-impact price cycles. This volatility favors high-frequency and range-trading strategies that capitalize on swift price reversals.

With this, we started experimenting with diverse statistical methods and machine learning approaches that can be leveraged to capitalize on specific market patterns and conditions, thereby generating alpha.

1.2 Statistical Approach and Learning

In our strategy for BTC/USDT, we incorporated the Hull Moving Average (HMA), a refined moving average developed by Alan Hull, which prioritises speed and accuracy. The HMA minimises lag by combining short- and long-term weighted averages, offering quick trend identification while reducing noise and false signals. This responsiveness allows for early detection of trend reversals, making it a robust choice for high-performance trading, especially in high-volatility markets. Our approach paired the HMA with a Super Trend indicator, achieving strong results with no added risk management or leverage. This combination improved trend detection accuracy, ultimately outperforming market returns by nearly 5x. While we also tested the Hull-WEMA approach, a zero-lag method combining HMA and Weighted Exponential Moving Average, it didn't match the HMA's performance in our setup, so we retained HMA as our primary indicator.

In our strategy for ETH/USDT, we incorporated technical indicators—Hull Moving Averages (HMAs), Relative Strength Index (RSI), and Bollinger Bands (BB)—with a polynomial regression model to dynamically optimize parameters based on market conditions. Key features include:
Dynamic HMA Parameters: Optimized using polynomial regression for responsiveness to market trends. RSI and BB Filters: Confirm trend validity and avoid overbought/oversold conditions. Time-Based Filters: Exclude unfavorable trading periods based on historical data. Polynomial Regression helps adapt HMA parameters by capturing ETH's decelerating growth, allowing for time-sensitive adjustments (shorter HMAs in volatile periods, longer HMAs during stable growth).
Entry Conditions: Include HMA crossovers, RSI validation (below 70), and favorable BB width (0.2-2). Exit Conditions: Triggered by HMA reversals or stop-loss based on recent highs/lows.
The stop-loss mechanism adapts dynamically to market conditions, ensuring timely exits. The strategy is backed by historical data, with backtesting showing profitable trades in volatile periods (2020–2021) and adjustments for lower volatility in 2022–2023.
This approach efficiently integrates technical indicators with statistical modeling, optimizing performance for ETH trading.

1.3 ML approach

1.3.1 Problem Framing for BTC/USDT and ETH/USDT Algorithmic Trading Strategy

The core objective is to develop a machine learning model that can reliably predict short-term price movements and returns for BTC/USDT and ETH/USDT markets without introducing look-ahead bias. The model should capture intrinsic patterns and behaviours in cryptocurrency markets, enabling algorithmic trading strategies that consistently outperform benchmark returns.

To achieve a robust, benchmark-beating strategy, our model must address several specific challenges and objectives:

Pattern Recognition in Intrinsic Market Behaviors: Cryptocurrencies like BTC and ETH exhibit unique price behaviors, with BTC often following prolonged trends and ETH displaying higher volatility and shorter cycles. The problem involves identifying and learning these distinct, asset-specific patterns—like BTC's trend-following nature and ETH's high-frequency reversals. By accurately modeling these behaviors, the goal is to develop a reliable basis for informed, market-specific trading actions.
Predictive Modeling without Look-Ahead Bias: The model must be carefully designed to prevent look-ahead bias, ensuring that future data does not inadvertently influence predictions. This requires rigorous time-series data handling and validation techniques, such as rolling-window cross-validation, to maintain the predictive integrity of the model. Avoiding look-ahead bias is crucial in developing a reliable trading strategy that holds up under live market conditions and ensures real-time predictability.
Developing a Multi-Model Ensemble for Market Adaptability: Given the distinct liquidity, volatility, and price behavior characteristics of BTC and ETH, we aim to ensemble a set of models that incorporate various machine learning and statistical approaches to enhance market adaptability. The ensemble approach will include diverse models—such as XGBoost, LSTM, GARCH, SARIMA, and SVM classifiers—to capture different aspects of price dynamics and leverage model diversity, ensuring robust performance across both stable and volatile periods.

1.3.2 Our Model

Our research focused on identifying key technical indicators to predict price dynamics and movement directions effectively. Using feature importance scores from Random Forest models and correlation analysis, we refined the feature set, eliminating noise and redundancy. Insights from Kaggle competitions informed model architecture choices, emphasizing accuracy and generalizability. The final model predicts returns at the n-th minute, leveraging optimized indicators and methodologies for improved prediction accuracy.
Data Processing: Daily ETH/USDT and BTC/USDT data were pre-processed by forward-filling missing values, standardizing features, and engineering trend, momentum, and volume-based indicators. A time-series split ensured temporal order, and 10-fold cross-validation made the model robust.
Model Choice: We used an ensemble of XGBoost, LightGBM, and CatBoost to handle high-dimensional, noisy, and volatile cryptocurrency data. GridSearchCV with a time-series split optimized hyperparameters for each algorithm.
Performance: R^2 scores were used for evaluation, indicating the variance in returns captured by the model. The ETH model achieved an R^2 of -0.0488, and the BTC model achieved an R^2 of -0.4098, signaling scope for further refinement.

1.4 RL approach

We explored Reinforcement Learning (RL) in trading by reviewing actor-critic algorithms (PPO, A2C, DDPG) and ensemble strategies. Inspired by *"Deep Reinforcement Learning for Automated Stock Trading"* (Yang et al., 2020), we adopted a Markov Decision Process (MDP) framework, integrating technical indicators (RSI, MACD, ADX) and using 2-hour BTC and ETH price data with engineered features.

1.4.1 Our Model

Our RL-based strategy uses agents trained in a simulated environment, optimizing cumulative returns through MDP components:

- **State:** Includes OHLCV, technical indicators, portfolio details, and market regimes.
- **Action:** Buy, sell, or hold, normalized to $[-1, 1]$.
- **Reward:** Net worth changes over time.

Market regimes (e.g., bear, bull) guide dynamic decision-making, while an ensemble of PPO, A2C, DDPG, SAC, and TD3 agents aggregates predictions to ensure robust and adaptive trading signals.
Despite extensive experimentation, the RL model leaned toward a buy-and-hold strategy, hindered by simplistic reward functions. Future improvements will focus on incorporating risk-adjusted metrics like the Sharpe ratio and profit per trade to enhance performance in dynamic markets.

2 Strategy Overview

2.1 BTC/USDT Strategy

2.1.1 How we started and come up with strategy

As we were searching for new indicators to improve the model's performance, we stumbled upon this indicator called Hull moving average(from the family of moving averages).

The Hull Moving Average (HMA) is a refined balance between accuracy and responsiveness, crucial for high-performance trading. Developed by Alan Hull in 2005, it reduces lag, enhancing trend signals and decision-making speed.

The HMA uses weighted moving averages in a unique two-step calculation, combining short-term and long-term averages. This process improves accuracy while filtering short-term fluctuations, enabling early trend identification.

Benefits include:

- **Enhanced Trend Identification:** Due to its quick responsiveness, HMA helps catch trend reversals earlier than SMAs and EMAs, giving timely buy or sell signals.
- **Versatility Across Market Conditions:** HMA's parameters can be adjusted for different timeframes and volatility levels, making it adaptable to varying market conditions, especially useful in high-volatility environments.
- **Fewer False Signals:** Its smoothness helps reduce noise and false signals, decreasing the likelihood of entering trades on short-term fluctuations, which can save on trading costs.

However, the HMA may become less reliable in volatile markets. Combining it with indicators like MACD or Stochastics can enhance precision and confirm trend strength. Implementing risk management further improves the strategy.

Like, in our strategy we used HMA with a super trend indicator without including risk management strategies, leverage, or other indicators, yet we beat the market returns by almost 5x. This demonstrates HMA's power.

We also stumbled upon this research paper written by Seng Hansun, Vincent Charles, Tatiana Gherman and Vijayakumar Varadarajan namely Reference

2.1.2 What's the strategy

Key Features and Indicators

Hull Moving Average (HMA)

- **Purpose:** The HMA is a refined trend-following indicator designed to minimize lag and produce a smoother moving average line.
- **Calculation:** The HMA calculation begins with two WMAs—first, a shorter-period WMA based on half of the full period, and second, a full-period WMA.
- **Trade Signal:** A buy signal occurs when the fast HMA (e.g., 10-period) crosses above the slow HMA (e.g., 30-period), indicating potential upward momentum. Conversely, a sell signal is generated when the fast HMA crosses below the slow HMA, signaling a downward trend.

Supertrend Indicator

- **Role:** The Supertrend indicator integrates volatility into decision-making using the Average True Range (ATR).
- **Calculation:** The Supertrend uses ATR values to create an upper and lower band around the price.
- **Trade Alignment:** By aligning signals with HMA crossovers, the Supertrend filters out false entries in volatile or sideways market conditions.

2.2 ETH/USDT Strategy

2.2.1 Introduction to the Strategy

The presented strategy combines a robust set of technical indicators—Hull Moving Averages (HMAs), Relative Strength Index (RSI), and Bollinger Bands (BB)—with a polynomial regression model to adaptively optimize indicator parameters over time. By employing a data-driven approach, this strategy addresses market cyclicality and volatility trends in Etherium (ETH).

Key Features:

- **Dynamic HMA Parameters:** Tailored using polynomial regression to reflect market conditions.
- **RSI and BB Filters:** Adds additional layers of confirmation for trend validity.
- **Time-Based Trading Filters:** Avoids potentially unfavorable periods based on past market behavior.

2.2.2 Polynomial Regression Analysis

The ETH market exhibits logarithmic growth trends, where price increases become less explosive over time. This deceleration pattern can be captured using polynomial regression, which provides a predictive model of the ETH price trajectory.

Role in Strategy Design:

- **Parameter Optimization:** Polynomial regression identifies slowing market trends and informs the selection of time-sensitive Hull Moving Average (HMA) lengths. For example, as market volatility decreases, longer HMAs are used to smooth out noise while maintaining responsiveness to trends.
- **Market Contextualization:** Polynomial regression enables the algorithm to dynamically align its behavior with macro market conditions, ensuring relevance in different market phases.

2.2.3 Explanation of Indicators

Hull Moving Average (HMA) The HMA is designed to reduce lag, providing smoother and faster-moving averages compared to traditional moving averages. This is achieved by weighting recent prices more heavily, making the HMA highly responsive to price changes.
Why HMA Works: Its responsiveness to trends allows for earlier signal detection in volatile assets like ETH.
Dynamic Adjustment: The HMA length varies based on polynomial regression insights, adapting to the market's changing volatility.
Relative Strength Index (RSI) The RSI measures the strength and velocity of price movements to identify overbought (¿70) or oversold (¡30) conditions.
Why RSI Works: Momentum shifts often precede price reversals, making RSI a reliable tool for validating potential trade entries.
Integration: Combined with HMA crossovers, RSI ensures that trades align with both trend and momentum conditions.
Bollinger Bands (BB) and Width Filter Bollinger Bands plot price volatility relative to a simple moving average (SMA). The normalized Bollinger Band width (BB Width) quantifies the range of price movements.
Why BB Width Works: Narrow bands indicate consolidation phases, often preceding price breakouts, while wide bands suggest heightened volatility. Filtering trades based on BB Width avoids whipsaws in low-volatility environments.
Normalized Filter: Ensures the strategy operates in favorable volatility ranges (0.2 to 2).

2.2.4 Parameter Optimization via Polynomial Regression

The strategy's innovation lies in its time-dependent HMA parameterization, derived from polynomial regression. ETH's logarithmic price regression provides:

- **Insight into Market Phases:** Deceleration in ETH's exponential growth is captured by reducing HMA sensitivity over time.
- **Time Ranges and Adjustments:**
  - **2020–2021:** Highly volatile, shorter HMA lengths for quick trend adaptation.
  - **2022–2023:** Moderately slowing market, medium HMA lengths for balanced trend detection.
  - **2024:** Stabilizing growth, longer HMA lengths for smoother signal extraction.

2.2.5 Trading Conditions

Entry Conditions:

- HMA Crossover: Fast HMA (FHMA) crossing above Slow HMA (SHMA) signals a potential upward trend.
- RSI Validation: RSI must remain below 70, indicating no overbought conditions.
- BB Width Filter: Normalized BB Width must be within the range of 0.2–2, ensuring suitable volatility conditions.
- Time Constraints: Trades are filtered to exclude the period between May 2021 and May 2022, a historically adverse trading phase.

Exit Conditions:

- HMA crossover in the opposite direction signals a trend reversal.
- Stop-loss levels based on the 25-period lowest low (for longs) or highest high (for shorts) provide additional safety.

2.2.6 Stop-Loss Strategy

The stop-loss mechanism is designed to minimize risks:

- **Trend-Based Stop-Loss:** Tracks local highs and lows over a 25-period window, ensuring exits occur before significant adverse price movements.
- **Dynamic Adjustment:** Adapts to changing market conditions, reducing unnecessary stop-outs during consolidations.

2.2.7 Code Overview

Key Features:

- Precomputed HMAs: Efficiently calculates and stores HMAs with varying lengths.
- Time-Sensitive Parameters: Conditional logic selects appropriate HMAs based on the date range.
- BB Width Normalization: Adds a novel dimension to Bollinger Band analysis, improving trade precision.
- Time Filters: Historical data-driven insights prevent trades during unfavorable market conditions.

2.2.8 Backtesting and Performance Insights

Observations:

- 2020–2021: High volatility favored shorter HMA lengths, resulting in frequent but profitable trades.
- 2022–2023: Reduced volatility required adjustments to parameters, smoothing trade signals.
- 2024 and Beyond: Long-term growth patterns necessitate conservative settings, reducing noise.

2.2.9 Conclusion

This strategy exemplifies the synergy between technical indicators and advanced statistical modeling. By incorporating polynomial regression to dynamically adjust indicator parameters, it adapts seamlessly to BTC's evolving market conditions. The additional layers of RSI, Bollinger Bands, and time filters enhance reliability, making it a robust tool for algorithmic trading in cryptocurrency markets.

2.3 Our ML Model

2.3.1 How We Started and Came Up with This Strategy

The goal of this strategy was to predict Ethereum (ETH) and Bitcoin (BTC) price movements against Tether (USDT) to develop a profitable trading approach. We focused on indicators like trends, volatility, momentum, and volume to capture key market features. And also using the **chunking** of the dataset preserving the temporal order while training along with the cross-validation methods.

To address the high volatility and complexity of cryptocurrency markets, we framed the machine learning problem as predicting returns after n minutes from a given data point—a common approach in high-frequency trading.

We adopted an ensemble modeling approach using **XGBoost**, **LightGBM**, and **CatBoost** to improve robustness and accuracy. This ensemble ensured a reliable and adaptive strategy for dynamic market conditions.

2.3.2 Research We Did

Our research involved a detailed exploration of technical indicators to capture key aspects of price dynamics and movement direction. We experimented with a wide range of indicators and back-tested their historical effectiveness. Key areas of investigation included: ‘

- Selecting indicators based on **importance scores from Random Forest** models and their **correlations** to the target variable, ensuring a focus on features with the highest predictive power.
- Testing feature selection techniques to optimize the feature set and eliminate noise or redundancy.
- Analyzing model performance across hyperparameters and leveraging insights from Kaggle stock market forecasting competitions helped us identify a well-suited model architecture, balancing accuracy and generalizability.

Our final model aims to predict the **return at the n-th minute** from a given time point, leveraging a carefully optimized set of indicators and refined methodologies to achieve high prediction accuracy.

2.3.3 ML Lifecycle

Data Ingestion and Pre-Processing

- **Data:** We used daily historical data for ETH/USDT and BTC/USDT covering data given by the zelta. The dataset included price and volume data with a comprehensive set of 60 technical indicators initially selected.
- **Pre-Processing:**
  - Missing data: was handled using forward-fill methods to maintain data consistency.
  - Features: were standardized to ensure compatibility across machine learning models.
  - Technical indicators: were engineered to capture trend, momentum, and volume-based signals.
  - Train-Test Split: The data was split chronologically, with test data as the last 10000 dates, and it could be changed as per the requirement.
  - Time-Series-Split: used to maintain the temporal order of the data and 10-fold training is done on the data for making it robust.

Model (Algorithm)

- **Model Choice:** We adopted an ensemble modeling approach using **XGBoost**, **LightGBM**, and **CatBoost** to improve robustness and accuracy. These models were selected due to their effectiveness in handling binary classification tasks with high-dimensional features and their ability to identify complex patterns in noisy, high-volatility data—typical of cryptocurrency markets. The ensemble approach ensured a reliable and adaptive strategy that could adjust to the dynamic and constantly changing market conditions.
- **Hyperparameter Tuning:** A GridSearchCV approach was used with 10-fold cross-validation along with the time series split to ensure the temporal order, testing various parameters to find the best model settings for each algorithm, ensuring optimal performance in different market conditions.
- **Best Model:** After tuning, the best model was identified based on performance across the validation sets, providing a balanced and accurate solution for predicting returns in the cryptocurrency market.

How It's Working

- **Prediction:** In our model, we use $\mathbf{R^2}$ **score** as the evaluation metric, which is a standard for regression problems. The R^2 score, also known as the coefficient of determination, indicates how well the predicted values match the actual values. It measures the proportion of variance in the dependent variable that is predictable from the independent variables.

  The formula for calculating the R^2 score is:

  $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

  where:

  - y_i is the actual value for the i-th observation,
  - $\hat{y}_i$ is the predicted value for the i-th observation,
  - $\bar{y}$ is the mean of the actual values,
  - n is the number of data points.

- **ETH $\mathbf{R^2}$ Score**: -0.04877906674060139

- **BTC $\mathbf{R^2}$ Score**: -0.40984356957489454

2.4 Our RL Model

2.4.1 How We Started and Came Up with This Strategy and Research We Did

We began by exploring the applications of **Reinforcement Learning (RL)** in financial markets, focusing on its ability to optimize trading decisions dynamically. Our research included reviewing literature on **actor-critic algorithms** (PPO, A2C, DDPG) and ensemble strategies, inspired by works such as "Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy" (Yang et al., 2020). We selected a **Markov Decision Process (MDP)** framework to model stock trading, defining state, action, and reward functions. Additionally, we incorporated technical indicators (e.g., RSI, MACD, ADX) to enhance decision-making. Our dataset consisted of BTC and ETH price data at a 2-hour timeframe, preprocessed to include both market and technical features.

2.4.2 What Is Our Strategy

Our strategy is built around **Reinforcement Learning (RL)** agents trained in a simulated trading environment designed to emulate real-world conditions, including transaction costs and dynamic market states. The agents aim to optimize trading decisions (buy, sell, or hold) by learning to maximize cumulative returns within the constraints of a **Markov Decision Process (MDP)**, where:

- **State (S)**: Comprises market OHLCV data, technical indicators (e.g., RSI, MACD, ADX, CCI), portfolio details (shares held, cash balance, net worth), and contextual features like trading time and regime predictions.

- **Action (A)**: Represents the magnitude of buying, selling, or holding an asset, normalized to the range $[-1, 1]$.

- **Reward (R)**: Encodes trading profitability and market alignment, though in this iteration, it was simplistically defined as:

  $$R_t = \text{Net Worth}_t - \text{Initial Balance}$$

To enhance robustness, we incorporated **regime prediction** using a classification model based on short- and long-term moving averages, volatility, and historical price patterns. Market regimes are classified into five categories:

$$\text{Regime Label} = \begin{cases} 0.0 & \text{Strong Bear Market} \\ 0.25 & \text{Bear Market} \\ 0.5 & \text{Sideways Market} \\ 0.75 & \text{Weak Bull Market} \\ 1.0 & \text{Strong Bull Market} \end{cases}$$

These labels help contextualize agent decisions, allowing for dynamic adaptation to market conditions.
The **ensemble strategy** aggregates predictions from five RL agents—**PPO, A2C, DDPG, SAC, TD3**. Each agent is an actor-critic model that estimates an optimal policy $\pi(a|s)$ and value function $V(s)$. The policy $\pi(a|s)$ maps state s to a probability distribution over actions a, with the update driven by the **advantage function**:

$$A(s_t, a_t) = Q(s_t, a_t) - V(s_t),$$

where $Q(s_t, a_t)$ is the expected return of action a_t in state s_t, and $V(s_t)$ is the baseline return for state s_t.

The agents learn by maximizing the expected cumulative discounted reward:

$$\mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R_t \right],$$

where $\gamma \in [0, 1]$ is the discount factor emphasizing short-term rewards.

The ensemble model integrates individual agent actions through an averaging mechanism:

$$a_{\text{ensemble}} = \frac{1}{N} \sum_{i=1}^{N} a_{\text{agent}_i},$$

where a_{agent_i} is the action predicted by the i-th agent, and N is the total number of agents. This mitigates overfitting and provides more stable trading signals across volatile market conditions.
The inclusion of regime-based features and the ensemble approach ensures that the strategy is adaptive to market dynamics and minimizes reliance on any single agent's decisions. Future refinements to reward design and regime-sensitive weighting mechanisms could enhance performance significantly.

2.4.3 Conclusion and Results

Despite extensive experimentation with various reward functions, the RL-based model did not achieve satisfactory performance in real-market conditions. We experimented with different reward schemes, such as **portfolio value**, **return per trade**, and **profitability per action**. However, the results were not significantly improved, as the model continued to favor a buy-and-hold strategy. The primary issue stemmed from the design of the reward function, which remained overly simplistic, focusing only on the difference between net worth and initial balance. This structure failed to encourage the generation of efficient trading signals, especially in dynamic and volatile market environments.
Future work will need to focus on developing a more nuanced and market-sensitive reward function. Incorporating risk-adjusted metrics such as the **Sharpe ratio**, **maximum drawdown**, and **profit per trade** could provide more actionable insights and better align the agent's behavior with optimal trading strategies. These refinements will help the model better adapt to market fluctuations and improve overall performance.

2.5 Pairs Trading Strategy

In developing our algorithmic trading strategy, we also focused on pairs trading due to the high correlation between BTC and ETH prices. Pairs trading typically allows traders to exploit temporary price divergences between two correlated assets by taking a long position on one asset and a short position on the other. With BTC and ETH, we expected this method to yield profitable opportunities given their strong correlation, assuming one asset might temporarily lead or lag the other. However, upon deeper analysis, we discovered that the lag between BTC and ETH was virtually zero, meaning they moved almost in sync. This simultaneous movement limited our ability to capture profitable spreads, as any divergence between the two assets was short-lived and difficult to capitalize on. Without a meaningful lag, our pairs trading approach lacked the separation needed for entry and exit signals. Recognizing these limitations, we decided to explore alternative strategies that could better leverage other market behaviors, such as trend-following and momentum-based approaches, to achieve more reliable returns. This shift in strategy marks an important pivot in our project, as we continue testing and refining models to improve adaptability and performance in the highly volatile cryptocurrency market.

3 Performance Metrics and Visualizations

3.1 ETH/USDT strategy

3.1.1 ETH Metrics

We ran our ETH ML-based algorithm with both leverage 1 and leverage 3. Unfortunately, due to the nature of our model, we trained on 2020-2021 ETH data and ran a backtest on 2021-2022 data. Thus, this data only exists for 1 year, with benchmark returns of 900%.

The basic metrics generated from your ETH data and SDK are shown below:

Metric	Value
Net Profit	14055% (Compounding)
Total Trades	282
Win Rate	43%
Max Drawdown	34%
Sharpe Ratio	0.778
Sortino Ratio	3.45
Commission Paid	$18103

Table 1: Performance Metrics

3.1.2 ETH Visualisation

3.2 BTC Strategy

3.2.1 BTC Metrics

Our metrics show a 4x market beating strategy as of now, with somewhat high drawdowns and recovery time. This strategy is sure to improve as we add more risk management measures (like stop losses and more indicators to ensure our trades are taken at the right time.)

Metric	Compounding (Leverage 1)
Initial Balance	$1,000
Final Balance	$13,018.77
Profit Percentage	1,201.87%
Total Trades	68
Winning Trades	30
Losing Trades	38
Win Rate	44.12%
Maximum Drawdown (%)	39.64%
Average Drawdown (%)	10.16%
Sharpe Ratio	3.29
Sortino Ratio	21.17
Total Fees	$519.55
Time to Recovery (TTR)	128 days
Average Time to Recovery (TTR)	11.75 days

Year	2019	2020	2021	2022	2023
Index	1	2	3	4	5
Benchmark Beaten?	Yes	No	Yes	Yes	No
Benchmark (%)	-28.37	301.54	56.92	-64.64	155.66
Final Balance	773.80	1,150.64	17,351.40	429.94	1,960.00
Initial Balance	1,000.00	1,000.00	1,000.00	1,000.00	1,000.00
Long Trades	4	10	4	10	7
Maximum Adverse Excursion	17.04	22.62	11.51	38.81	9.60
Profit (%)	-22.62	15.06	1,635.14	-57.01	96.00
Short Trades	4	9	4	9	7
Total Trades	8	19	8	19	14
Win Rate	25.00%	42.11%	87.50%	31.58%	50.00%

3.2.2 BTC Visualisation

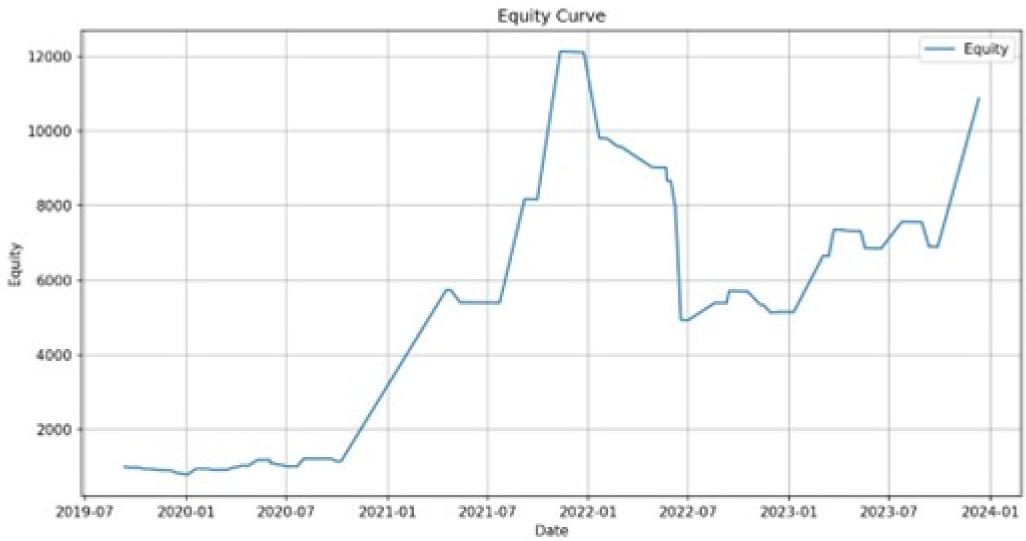

Figure 1: Equity Over Time

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4 Unique Approaches and Innovations

4.1 Enhancing Trade Frequency with Super Trend and Hull Moving Average (HMA)

Current Approach: We have been utilizing a combination of the Super Trend indicator and the Hull Moving Average (HMA) on smaller timeframes, such as the 2-hour charts for Bitcoin (BTC). While the HMA is excellent at detecting quick trend changes, this setup has resulted in a very limited number of trades. **Challenges Encountered:**

- **Low Trade Frequency:** On smaller timeframes, the number of trades is too few, limiting our ability to capitalize on smaller price movements.
- **Missed Opportunities:** Despite the HMA's efficiency in capturing instant trend shifts, the overall strategy doesn't generate enough trading signals to fully exploit market fluctuations.

Proposed Enhancements: To address these issues, we are considering a multi-timeframe approach:

- **Overall Trend Detection:** We will use the Super Trend indicator on a larger timeframe, such as the daily chart, to identify the primary market trend.
- **Trade Execution on Lower Timeframes:** Trades will be executed based on HMA signals on shorter timeframes like the 1-hour or 2-hour charts.

Trade Direction Filtering:

- **Bullish Trend:** If the daily Super Trend indicates an uptrend, we will only take long positions based on the HMA signals.
- **Bearish Trend:** Conversely, if the daily Super Trend signals a downtrend, we will restrict ourselves to short positions.

Expected Benefits:

- **Increased Trade Opportunities:** By leveraging lower timeframes for trade execution within the context of the broader trend, we anticipate capturing more frequent and smaller price movements.
- **Better Trend Alignment:** Ensuring trades align with the dominant market trend should enhance the probability of successful trades.

4.2 Optimizing Moving Average Crossover Strategies with a Moving Average Ribbon

Current Approach: Traditionally, our moving average (MA) crossover strategy relies on the intersection of two MAs with different periods. While this method provides clear signals, we sometimes find the timing and accuracy lacking. **Challenges Encountered:**

- **Signal Timeliness:** The two-MA crossover can sometimes be too early, causing false signals.
- **False Signals:** Occasional false crossovers can lead to unprofitable trades, especially in volatile markets.

Proposed Enhancements: To improve this, we are looking into creating a moving average ribbon:

- **Moving Average Ribbon Setup:** Incorporate three to four MAs with varying periods (e.g., 10-period, 20-period, 50-period, and 100-period) to form a ribbon-like structure.
- **Enhanced Trading Signals:**
  - **Bullish Signals:** When shorter-term MAs cross above longer-term MAs and the ribbon starts to slope upwards.
  - **Bearish Signals:** When shorter-term MAs cross below longer-term MAs and the ribbon begins to slope downwards.

Expected Benefits:

- **Increased Accuracy:** Multiple MAs provide a more detailed view of the trend, reducing the likelihood of false signals.
- **Better Trend Confirmation:** The ribbon helps confirm the strength and direction of the trend, ensuring that our trades are more reliably aligned with market conditions.

4.3 Avoiding Trades in Sideways or Choppy Markets

Current Approach: We have observed that moving average-based strategies tend to underperform during sideways or choppy market conditions, leading to false signals and potential losses. **Challenges Encountered:**

- **False Signals:** In non-trending markets, MA crossovers can generate misleading signals.
- **Reduced Profitability:** Trading in choppy conditions often results in unprofitable trades, which impacts the overall performance of our strategy.

Proposed Enhancements: To mitigate these issues, we are implementing filters to avoid trading during low-volatility or non-trending periods:

4.3.1 Normalized Bollinger Band Width:

$$\text{Normalized Band Width} = \frac{\text{Upper Bollinger Band} - \text{Lower Bollinger Band}}{\text{Moving Average}}$$

- **Purpose:**
  - This metric normalizes market volatility, making it adaptable across different price levels.
  - A lower normalized width indicates a choppy or low-volatility market.
- **Implementation:**
  - We will set a threshold for the normalized band width and avoid trading when the width falls below this level, signaling a sideways market.

4.3.2 Avoid Trading When Moving Averages Are Converging:

- **Indicator:** Converging MAs suggest a weakening trend and potential sideways movement.
- **Implementation:** We will define conditions where trading is halted if specific MAs are positioned within the high and low range of recent candlesticks. For instance, if a short-term MA is within the high-low range of the current candle, it may indicate consolidation.

Expected Benefits:

- **Reduced False Signals:** By filtering out periods of low volatility and consolidation, we can minimize the risk of entering unprofitable trades.
- **Enhanced Strategy Performance:** Focusing on trending markets should improve the overall effectiveness and profitability of our trading strategy.

4.4 Implementing Dynamic Trailing Stop Loss Based on Market Volatility

Current Approach: Traditionally, we have used fixed percentage trailing stop losses (e.g., 2**Challenges Encountered:**

- **Inflexibility in Low Volatility:** In less volatile markets, a fixed stop loss like 3
- **Ineffectiveness in High Volatility:** In highly volatile markets, the same fixed stop loss might not provide sufficient protection, resulting in larger losses.

Proposed Enhancements: Instead of a fixed percentage, we are exploring a volatility-based trailing stop loss:

4.4.1 Volatility-Based Trailing Stop Loss:

$$\text{Trailing Stop Loss} = (\text{High} - \text{Low}) \times \text{Multiplier}$$

- **Multiplier:** Typically set between 1.5 to 2, adjustable based on the asset and trading strategy.
- **Advantages:**
  - **Adaptive to Market Conditions:** Automatically adjusts to current market volatility, providing tighter stops in low volatility and wider stops in high volatility.
  - **Potential for Better Risk Management:** May reduce the likelihood of being stopped out by normal price fluctuations while still protecting against significant adverse moves.

- **Alternative Consideration:** While the Average True Range (ATR) is a common method for volatility-based stop losses, we believe that using the previous candle's volatility could offer tighter and potentially more effective stop levels.

Implementation Tips:

- **Backtesting:** We plan to rigorously test this volatility-based trailing stop loss in various market conditions to ensure it provides the desired balance between protection and flexibility.
- **Adjustment:** Fine-tuning the multiplier will be essential to match the specific volatility characteristics of the traded asset and the chosen timeframe.

Expected Benefits:

- **Improved Flexibility:** Adapts to changing market conditions, enhancing the effectiveness of stop loss levels.
- **Enhanced Strategy Performance:** Potentially reduces losses during volatile periods while preventing premature exits during stable periods, thereby optimizing overall strategy profitability.

So these are some of the unique aprroaches and innovation that we thought of and you can try to apply it in your strategy for better results.