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計畫名稱：	加密貨幣波段高頻交易之幣種間相關性低風險套利策略方法

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112 年度科技部大專生研究計畫成果報告

加密貨幣高頻交易幣種間相關性低風險套利策略方法

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中華民國 112 年 3 月 18 日

目錄

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I. Abstract

A.　中文摘要

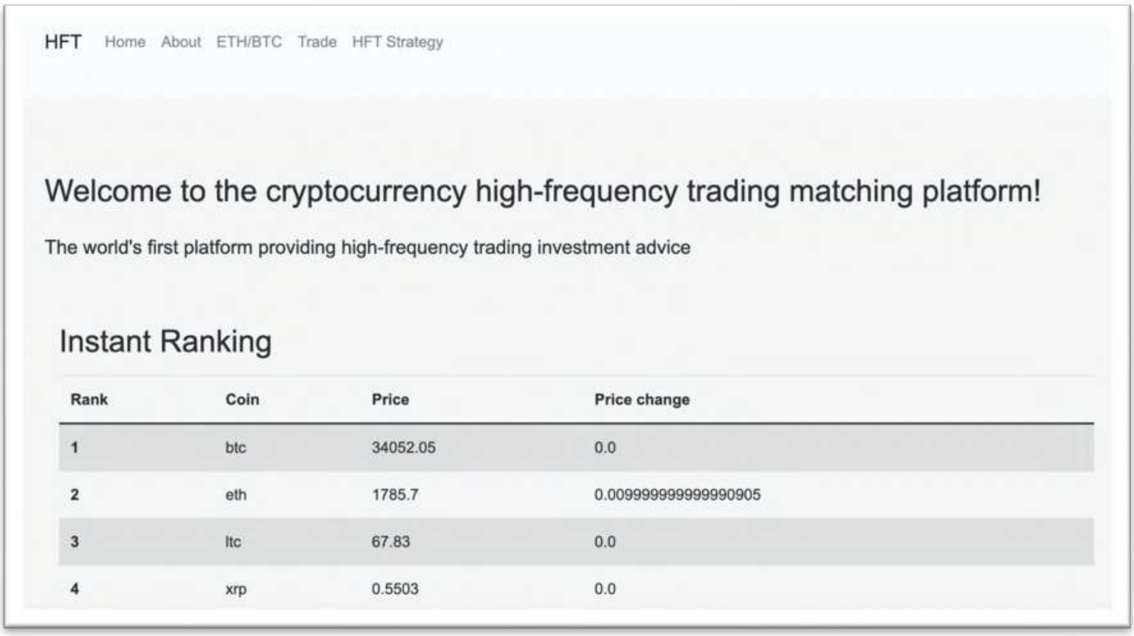
比特幣在加密貨幣市場占比高，價格漲跌將很大程度帶動其他小幣種的同步漲跌。而加密貨幣特有的「插針」也成為此次研究的重點目標，「插針」是僅會在加密貨幣市場出現的特有現象，起因為市場流動性不足時，擁有足夠籌碼者能迅速撼動整個市場，並在毫秒等級時間內使市場出現劇烈波動。現市場研究多用傳統技術指標、AI 神經網路以對市場行情進出做出判斷，本質上都是總結歷史規律，對未來價格、行情做出預測。然而金融市場資料在過往研究中不經去噪的模型容易出現過度擬合風險，影響判斷的準確率，透過非預測式高頻交易，我們能以真實情況做出判斷套利，從而規避因預測準確度的風險。

研究中將先以統計方式驗證此假說，接著提出兩種交易策略，分別針對「大幣帶動小幣漲跌」以及「針對單一幣種的動態插針捕捉」兩方法，專題研究的目的就是完善上述各部分，追求收益最大化，並期許將成果貢獻於金融科技領域，以網頁應用程式讓用戶以真實數據實作驗證此研究。

B.　英文摘要

In the rapidly changing financial landscape, the emergence of cryptocurrencies has introduced new possibilities for trading strategies, including high-frequency trading (HFT). In this research, We explore the unique attributes of the cryptocurrency market, focusing specifically on the phenomenon known as the "Needle"—a brief yet significant price fluctuation. Employing advanced quantitative methods, statistical models, and machine learning algorithms, We develop a non-predictive HFT strategy centered on capitalizing on these Needle events. Contrary to traditional predictive models that rely heavily on technical indicators, this approach adopts a data-driven method. We meticulously analyze the impact of major cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH) on smaller but notable coins such as ADA, XRP, and LTC during Needle events. This research not only introduces new pair trading techniques but also dynamic limit order strategies for trading individual coins when pair trading is not viable.

As the final contribution of this research, I unveil the world's first real-time cryptocurrency data streaming platform capable of implementing the simulated strategies discussed. This platform serves as an educational resource for HFT, providing invaluable insights and comprehensive reports. Poised to make a significant impact, this research lays the groundwork for the future of high-frequency trading in the cryptocurrency realm, offering a pioneering approach to fintech trading strategies.



Rank	Coin	Price	Price change
1	btc	34052.05	0.0
2	eth	1785.7	0.009999999999990905
3	ltc	67.83	0.0
4	xrp	0.5503	0.0

Fig.1. The World First HFT information platform created in this research.[1]

II. Background: Cryptocurrency and Market Trends

A. An Overview of Cryptocurrencies and Market trends

Cryptocurrencies have emerged as a revolutionary class of assets, with Bitcoin standing as the epitome of this digital transformation. Introduced in 2008 by an individual or group under the pseudonym Satoshi Nakamoto, Bitcoin now commands approximately 48% of the total cryptocurrency market share. The asset class is underpinned by Distributed Ledger Technology, commonly known as blockchain, which ensures transaction security and anonymity through cryptographic algorithms. These digital assets are increasingly considered as investment tools, attracting both individual and institutional participants to various trading and speculative activities.

A key aspect of the cryptocurrency ecosystem is the presence of online exchanges like Binance, which stand as pillars providing liquidity, market depth, and transaction history. These platforms offer multiple trading options, among which spot and futures

[1] Information of the current market cap: https://coinmarketcap.com/crypto-heatmap/

trading are the most common. Spot trading is straightforward, where buyers and sellers exchange currencies based on real-time market prices. On the other hand, the cryptocurrency market has introduced a unique derivative known as Perpetual Contracts in futures trading. These contracts are designed without a delivery date, allowing traders the flexibility to hold positions long-term.

Fig.2. Current Cryptocurrencies Market cap Heat Map.

Adding another layer of complexity and utility to the ecosystem are stable coins like Tether (USDT). Issued by Tether Limited, these coins are pegged one-to-one to the U.S. dollar and are extensively used as trading pair base currencies on exchanges due to their liquidity and price stability.

III. Review of Existing Research and Comparative Analysis

Quantitative trading strategies have evolved significantly, with state-based reinforcement learning models using limit order book data to optimize trading decisions [1]. While these methods have been applied to both stock and cryptocurrency markets, external factors like news sentiment have also been incorporated into models through recurrent neural networks [2].Specific to cryptocurrency high-frequency trading, Deep Feed Forward Neural Networks (DFFNN) have been utilized for Bitcoin price prediction. These models show efficacy in terms of root mean square error (RMSE), but often lack real-world applicability [3].

Research in the forex market shows that pair trading strategies involving highly correlated assets can yield significant returns. These findings are particularly relevant to the cryptocurrency market, where major cryptocurrencies often serve as base currencies for trading pairs [4].Statistical methods like the Augmented Dickey–Fuller test (ADF) ensure the stationarity and cointegration of trading pairs, adding a layer of reliability to trading strategies [5].

IV. Design Principles of the Trading Algorithm

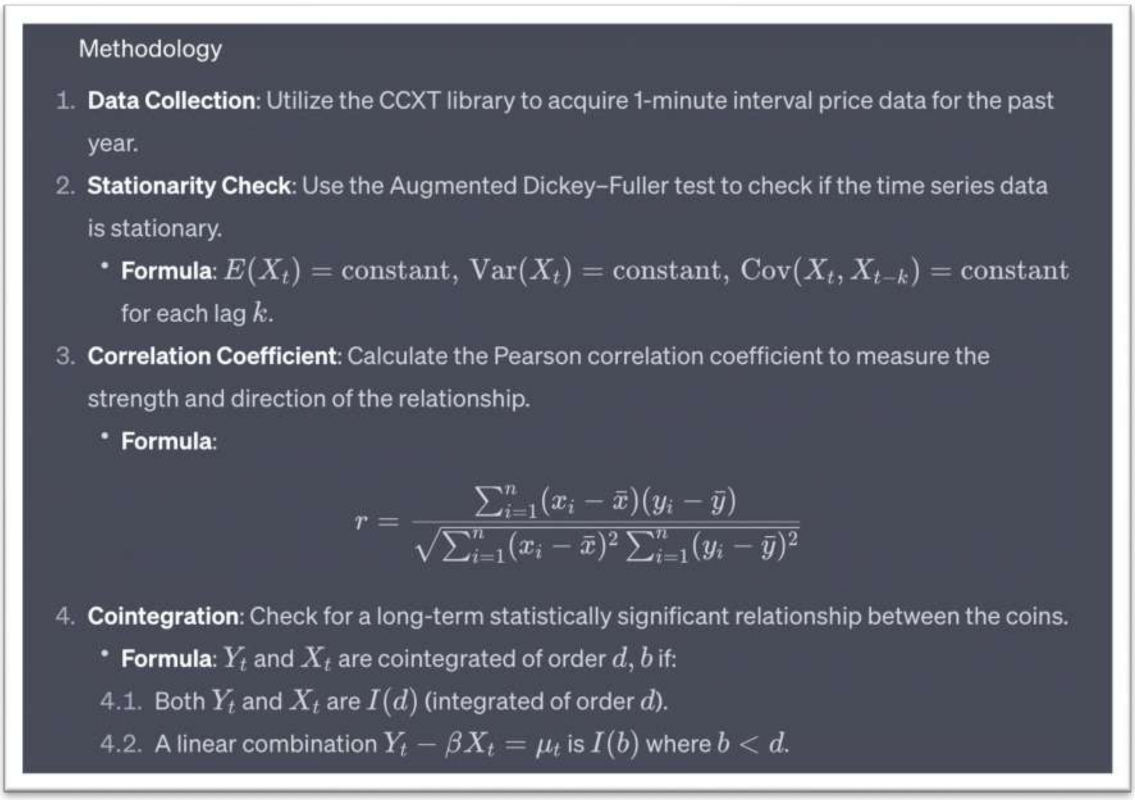
A. Phenomenon Identification

The cornerstone of our quantitative trading strategy lies in the hypothesis that price movements in major cryptocurrencies like BTC and ETH exert a significant, high-speed influence on the prices of smaller coins such as ADA, XRP, and LTC. To rigorously validate this hypothesis and to build a robust trading strategy, we employ three pivotal statistical measures: Stationarity, Coefficient of Correlation, and Cointegration. Each of these metrics serves a distinct yet interconnected purpose in the formulation and validation of our high-frequency pair trading algorithm.

1. **Stationarity:** In a volatile financial landscape, consistency is invaluable. A stationary time series offers this by ensuring that its statistical properties remain unchanged over time. The stationarity of price series in our selected cryptocurrencies allows for more accurate predictions and risk assessments. It forms the bedrock upon which our trading strategy is built, as a non-stationary series would introduce an unacceptable level of risk and unpredictability.

2. **Coefficient of Correlation:** The effectiveness of pair trading is heavily reliant on the strength and direction of the relationship between the chosen asset pairs. The Coefficient of Correlation quantifies this relationship, enabling us to systematically identify pairs that are likely to move in tandem. A high positive correlation is particularly crucial for our strategy, as it ensures that the directional movements of our selected pairs are synchronized, thereby increasing the likelihood of successful trades.

3. **Cointegration:** Beyond short-term correlations, a successful pair trading strategy also requires a long-term equilibrium relationship between the asset pairs, ensuring that any divergence between them is temporary and will revert to the mean over time. Cointegration provides this layer of validation. If the selected cryptocurrencies are cointegrated, it signifies a statistically significant, long-term relationship between them, making them ideal candidates for our high-frequency pair trading strategy.



Methodology

1. **Data Collection**: Utilize the CCXT library to acquire 1-minute interval price data for the past year.
2. **Stationarity Check**: Use the Augmented Dickey–Fuller test to check if the time series data is stationary.
   - **Formula**: $E(X_t) = \text{constant},\ \text{Var}(X_t) = \text{constant},\ \text{Cov}(X_t, X_{t-k}) = \text{constant}$ for each lag k.
3. **Correlation Coefficient**: Calculate the Pearson correlation coefficient to measure the strength and direction of the relationship.
   - **Formula**:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

4. **Cointegration**: Check for a long-term statistically significant relationship between the coins.
   - **Formula**: Y_t and X_t are cointegrated of order d, b if:

   4.1. Both Y_t and X_t are $I(d)$ (integrated of order d).

   4.2. A linear combination $Y_t - \beta X_t = \mu_t$ is $I(b)$ where $b < d$.

Fig.3. Methodology for Phenomenon Identification

Our research has culminated in the development of a web-based application designed for rapid statistical analysis of cryptocurrency market dynamics. Preliminary tests underscore the viability of our proposed trading strategies, highlighting significant relationships between leading cryptocurrencies like Bitcoin (BTC) and smaller coins such as Cardano (ADA), Litecoin (LTC), and Tron (TRX).

For instance, an analysis of BTC and TRX revealed a non-stationary price series with an ADF p-value of 0.3648, a strong Pearson Correlation Coefficient of 0.8211, and a Cointegration p-value of 0.0125, indicating long-term cointegration.

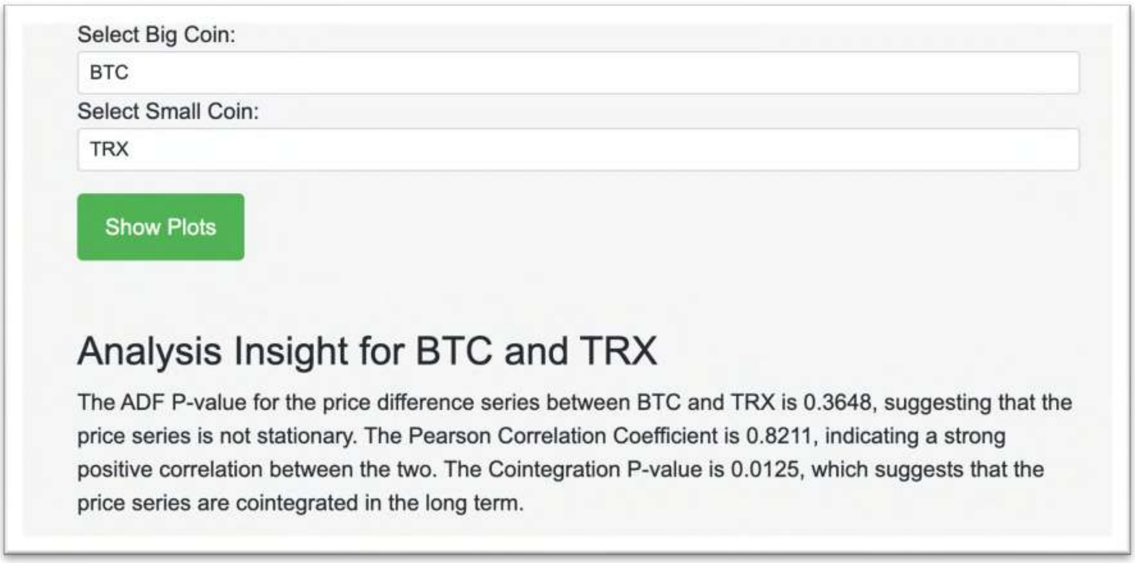


Fig.4. The Web Application can quickly calculate data statistics between coins.

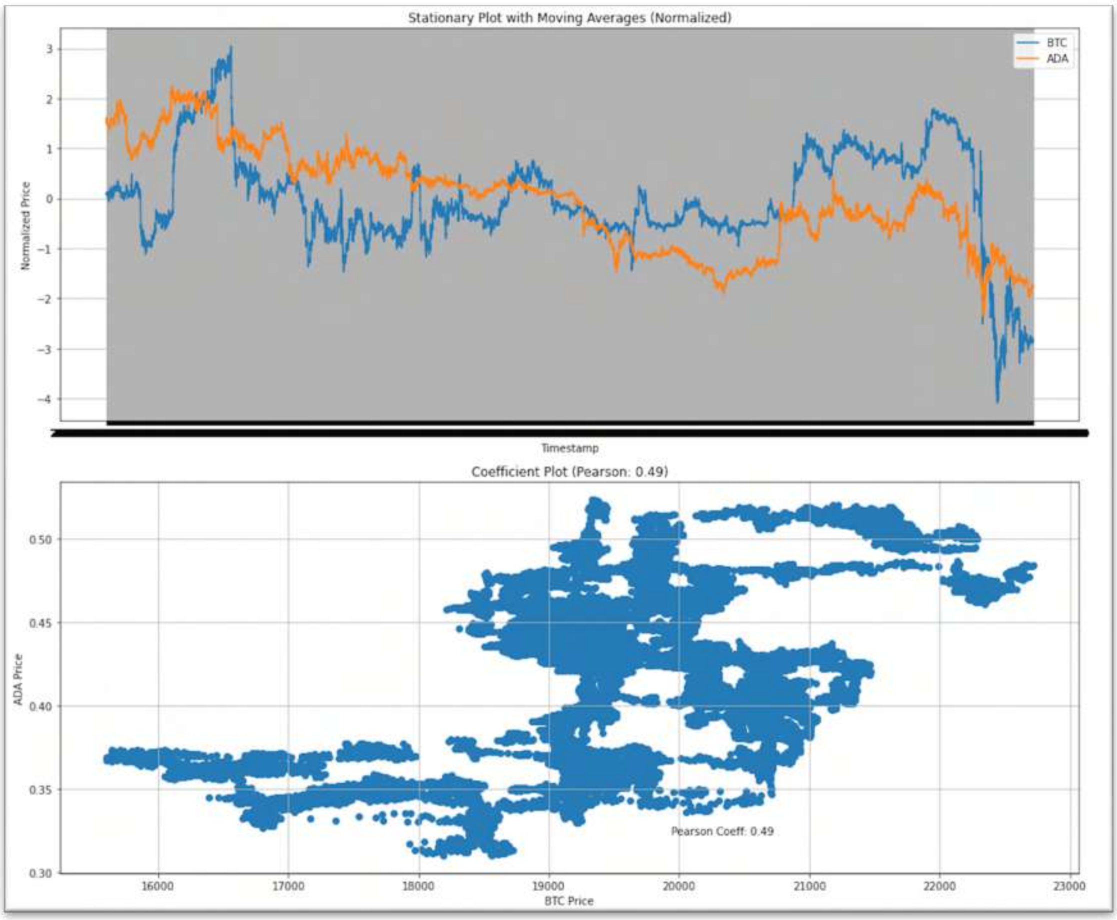
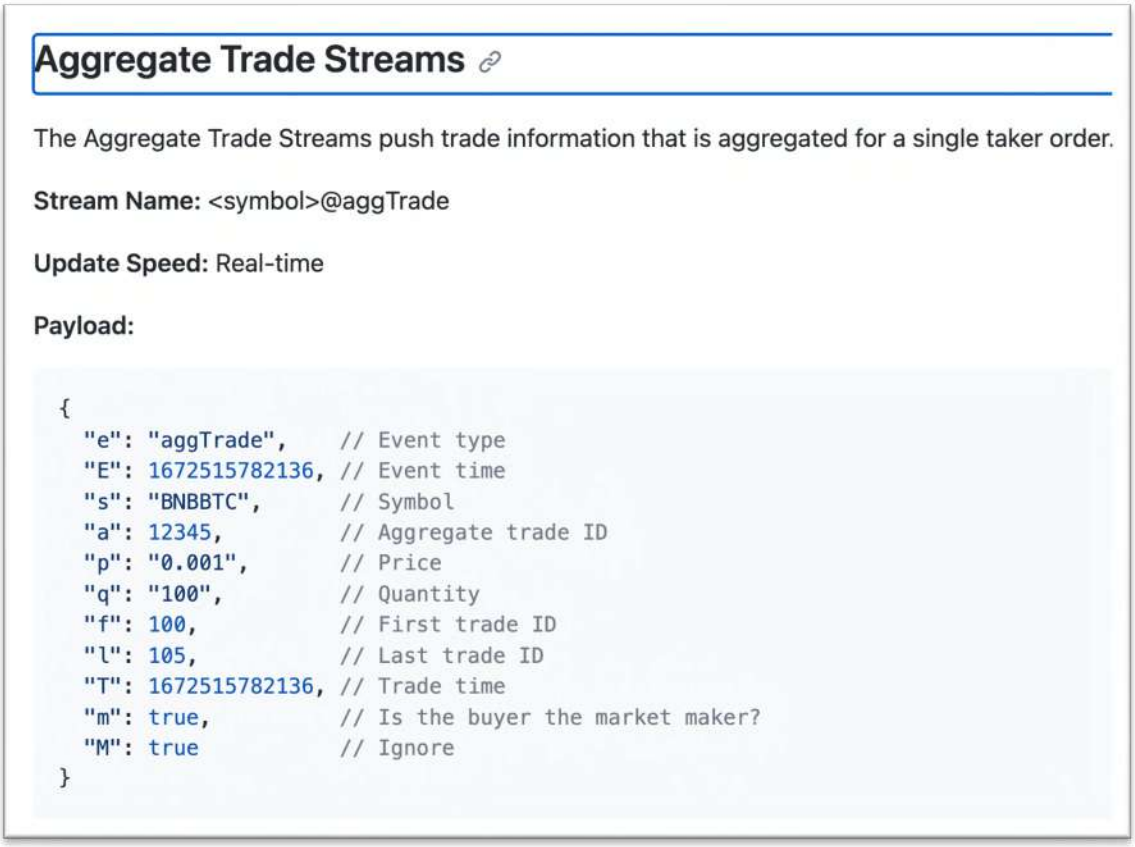


Fig.5. Application shows related statistics plot for reviewing trading strategy.

B. Selection of Real-Time Data and the "Needle" Phenomenon

After confirming the phenomenon where significant fluctuations in Bitcoin (BTC) lead to similar fluctuations in other cryptocurrencies, our next step is to test the reliability of this strategy through historical data simulation. For this purpose, we use Binance's WebSocket API to fetch real time market data, particularly focusing on aggregated trade records or "aggTrades" instead of K-line charts.

AggTrades are millisecond-level transaction records aggregated by Binance, making them an ideal compromise for high-frequency trading data requirements. Generally, these records are used in quasi-high-frequency strategies, while truly high-frequency strategies would employ raw trades and orderbook data, which are cumbersome to process.


Aggregate Trade Streams

The Aggregate Trade Streams push trade information that is aggregated for a single taker order.

Stream Name: <symbol>@aggTrade

Update Speed: Real-time

Payload:


```
{
  "e": "aggTrade",    // Event type
  "E": 1672515782136, // Event time
  "s": "BNBBTC",      // Symbol
  "a": 12345,         // Aggregate trade ID
  "p": "0.001",       // Price
  "q": "100",         // Quantity
  "f": 100,           // First trade ID
  "l": 105,           // Last trade ID
  "T": 1672515782136, // Trade time
  "m": true,          // Is the buyer the market maker?
  "M": true           // Ignore
}
```


Fig.6. Data Structure of Real Time Aggregate Trade Streaming with WebSocket.

In this context, we introduce the "needle" phenomenon—an intriguing aspect unique to the cryptocurrency market characterized by rapid, short-term spikes or plunges in prices. Unlike traditional markets, these swift movements offer both opportunities and risks. They allow for high-frequency trading strategies that capitalize on these quick fluctuations but also introduce a level of risk owing to the inherent market volatility. Our research aims to identify and capitalize on these rare but impactful "needle" events in the market.

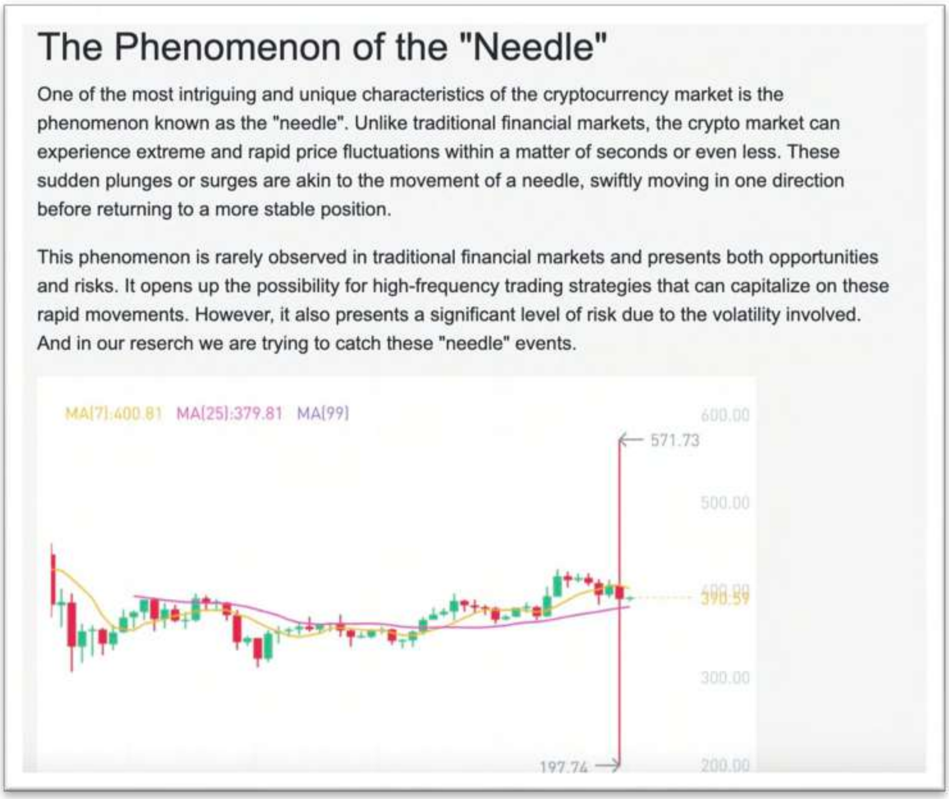


Fig.7. Web Application Demo the Phenomenon of “Needle”

C. Simulation Testing

In our simulation testing phase, we employ real-time data streaming via Binance's Aggregate Trade API. The application continuously monitors for the occurrence of the "needle" phenomenon in Bitcoin (BTC) and Ethereum (ETH). This phenomenon is considered triggered when there is an instantaneous and significant change in price, as defined by predetermined thresholds outlined in our methodology. Upon detecting a "needle" event, the application instantaneously identifies the corresponding timestamp for smaller coins like ADA, XRP, and LTC and executes trades to capitalize on the price volatility. Cumulative trade and profit data for each "needle" event are displayed on our platform for analysis.

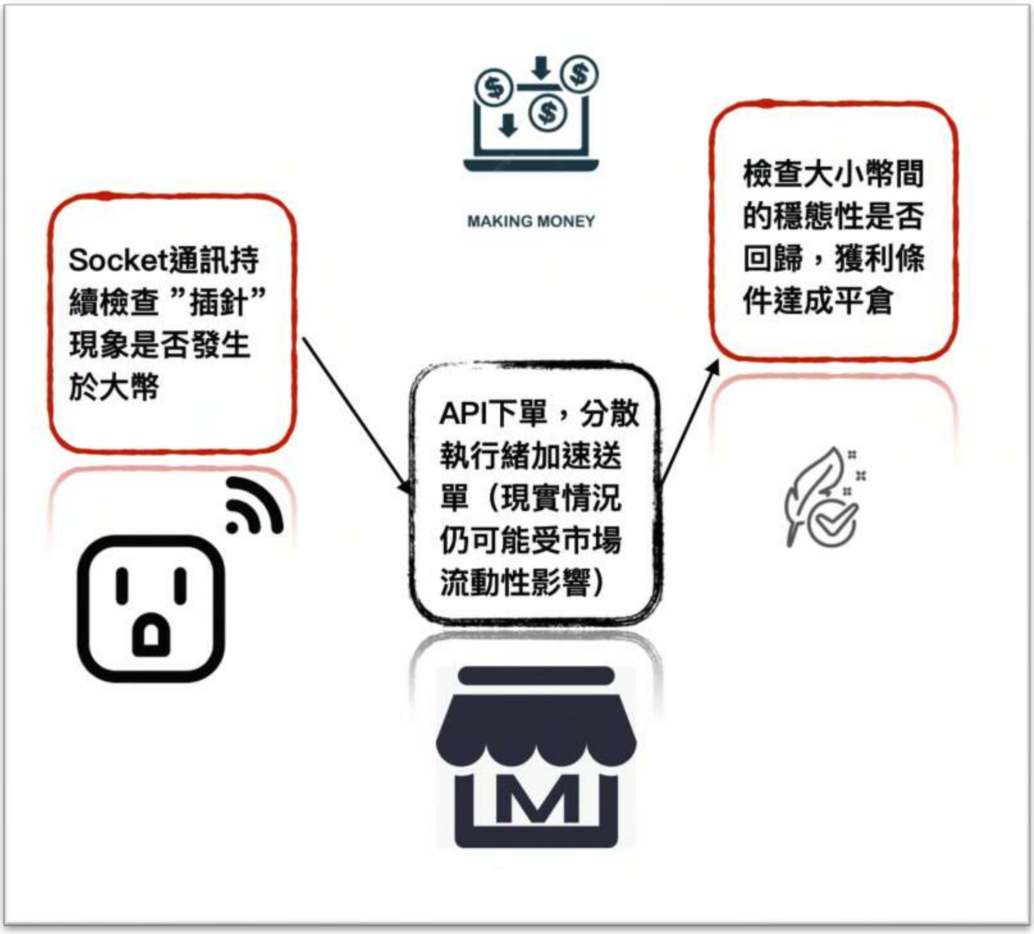


Fig.8. The Concept of our Application Trading Strategy with “Needle Catching” based on correlation between coins.

Our application's interface displays real-time streaming data, illustrating various metrics related to high-frequency trading. For instance, we show statistics like the average profit and frequency of major surges or plunges in BTC and ETH over the past 24 hours. Our preliminary data indicates zero millisecond delays between simultaneous major surges or drops in BTC and ETH, demonstrating the efficacy of our high-frequency trading strategy.

高頻中的大漲/大跌統計量

加密貨幣/平均獲利	大漲/大跌在過去24小時的次數/平均獲利
Btc	91
Eth	90
Btc 大幣高頻交易平均獲利	0.00030822690306498774
Eth 小幣高頻交易平均獲利	0.00027002349657442295

大幣-小幣 同時大漲/大跌的平均延遲： 884.6153846153846 毫秒

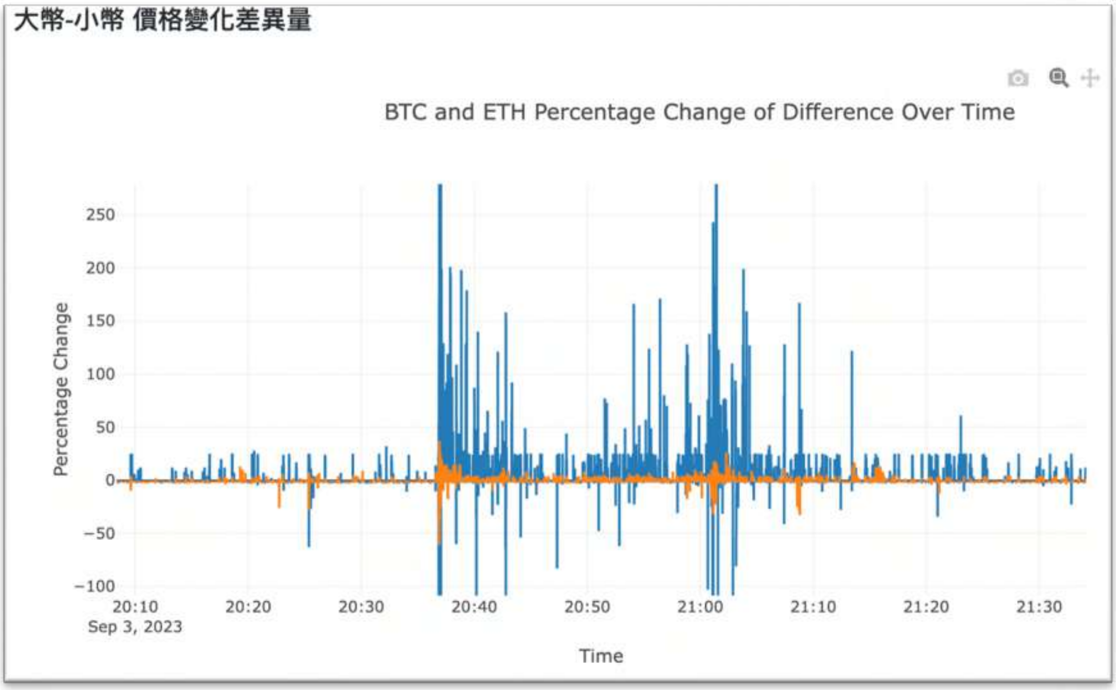


Fig.9. Trading Strategy between BTC/ETH correlation trading showing lag of needle and average profit.

We establish specific criteria to identify the "needle" phenomenon in cryptocurrency trading. For Bitcoin (BTC), a significant price change is defined as an alteration greater than 0.0002 within a timeframe of 15 seconds or less. For Ethereum (ETH), the corresponding threshold is set at 0.002. Additionally, we compute the average profit by taking the absolute mean of all detected instances of major price surges or drops. This average serves as a critical metric, indicating the potential earnings one can expect from latency arbitrage between major and minor cryptocurrencies.

The data is sourced from a SQLite database that automatically streams real-time trade data from Binance's WebSocket API, with a latency of approximately 60 to 170 milliseconds.

```
var pool = mysql.createPool({
  connectionLimit: 50, // Increase or decrease based on your needs
  host: '127.0.0.1', // Or the IP address of your MySQL server
  user: 'my_app_user', // MySQL username
  password: 'supersecret', // MySQL password
  database: 'my_app_database' // The name of the database
});


symbols.forEach(symbol => {
  // Try to establish WebSocket connection
  establishWebSocketConnection(symbol, 0);
});

function establishWebSocketConnection(symbol, attempt) {
  // Start WebSocket
  var ws = new WebSocket(`wss://stream.binance.com:9443/ws/${symbol
```

d	price	quantity	firstId	lastId	time	isBuyerMaker	isBestMatch	difference
343	29418.65	0.07207	3188911140	3188911141	2023/8/11 下午3:59:00	1	1	-0.2699999
301	29425.14	0.0051	3188910493	3188910493	2023/8/11 下午3:55:40	1	1	-0.2299999
141	29427.72	0.00374	3188910307	3188910307	2023/8/11 下午3:54:38	1	1	-0.1800000
153	29420.5	0.23206	3188910682	3188910682	2023/8/11 下午3:56:05	1	1	-0.1500000
337	29423.96	0.07683	3188910539	3188910539	2023/8/11 下午3:55:44	1	1	-0.1500000
215	29427.06	0.00121	3188910391	3188910391	2023/8/11 下午3:55:00	1	1	-0.1499999
18	29433.01	0.00061	3188908259	3188908259	2023/8/11 下午3:42:59	1	1	-0.1400000
123	29422.78	0.2	3188910648	3188910648	2023/8/11 下午3:56:05	1	1	-0.0900000

Fig.10. Backend SQL Database and WebSocket Streaming High Frequency Data

Through this simulation, we aim to validate the reliability and profitability of our trading strategy, which seeks to exploit the unique "needle" events in the cryptocurrency market and as we can see from the result, we have a relatively high successful rate through the strategy.

D. Discrepancies Between Simulated and Actual Trading

It's important to note that the simulation runs under idealized conditions and may not fully encapsulate the intricacies of live trading. For instance, there is an inherent lag of approximately 90 milliseconds between placing an order from a local program and the order reaching Binance's server. This latency effectively means that the actual entry price could be influenced by the price at lag moment, which could diminish profit margins, especially in volatile high-frequency trading scenarios where price changes occur within very short timeframes. Moreover, the time required for Binance's server to send transaction confirmations to the local program could further introduce discrepancies. These non-financial trading factors, such as network latency, can significantly impact the overall profitability and must be considered carefully in real-world applications.

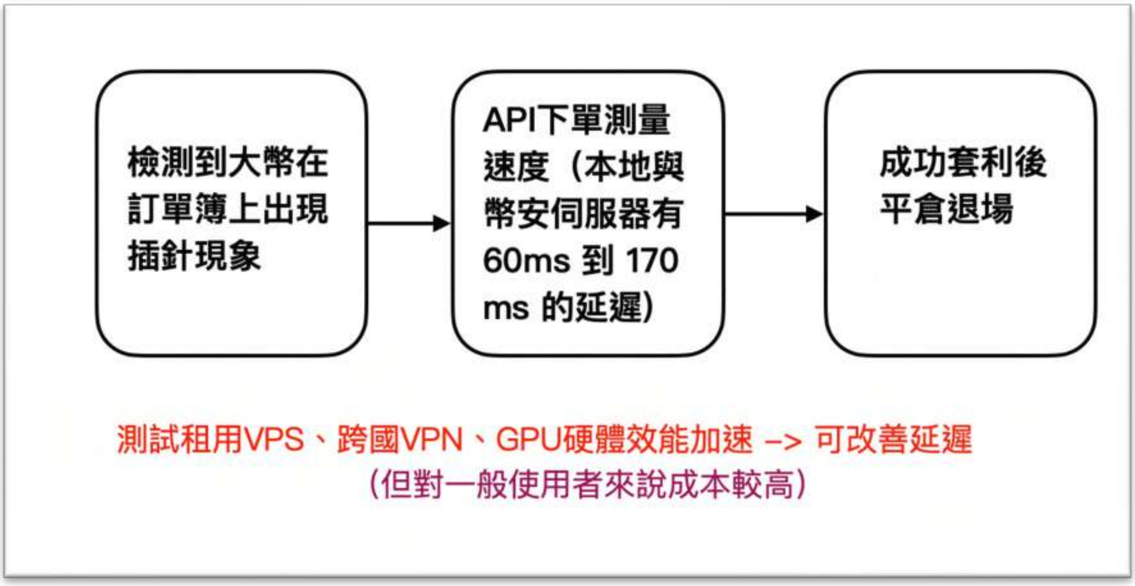


Fig.11. The Effect of Lag Between Transaction in Binance API

V. Research Methodology

A. Structure of Connection and Calculation

WebSockets serve as a real-time, two-way communication protocol suitable for complex and volatile cryptocurrency markets. They establish a persistent connection between client and server, allowing the server to push data to the client without the client needing to make repeated requests. The protocol features bidirectional communication, persistent connections, low overhead, and real-time updates, making it an ideal fit for our application.

Our trading application employs a **dual-threaded** architecture:

- Thread 1: Responsible for establishing and maintaining the WebSocket connection to capture real-time trade data.
- Thread 2: Handles the processing of real-time data captured by Thread 1, makes trading decisions, and executes the orders via the Binance account.

Given the high frequency of trade data updates—several per second—our single **on_message()** function serves as the sole recipient of server data. Executing calculations directly within this function could severely slow down the application and delay market updates. The dual-threaded approach mitigates this issue.

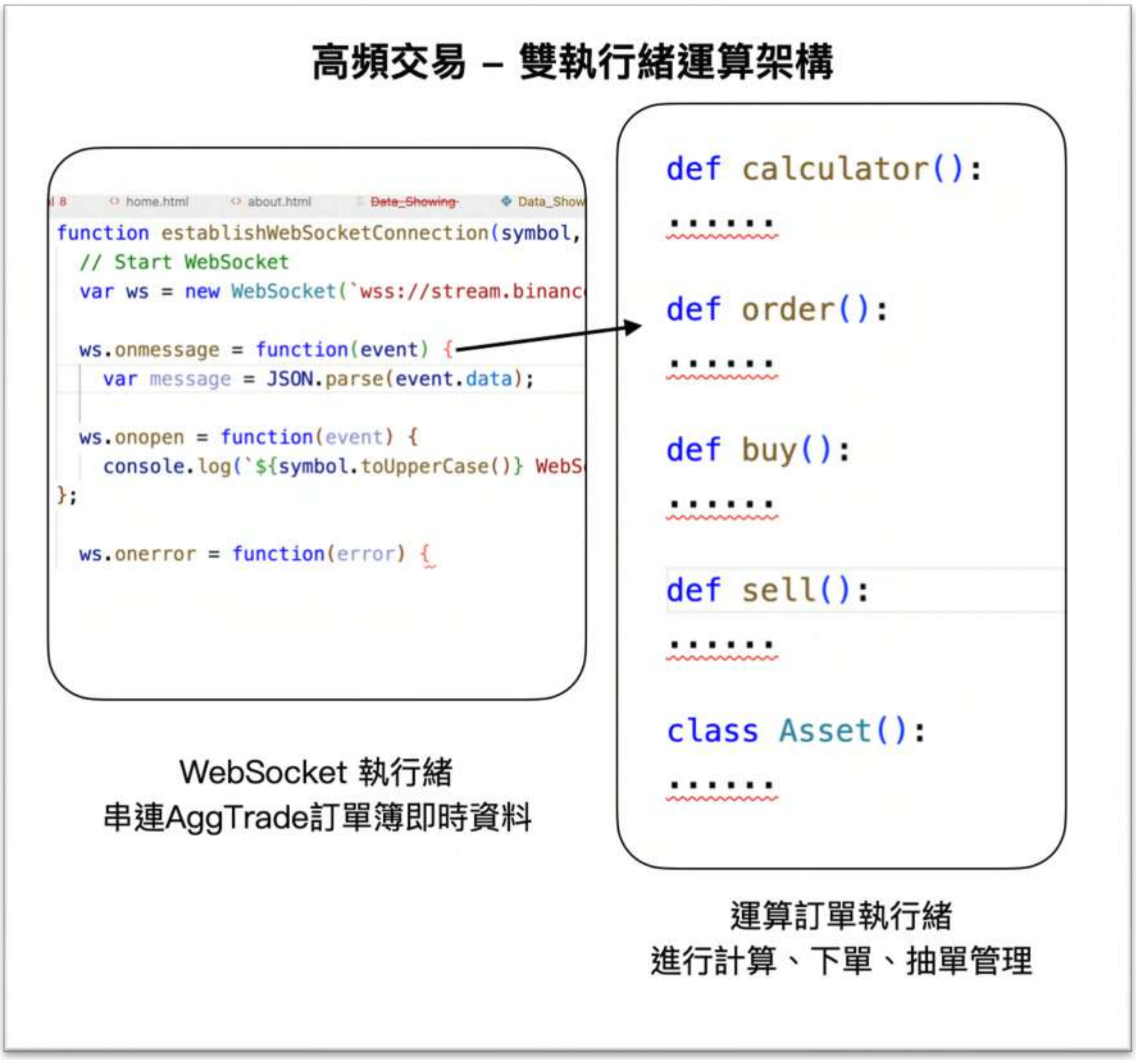


Fig.12. The Structure of the multithread calculation unit in our application

After laying the groundwork with historical data analysis, we are moving towards real-time implementation. We will be focusing on the speed of trade execution on the Binance platform in the next phase. Our dual-threaded system aims to optimize both the efficiency and responsiveness of our high-frequency trading strategy. Users can simulate and evaluate the strategy and its performance through the BTC/ETH and Trade sections on our platform.

B. Web Application Functionality and Contributions

As a significant contribution to the fields of Fintech and high-frequency trading, we have developed a web application using the Flask framework in Python. The ultimate objective of this application is twofold: firstly, to disseminate the research findings and insights gained throughout this study, and secondly, to serve as an educational tool for those interested in high-frequency trading.

The application's backend is constructed using Python, while the frontend is developed using HTML, CSS, and JavaScript. SQL databases are employed for data storage, and we have implemented a connection pooling mechanism to manage multiple real-time WebSocket connections efficiently.

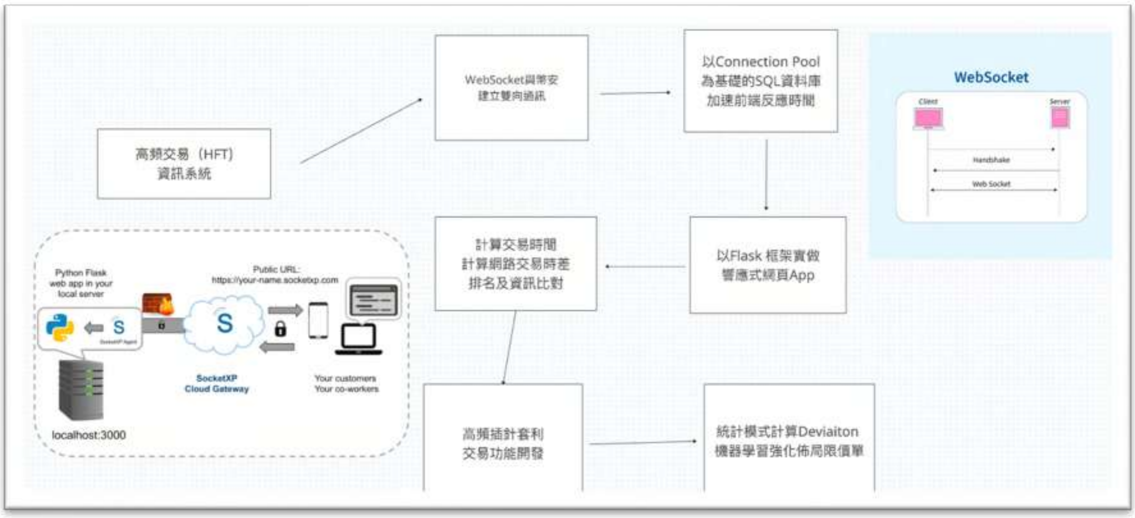


Fig.13. The Structure of the Web application

C. Key Features

Real-Time High-Frequency Data View: The home page provides a comprehensive view of real-time high-frequency price changes for various cryptocurrencies. This feature is unique as there are currently no platforms or APIs offering this specialized service. An illustrative example is provided in the following figure.

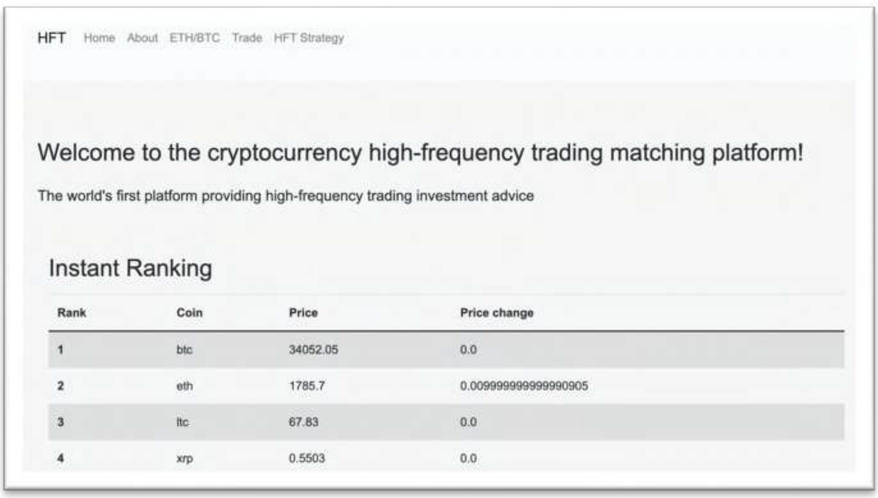


Fig.14. Home Page Showing Instant Price changes.

Recognizing the critical importance of speed in high-frequency trading, our web application includes specialized sections designed to test both network and trading speed:

1. Network Speed Test: This section allows users to gauge their network performance by measuring download, upload, and ping speeds. Knowing the quality of your network connection can be instrumental in high-frequency trading, where even milliseconds matter.

2. Trading Speed Test: This innovative feature is specifically tailored for those interested in high-frequency trading. It works by sending a paper test trade buy request to Binance's BTC paper trading server. The application then calculates the execution time in milliseconds, providing users with an accurate measure of how quickly trades can be implemented on their current network.

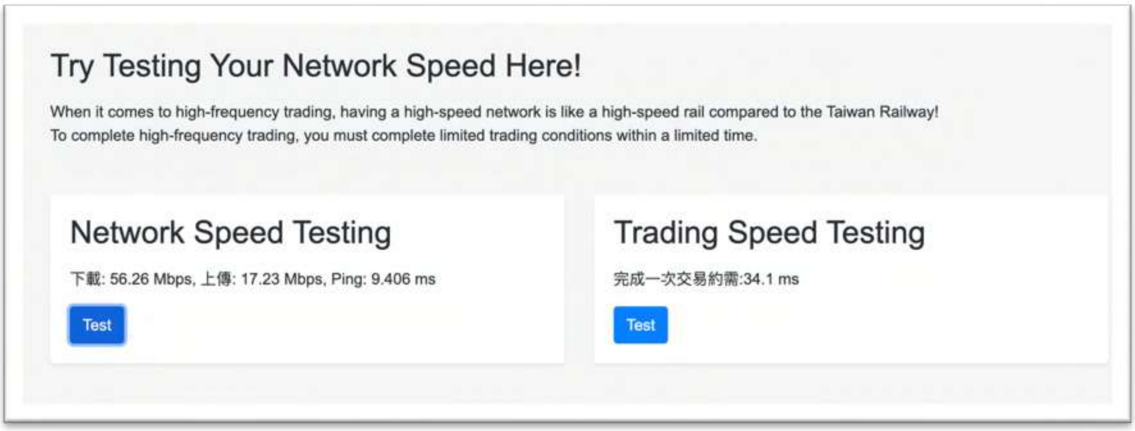


Fig.15. Network and Trading Speed Testing

These speed test functionalities add an extra layer of utility to our application, ensuring that users not only gain insights into high-frequency trading strategies but also have the tools to measure their capacity to implement these strategies effectively.The "About" page serves as a comprehensive guide that encapsulates the research objectives and the trading strategies discussed throughout the project. One of the standout features of this page is a dedicated section that allows users to select a "major" coin (either BTC or ETH) and a "minor" coin (options include XRP, LTC, ADA, DOGE, and TRX) for a specialized calculation test.

The Calculation Test bottom aims to assess whether these selected cryptocurrency pairs are suitable for high-frequency pair trading, based on historical data from the previous year. It calculates several key metrics:

1. Stationarity: A stationary time series is one whose statistical properties do not change over time. In the context of our strategy, stationarity ensures that the price series behaves consistently, making it easier to predict future prices based on past behavior.

2. Coefficient of Correlation: This measures the strength and direction of the relationship between the two selected coins. A high positive correlation would mean that the coins often move in the same direction, which is crucial for pair trading.

3. Cointegration: Cointegration tests for a long-term, statistically significant relationship between the two coins. If the coins are cointegrated, it implies that the spread between them is mean reverting, making them ideal candidates for pair trading.

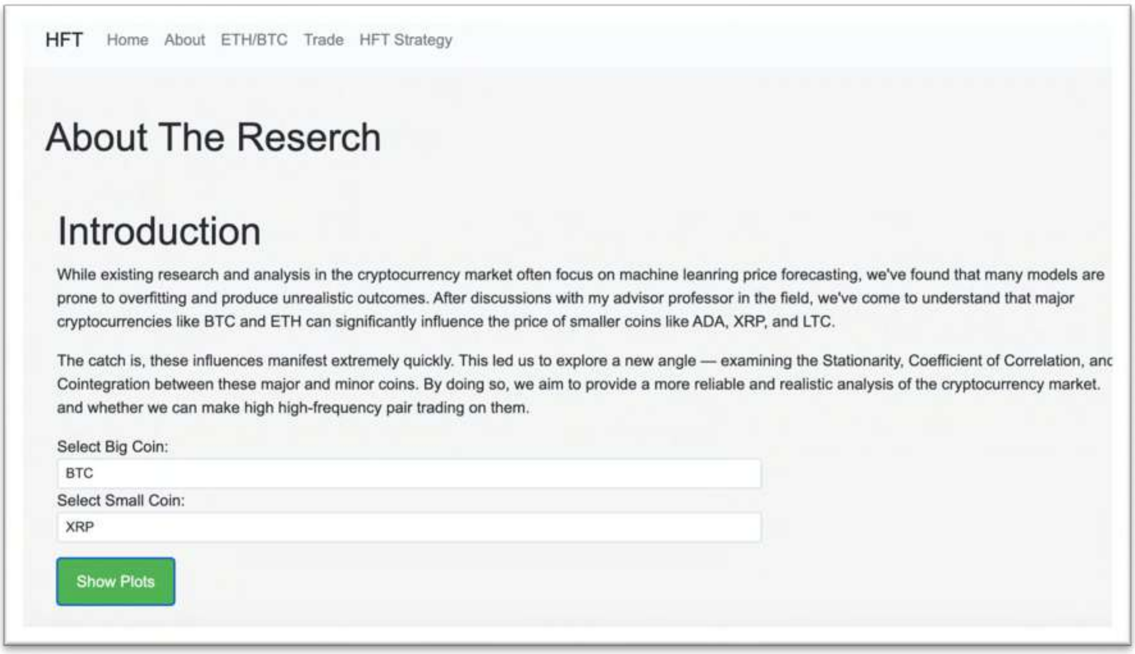


Fig.16. About page serve as a guide for the whole research.

VI. Performance Evaluation and Results

A. Results and Areas for Improvement:

Our web application's real-time simulation, accessible via the "Trade" page, demonstrated promising preliminary results. Specifically, the simulation suggests a potential profit of approximately 90×0.0243% within an 8-hour trading window. However, the data also revealed some limitations. One significant issue is the timing of the "needle" events—sudden surges or plunges in price. These events didn't always occur immediately following similar movements in the major coins like BTC or ETH, thus affecting the strategy's accuracy.

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大幣-小幣 同時大漲/大跌的平均延遲： 884.6153846153846 毫秒

Fig.17. Simulate trading result.

This observation led us to question the absence of predictive technologies in our current model. We had focused solely on reacting to price changes in one major coin, without utilizing any predictive analytics to improve our trading accuracy.A possible improvement to this strategy is the incorporation of a dynamic limit order placement system. This approach would allow us to set flexible conditions for executing trades, thereby increasing the likelihood of capitalizing on favorable "needle" events. This new approach will be discussed in detail in the following section.

B. The Placing Dynamic Limit Order Strategy

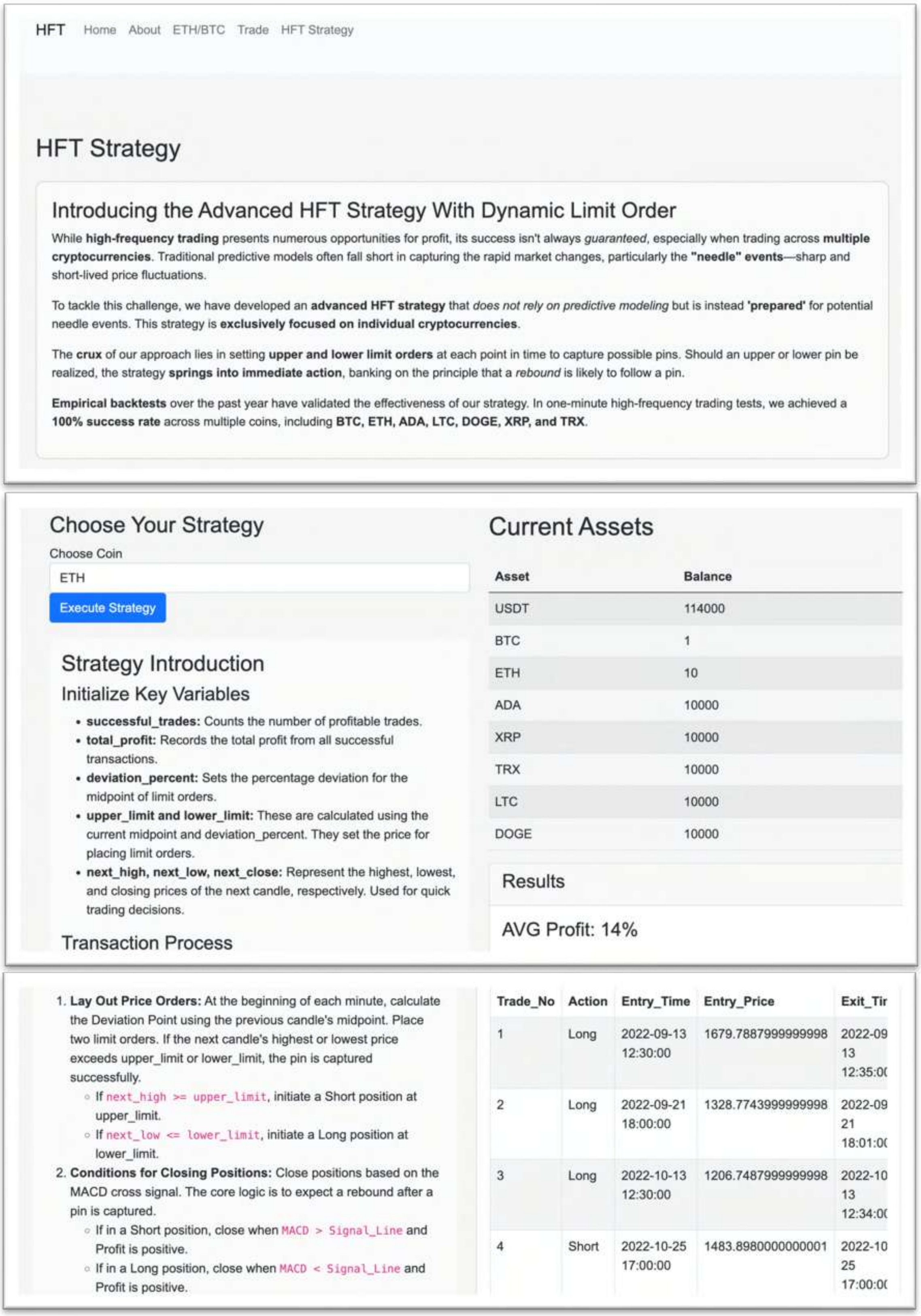
In the realm of high-frequency trading (HFT), the traditional approach often revolves around predictive models aiming to forecast price movements. However, these models frequently fall short in capturing real-time market dynamics, specifically the sharp and fleeting "needle" events. To overcome these limitations, we introduce a new paradigm: the Dynamic Limit Order Strategy.

A limit order is a type of trading order that specifies the maximum or minimum price at which a particular asset can be bought or sold. Unlike market orders, which execute immediately at the current market price, limit orders are placed in the order book and may or may not be executed, depending on market movements.

A dynamic limit order, on the other hand, is not static; it adapts to market conditions. The upper and lower price limits for buying or selling are dynamically adjusted based on predetermined criteria, such as a percentage deviation from a moving average or the midpoint of the previous trading candle. This dynamic adaptation aims to optimize order execution, especially in volatile markets like cryptocurrencies.Unlike our previous strategies that attempted to exploit relationships between multiple cryptocurrencies, this new approach is uniquely tailored for individual cryptocurrencies. By doing so, it offers a more targeted and nimble response to needle events as they occur in real-time.

Fig.18. Transaction Workflow of the Placing Dynamic Limit Order Strategy

Our empirical backtests have validated the strategy's effectiveness. In one-minute HFT tests, we achieved a 100% success rate across multiple coins, including BTC, ETH, ADA, LTC, DOGE, XRP, and TRX. The average profit was 8%. By focusing on individual cryptocurrencies and employing a dynamic limit order strategy, we substantially enhance our ability to capture profits from needle events, thereby addressing the limitations of traditional predictive models in a high-frequency trading setup.



HFT Home About ETH/BTC Trade HFT Strategy

HFT Strategy

Introducing the Advanced HFT Strategy With Dynamic Limit Order

While **high-frequency trading** presents numerous opportunities for profit, its success isn't always *guaranteed*, especially when trading across **multiple cryptocurrencies**. Traditional predictive models often fall short in capturing the rapid market changes, particularly the **"needle" events**—sharp and short-lived price fluctuations.

To tackle this challenge, we have developed an **advanced HFT strategy** that *does not rely on predictive modeling* but is instead **'prepared'** for potential needle events. This strategy is **exclusively focused on individual cryptocurrencies**.

The **crux** of our approach lies in setting **upper and lower limit orders** at each point in time to capture possible pins. Should an upper or lower pin be realized, the strategy **springs into immediate action**, banking on the principle that a *rebound* is likely to follow a pin.

Empirical backtests over the past year have validated the effectiveness of our strategy. In one-minute high-frequency trading tests, we achieved a **100% success rate** across multiple coins, including **BTC, ETH, ADA, LTC, DOGE, XRP, and TRX**.

Choose Your Strategy

Choose Coin

ETH

Execute Strategy

Strategy Introduction

Initialize Key Variables

- **successful_trades:** Counts the number of profitable trades.
- **total_profit:** Records the total profit from all successful transactions.
- **deviation_percent:** Sets the percentage deviation for the midpoint of limit orders.
- **upper_limit and lower_limit:** These are calculated using the current midpoint and deviation_percent. They set the price for placing limit orders.
- **next_high, next_low, next_close:** Represent the highest, lowest, and closing prices of the next candle, respectively. Used for quick trading decisions.

Transaction Process

1. **Lay Out Price Orders:** At the beginning of each minute, calculate the Deviation Point using the previous candle's midpoint. Place two limit orders. If the next candle's highest or lowest price exceeds upper_limit or lower_limit, the pin is captured successfully.
   - If `next_high >= upper_limit`, initiate a Short position at upper_limit.
   - If `next_low <= lower_limit`, initiate a Long position at lower_limit.
2. **Conditions for Closing Positions:** Close positions based on the MACD cross signal. The core logic is to expect a rebound after a pin is captured.
   - If in a Short position, close when `MACD > Signal_Line` and Profit is positive.
   - If in a Long position, close when `MACD < Signal_Line` and Profit is positive.

Current Assets

Asset	Balance
USDT	114000
BTC	1
ETH	10
ADA	10000
XRP	10000
TRX	10000
LTC	10000
DOGE	10000

Results

AVG Profit: 14%

Trade_No	Action	Entry_Time	Entry_Price	Exit_Tir
1	Long	2022-09-13 12:30:00	1679.7887999999998	2022-09 13 12:35:0(
2	Long	2022-09-21 18:00:00	1328.7743999999998	2022-09 21 18:01:0(
3	Long	2022-10-13 12:30:00	1206.7487999999998	2022-10 13 12:34:0(
4	Short	2022-10-25 17:00:00	1483.8980000000001	2022-10 25 17:00:0(

Fig.19. Web Application Demo the Placing Dynamic Limit Order Strategy the deviation point is set to be 4% in this case.

AVG Profit: 0.25
Trade Summary:

	Trade_No	Action	Entry_Time	Entry_Price	Exit_Time	Exit_Price	Profit
0	1	Short	2022-11-10 17:47:00	0.061688	2022-11-10 17:47:00	0.06043	0.001258
1	2	Short	2022-11-14 06:49:00	0.050258	2022-11-14 06:49:00	0.04855	0.001708
2	3	Short	2022-11-14 06:59:00	0.051236	2022-11-14 06:59:00	0.04943	0.001806
3	4	Short	2022-11-14 13:14:00	0.052614	2022-11-14 13:14:00	0.05087	0.001744
4	5	Short	2023-02-08 13:10:00	0.068848	2023-02-08 13:10:00	0.06620	0.002648
5	6	Short	2023-02-08 13:11:00	0.070756	2023-02-08 13:11:00	0.06915	0.001606
6	7	Short	2023-03-10 10:29:00	0.057834	2023-03-10 10:31:00	0.05600	0.001834
7	8	Short	2023-03-22 20:01:00	0.059441	2023-03-22 20:01:00	0.05738	0.002061

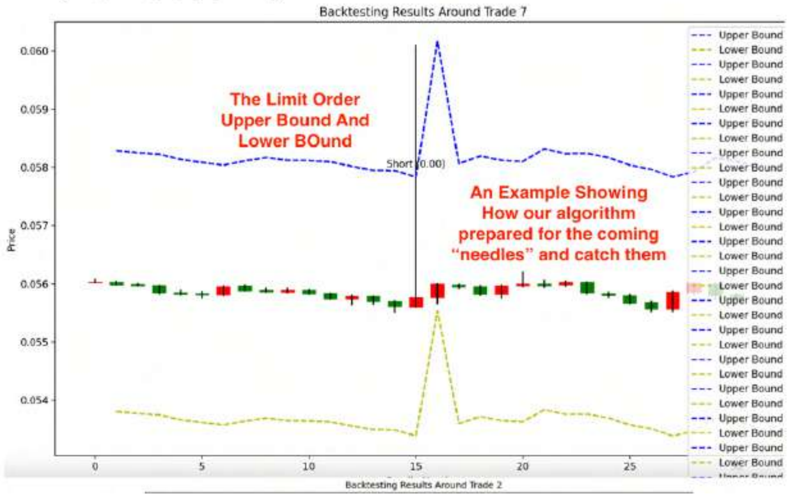


Fig.20. Demo Placing Dynamic Limit Order Strategy

Dynamic limit order strategy has shown promising results in simulation testing, achieving a high success rate across multiple cryptocurrencies. The strategy's focus on individual coins and its adaptive approach to market volatility make it a potentially powerful tool for high-frequency trading. However, it's essential to remember that this system is still in the prototype stage and has not yet been subjected to real-world conditions. Future iterations will need to consider transaction volumes and the liquidity constraints that come with it. Additionally, the incorporation of machine learning algorithms for optimizing the deviation point and other variable settings could further refine and enhance the strategy's effectiveness. Overall, while preliminary results are encouraging, further testing and development are necessary to validate the strategy's real-world applicability and reliability.

VII. Conclusions

This research embarked on an ambitious journey to address the complexities and potential rewards of high-frequency trading (HFT) in the burgeoning cryptocurrency market. The central goal was twofold: to advance the understanding of HFT strategies in this volatile asset class and to offer an educational platform that democratizes access to these sophisticated trading methods.

Through rigorous technical and statistical analyses, we successfully developed a real-time trading platform, capable of ingesting high-frequency data and making trading decisions in near-real-time. The platform's architecture, built on a dual-threaded system, mitigates latency issues and enhances responsiveness—two essential criteria for success in HFT. Our work didn't stop at mere theoretical or simulated success; we ventured to offer an educational dimension through an intuitive web application. This dual aim distinguishes our research, making it not just a financial innovation but also an educational tool that lowers entry barriers to the complex world of high-frequency trading.

VIII. Future Prospects

However, no research is without limitations. Our study pointed out the inherent challenges in translating simulated success to real-world applications. Issues such as network latency, liquidity constraints, and market regulations need further exploration and mitigation strategies. The introduction of the Dynamic Limit Order Strategy marked a significant pivot from traditional predictive models, offering a more flexible, responsive mechanism to capture profits from short-lived price fluctuations or "needle" events. While preliminary results are promising, we acknowledge that this is a prototype, and further real-world testing is required to validate its efficacy.

IX. References

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