

Event Detection and Latency Analysis in High Frequency Trading Dashboards

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Abstract

High frequency trading relies on millisecond-level decisions, where profitability is strongly influenced by both market responsiveness and system latency. Traditional dashboards offer real-time visualizations but fall short in detecting abrupt regime shifts or quantifying latency. This study presents an AI-aided Market Pulse and Latency Panel that integrates candlestick pattern recognition, change point detection and latency measurement into a unified dashboard. The system detects technical patterns, identifies structural market shifts, and quantifies infrastructural bottlenecks. Experimental results demonstrate that the panel enhances situational awareness by combining event detection with latency analytics, providing traders with actionable insights for strategy adjustment and infrastructural optimization.

Keywords: Event Detection, High Frequency Trading, Candlestick Pattern Recognition, Latency, Analysis, Change Point Analysis

Introduction

High Frequency Trading (HFT) operates in an environment where millisecond-level delays can determine profitability. Decisions must be executed almost instantaneously, and even slight latency exposes traders to adverse selection or missed opportunities. In this setting, monitoring both market dynamics and infrastructural responsiveness have become a defining factor of competitive advantage. Conventional trading dashboards provide real-time visualization of prices and basic indicators, yet they remain largely descriptive. They display what has already occurred but rarely detect abrupt regime shifts or quantify the responsiveness of analytic pipelines. This gap limits their value as decision-support tools in modern high frequency markets, where adaptive and latency-aware intelligence is increasingly essential.

Advances in artificial intelligence and statistical learning now enable more proactive approaches. Methods such as change point detection can identify structural shifts in streaming data, while latency metrics quantify system responsiveness in real time. Embedding these techniques into trader-facing dashboards offers the potential to transform static monitors into adaptive platforms that not only describe markets but also highlight execution risks.

This study introduces an AI-aided Market Pulse and Latency Panel that integrates three components: (i) candlestick pattern recognition, (ii) change point detection, and (iii) latency measurement. Together, these modules provide traders with insights into market state, regime shifts, and infrastructural bottlenecks.

Methodology

The proposed Market Pulse and Latency Panel integrates three modules, each designed to capture different dimensions of high frequency trading dynamics.

Candlestick pattern recognition

Candlestick analysis remains a cornerstone of technical trading, as price patterns often signal reversals or continuations. In this work, a rule-based recognition system is implemented to identify 17 patterns discussed in Nison (2021) such as Doji, Hammer and Engulfing formations. The module ingests intraday OHLC (open, high, low, close) data and applies predefined logical conditions to detect shape, shadow length, and positional relationships of candlesticks.

- Single-candle patterns are identified using threshold rules on body–shadow ratios.
- Two-candle formations (e.g., Bullish Engulfing) are detected by comparing successive candlesticks.
- Multi-candle structures (e.g., Morning Star, Three Black Crows) are recognized using rolling windows.

Detected patterns are indexed and overlaid on real-time charts, interpreting them for the traders.

Change point analysis

High frequency markets are characterized by abrupt regime shifts caused by liquidity shocks, order-book imbalances or external news. To detect such changes, a change point analysis (CPA) module based on the Pruned Exact Linear Time (PELT) algorithm (Killick, 2012) is employed. This method balances scalability and accuracy by combining dynamic programming with a pruning step (Jackson et.al, 2005), allowing multiple change points to be detected efficiently.

The CPA module operates iteratively on streaming price data. With each new observation, statistical properties such as mean and variance are re-evaluated. A kernel-based cost function with Radial Basis Function (RBF) kernels extends sensitivity to both shifts in level and volatility. Adjustable penalty and update-rate parameters allow the system to adapt between conservative (few breakpoints) and highly sensitive (frequent breakpoints) detection modes.

Latency metrics

Latency is quantified as the delay between a market event and its registration or execution within the system. Four components are measured:

- API Response Latency – time taken for an external API (Alpha Vantage) to respond to a data request.
- Network Latency – round-trip time of data packets, measured using system ping.
- Order Execution Latency – estimated range (40–400 ms) based on empirical studies of exchange execution delays.
- Round Trip Latency – cumulative measure incorporating API, network, and execution latency.

The panel continuously reports these metrics, providing users with transparency about system responsiveness and potential performance bottlenecks.

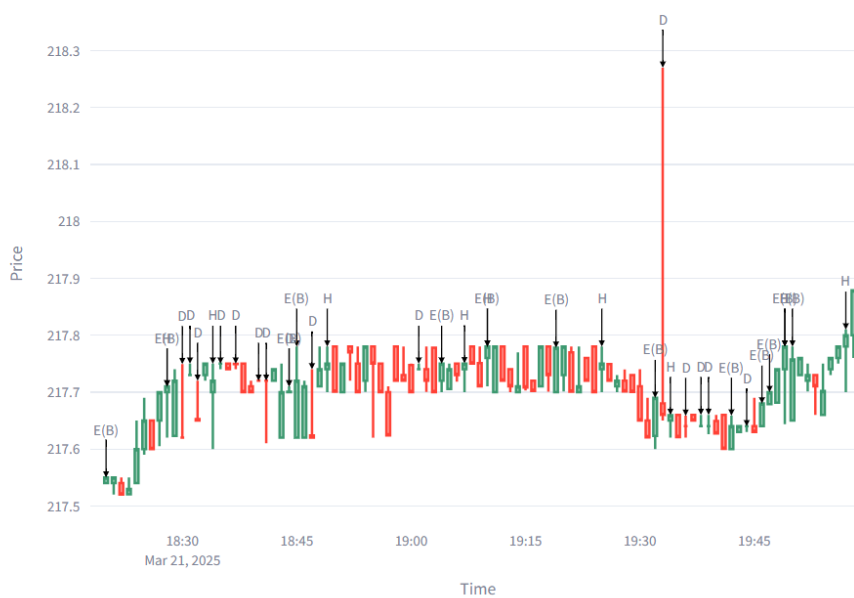
Results and Discussion

Experimental results

The proposed dashboard was evaluated using intra-day stock data from New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ) to demonstrate its responsiveness to high frequency market dynamics. Each module was tested independently and then integrated into the panel to highlight complementary insights.

Candlestick pattern recognition

The candlestick recognition module successfully detected and indexed technical patterns in real time. For example, Doji formations were consistently identified and flagged during periods of market indecision, while Bullish Engulfing and Hammer patterns aligned with subsequent upward movements. By overlaying indexed markers directly onto live charts, the system enabled users to interpret sentiment shifts at a glance. Clustering of patterns further indicated reversal zones, validating the usefulness of automated recognition in volatile conditions.



(a) Visual detection of combined patterns

Detected Patterns

Index	Pattern	Time	Meaning
0	Hammer	2025-03-21 19:57:00	Bullish reversal signal.
1	Bullish Engulfing	2025-03-21 19:50:00	Bullish reversal signal.
2	Hammer	2025-03-21 19:49:00	Bullish reversal signal.
3	Bullish Engulfing	2025-03-21 19:49:00	Bullish reversal signal.
4	Bullish Engulfing	2025-03-21 19:47:00	Bullish reversal signal.
5	Bullish Engulfing	2025-03-21 19:46:00	Bullish reversal signal.
6	Doji	2025-03-21 19:44:00	Market indecision, possible reversal.
7	Bullish Engulfing	2025-03-21 19:42:00	Bullish reversal signal.
8	Doji	2025-03-21 19:39:00	Market indecision, possible reversal.
9	Doji	2025-03-21 19:38:00	Market indecision, possible reversal.

(b) Interpretation with pattern breakdown

Figure 1: Doji, Hammer, and Bullish Engulfing detections on AAPL, March 21, 2025

Change point analysis

The change point module effectively captured structural regime shifts in price dynamics. Under high-penalty settings, only major breaks in trend were flagged, highlighting transitions between stable and volatile phases. Conversely, reducing the penalty parameter increased sensitivity, identifying subtle fluctuations at the cost of additional noise. These experiments illustrate a trade-off between precision and coverage, and demonstrate how adjustable parameters allow the dashboard to be tuned to different trading contexts - ranging from trend-following strategies to volatility-driven execution models.



Figure 2: CPA with Penalty = 50, Streaming Speed = 1.00

Latency metrics

Latency measurements revealed the responsiveness of the system infrastructure. The API response time occasionally exceeded one second due to server congestion, representing the primary bottleneck. Network latency remained stable at ~40 ms, consistent with strong connectivity, while order execution latency was incorporated as an estimated range (40–400 ms). The round-trip latency ranged between 1.5 and 1.9 seconds in test runs, underscoring the performance limitations of API-based feeds for high frequency applications. Despite these delays, the module provided transparent warnings to users, enabling informed strategy adjustments.

Overall, the experimental results confirm that the integrated dashboard extends beyond conventional visualization. It captures technical patterns, detects structural changes, and quantifies latency bottlenecks - thereby enhancing situational awareness in high frequency trading environments.

Conclusions

This study introduced an AI-aided Market Pulse and Latency Panel tailored for high-frequency trading environments, where even millisecond-level delays can influence profitability. By integrating three complementary modules - candlestick charting with indexed pattern recognition, change point analysis, and latency metrics - our dashboard extends beyond conventional descriptive visualization tools. It enables traders to not only observe market conditions but to also detect regime shifts in real time and quantify system responsiveness.

Our experimental results demonstrate that the panel effectively identifies technical patterns, captures structural breaks with tunable sensitivity, and provides transparent latency measures. The candlestick module highlights micro structural price behaviors, while the change point analysis offers adaptive

sensitivity to sudden market shocks. The latency metrics, in turn, contextualize these insights by showing how infrastructural delays affect real-time execution readiness. Together, these components present a holistic framework for enhancing situational awareness in high-frequency trading.

Nevertheless, limitations exist. The reliance on API-based data retrieval constrains true millisecond-level responsiveness, and order execution latency in our evaluation remains estimated rather than empirically measured. Furthermore, while the PELT-based change point detection method achieves robustness and scalability, deploying it on real tick-level streaming data requires more advanced infrastructure.

Future work will aim to extend the system with direct exchange connectivity, enabling precise measurement of execution latency and eliminating API bottlenecks. Integrating predictive models such as machine learning-based volatility forecasters or deep learning pattern recognition could further enhance anticipatory capabilities. Finally, deploying the panel in a live trading environment would allow validation of its practical benefits for execution quality and profitability.

By bridging descriptive dashboards and predictive-executive systems, the proposed panel contributes towards building truly real-time market intelligence for high-frequency trading.

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