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Towards Real-Time Market Intelligence: Event Detection and Latency Analysis in High Frequency Trading Dashboards

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Abstract

High Frequency Trading (HFT) relies on millisecond level decisions, where market responsiveness and system latency directly determine profitability. Traditional dashboards offer real-time visualizations but often fail to detect abrupt market shifts or quantify the delays in system reactions. This paper presents an AI-aided Market Pulse and Latency Panel that integrates candlestick pattern recognition, statistical change point analysis, and latency measurement into a unified trader-facing dashboard. The system identifies technical patterns, detects structural regime shifts, and quantifies latency. Experimental evaluations demonstrate that the panel captures both microstructural signals and broader regime changes while exposing critical latency bottlenecks, such as API-induced delays. By combining event detection with latency analytics, the panel advances dashboards beyond descriptive visualization, providing traders with actionable insights for strategy adjustment and infrastructural optimization.

Keywords: Candlestick pattern recognition, Change point analysis, Event detection, High frequency trading, Latency analysis.

Introduction

High Frequency Trading (HFT) represents one of the most technologically demanding areas in financial markets, where decisions must be made in milliseconds and profitability often depends on microsecond advantages. In this environment, the market pulse, the collective signals emerging from order flows, price movements, and volatility dynamics, must be continuously monitored to inform execution strategies. At the same time, latency, which is the delay between a market event occurring and its registration in a trader's system, has emerged as a defining factor in competitive advantage, with even slight delays exposing traders to adverse selection and missed opportunities.

Traditional financial dashboards, including widely used trading terminals and analytic tools, provide real-time market visualization and basic technical indicators. However, most of these platforms are limited to descriptive analytics (Hasbrouck & Saar, 2013). They report what has already occurred but rarely capture sudden structural changes in data streams or quantify latency in system responses. Consequently, traders are left without explicit insights into how quickly their systems register critical market events, which can impair both strategy development and execution efficiency.

Recent advances in artificial intelligence and statistical learning have opened new possibilities for real time market intelligence. Techniques such as change point detection allow systems to automatically identify abrupt regime shifts in price and volume data, while latency metrics provide quantitative measures of how swiftly these events are reflected in analytic platforms. Integrating these tools into trading, facing dashboards transforms them from static monitors into adaptive decisions, support systems capable of highlighting both what has changed and how quickly the change was registered.

This paper presents an AI-aided Market Pulse and Latency Panel designed for high frequency trading environments. The panel combines candlestick pattern recognition, statistical change point analysis, and latency measurement modules to deliver a holistic view of short-term market dynamics. By embedding latency analytics directly into the dashboard, the system moves beyond traditional visualization, providing traders with real-time intelligence on both market state and infrastructural responsiveness. The contributions of this study are threefold. A Market Pulse and Latency Panel that integrates event detection with latency measurement is developed and implemented. The panel's ability to identify structural market shifts using high frequency candlestick data is evaluated. The way latency metrics can provide actionable insights for optimizing execution pipelines in high frequency settings is demonstrated.

By positioning latency and event detection as first-class analytics, the work bridges a gap between descriptive dashboards and predictive-executive systems, offering a step towards real time market intelligence.

State of the art

This section explores the state of the art - the context, seminal works, advancements, and even gaps within literature. An attempt is made to build the foundation basis for the work that is done ahead in the research through this segment.

Candlestick chart with indexed pattern recognition

The Candlestick Chart with Indexed Pattern Recognition visually aids in detecting well known technical patterns in high frequency data. Candlestick pattern analysis is a fundamental in technical analysis, used widely by traders to get hints about possible market reversals, continuations or consolidating phases based on the price action. Since the early days of Japanese rice trading, this technique has been a cornerstone in technical analysis (Nison, 2001).

In traditional finance, patterns such as Doji, Engulfing Patterns, and Three White Soldiers are typically viewed as indicators of market indecision, reversal, or continuation of trend.

Several efforts have been conducted aiming to automate pattern recognition. These research efforts have used different statistical and machine learning techniques. Nison (2001) relied on predefined criteria. Using Convolutional Neural Networks (CNN) for image based pattern recognition is explored (Sezer et al., 2020). The model developed in this work builds on traditional pattern detection methods by streaming real time data using a configurable, user-friendly interface.

Change point analysis (CPA)

The CPA module is used for identifying sudden changes in underlying patterns of financial time series data. Market conditions can change abruptly in high frequency trading environments because of liquidity shocks, or events like unexpected news announcements. In real-time, detecting these structural changes provides traders with valuable information to alter strategies, reduce risks, or take advantage of the emerging opportunities. Change point detection is a well established technique in finance literature and has been used to identify structural breaks or regime changes within time series data. Conventional statistical techniques, such as the Cumulative Sum (CUSUM) Test (Page, 1954) and Bayesian Online Change Point Detection (BOCPD) (Adams & MacKay, 2007) have been widely applied to financial data sets (Jackson et al.,2005).

However, these traditional methods perform poorly with the nonlinear nature of modern financial markets and their own non linearities. The PELT algorithm (Killick et al., 2012) addresses these problems by offering scalability, with linear computational complexity, flexibility, with being compatible with a number of statistical models, and accuracy, with succeeding in detecting a number of change points simultaneously. The CPA module used in our dashboard provides important insights into the overall financial analytics dashboard. Through ongoing searches for structural breaks, it helps the Regime Switching Model and enhances the robustness of volatility forecasting models.

Latency metrics

In this work, four types of latencies, namely, API Response Latency, Order Execution Latency, Network Latency, and Round Trip Latency Range are considered.

API Response Latency is the time taken by an external API, for example, the Alpha Vantage API, to respond to a data request. It is usually quantified as the time between sending a request and getting a response in milliseconds (ms). High API latency can seriously weaken trading performance by making decisions based on outdated information.

Order Execution Latency is the delay between presenting an order to the trading platform and being notified of its execution. Order execution latency is of most significance to high frequency trading models, where the speed of execution is a vital determinant of profitability. For real world observation, order execution latency typically ranges from 40 ms to 400 ms. Optimization techniques like

Smart Order Routing (SOR), Direct Market Access (DMA), and improvements to the FIX Protocol have been brought in to minimize order execution latency (Aldridge, 2013).

Network Latency is the round-trip time (RTT) it takes for a data packet to traverse in both directions from the server to the client. The ping command typically measures the time that a packet moves from source to destination and back. Physical distance, network usage, routing inefficiency, and hardware capabilities influence network latency. High frequency traders typically counteract network latency by using advanced infrastructure like fiber optics, microwave communications, and low latency data centers in order to match their peers in performance.

The Round Trip Latency Range sums up all previous latencies to have a complete measure of system performance. This is calculated by taking the API Response Latency, Network Latency, and the range of Order Execution Latency to arrive at an overall delay.

Methodology

The proposed Market Pulse and Latency Panel integrates three modules, each designed to capture different dimensions of high frequency trading dynamics. The experimental data is comprised of stock market data obtained from the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ). These data were sourced through publicly available financial databases, specifically Yahoo Finance and Alpha Vantage.

Candlestick chart with indexed pattern recognition

The Japanese candlestick charting runs back in time to 18th century Japan, when Munehisa Honma gained control of a large family rice business. His trading methodology was noteworthy. He would monitor the fundamental value by using more than 100 men on or rooftops every four kilometres to monitor the rice supplies. He would change the balance of supply and demand on the marketplace by tracking daily price movements (Caginalp & Laurent, 1998).

The technicality of candlestick analysis is based on the premise that a person can gain notable insight into the strategies and predicaments of other market players by understanding the evolution of open, close, high and low prices. The dashboard model developed provides a real-time visualization for candlestick patterns and also interprets them for the user. The system is specifically designed to play with the short-term microstructure, aiding high frequency traders. Rule based pattern recognition logic is combined with intraday open, high, low, and close (OHLC) data.

In the model, 17 patterns (as listed in Table 1) that were discussed by Steve Nison in his book (Nison, 2001) are recognized using rule-based pattern recognition and interpreting the price movement. Our model uses a rule-based pattern recognition system to find these patterns. A set of mathematical conditions determines the shape, relationship to surrounding candles, and position of candlestick patterns. These predetermined logical conditions are applied to OHLC data to identify patterns.

Table 1.

Candlestick patterns and their interpretations based on (Nison, 2001).

Name	Pattern Description	Interpretation
Doji	Small-bodied candles with nearly equal open and close prices can have long upper and/or lower wicks.	Indicates market indecision; potential reversal when appearing after a trend.
Gravestone Doji	Looks like an inverted "T"; has a long upper wick and no (or very small) lower wick.	Bearish reversal signal shows buyers were unable to hold the highs.
Dragonfly Doji	Looks like a "T"; has a long lower wick and no (or very small) upper wick.	Bullish reversal signal shows sellers failed to push the market lower.
Hammer	Small candle body near the top with a long lower wick, resembling a hammer.	Bullish reversal signal at the bottom of a downtrend.
Hanging Man	Identical shape to the hammer but appears at the top of an uptrend.	Bearish reversal signal at the top of an uptrend.
Inverted Hammer	Small-bodied candles with a long upper wick and little to no lower wick.	Potential bullish reversal signal after a downtrend.
Shooting Star	Small candle body near the bottom with a long upper wick.	Bearish reversal signal at the top of an uptrend.
Bullish Engulfing	A large bullish candle completely engulfs the previous smaller bearish candle.	Strong bullish reversal signal; buyers overpower sellers.
Bearish Engulfing	A large bearish candle completely engulfs the previous smaller bullish candle.	Strong bearish reversal signal: sellers overpower buyers.
Bullish Harami	A small bullish candle appears within the range of the previous large bearish candle.	Bullish reversal shows decrease in selling pressure.
Bearish Harami	A small bearish candle appears within the range of the previous large bullish candle.	Bearish reversal indicates weakening of the buying pressure.
Morning Star	Three-candle pattern: a large bearish candle, followed by a small indecisive candle, then a large bullish candle.	Strong bullish reversal pattern over three candles.
Evening Star	Three-candle pattern: a large bullish candle, followed by a small indecisive candle, then a large bearish candle.	Strong bearish reversal pattern over three candles.
Three White Soldiers	Three consecutive long bullish candles, each closing near its height with little or no wicks.	Bullish continuation/reversal pattern; consistent buyer strength.
Three Black Crows	Three consecutive long bearish candles, each closing near its low with little or no wicks.	Bearish continuation/reversal pattern; consistent seller pressure.
Rising Three Methods	A long bullish candle, followed by three smaller bearish candles within its range, then another bullish candle.	Bullish continuation pattern with consolidation.
Falling Three Methods	A long bearish candle, followed by three smaller bullish candles within its range, then another bearish candle.	Bearish continuation pattern with consolidation.

- The model searches for particular conditions based on the relationship between open and close prices, shadow length, and relative body size for single-candle patterns like Doji and Hammer.
- For two-candle patterns like Bullish Engulfing or Bearish Harami, the model evaluates how the second candle relates to the first.
- For multi-candle patterns like Morning Star and Three Black Crows, the model applies a rolling window over the dataset, checking how a sequence of candles interacts. For Rising Three Methods (bullish continuation) and Falling Three Methods (bearish continuation), it detects a strong trend candle, followed by three smaller opposite candles within its range, and a final strong candle breaking in the trend direction.

Change point analysis

In high frequency trading, detecting sudden shifts in market dynamics is critical. This acts like a real-time "sensor" constantly checking: "Did a change occur?" "Did more than one change occur?" "When did they occur?"

Markets at high frequency levels are influenced by microstructural events: liquidity vanishing, order book imbalances, and aggressive executions. These do not evolve gradually; they cause abrupt structural shifts. That is exactly why CPA is essential to capture these shocks and react instantly. Even a few seconds of delay can mean lost opportunities. CPA also works as a controller. In live systems where multiple models run across regimes, CPA flags when a regime no longer fits the current environment in avoiding model drift.

The Pruned Exact Linear Time (PELT) method (Killick et al., 2012), a dynamic programming approach based on (Jackson et al., 2005), is adopted, enhanced with a pruning step. This keeps the segmentation exact while cutting computational costs. Change point detection identifies moments when the statistical properties of data shift. Radial Basis Function (RBF) kernels are also applied to capture changes in both mean and variance using a kernel-based cost function.

True high frequency CPA typically runs on streaming data with millisecond updates, requiring expensive low latency feeds through WebSockets. But due to limitations, our model takes a controlled approach. The snapshots from Alpha Vantage are used, which do not support real-time streaming. Instead, the data window is expanded iteratively. With each new price observation, the model re-evaluates using PELT - simulating streaming logic. This loop allows us to flag regime shifts in "near" real time, without sockets. By tuning update speed and penalty terms, sensitivity is configured: faster updates simulate tick-level environments, while lower penalties increase detection sensitivity.

Latency metrics

The purpose of the latency panel is to warn the users about*" how delayed our dashboard data might be?"*, so that they get a clear idea about how behind we might be in capturing the real time scenarios, even in milliseconds. The panel measures and reports four critical latency components.

API Response Latency: This measures the time our system takes to receive data from Alpha Vantage API upon a request. The API Response Latency is calculated using timestamps recorded before and after the API request using Python's time function, as shown in (1). It should be noted that the timestamps are measured in nanoseconds and later converted to milliseconds for consistency in reporting.

API Response Latency = End Time−Start Time1e6 (in milliseconds) (1)

The Network Latency (NL): This is calculated using *ping* command. The process is adjusted for compatibility between Windows and Unix based systems. This measures the time for a packet to travel from local system to Alpha Vantage, and then again from Alpha Vantage to local system.

Order Execution Latency: After examining academic material on Order Execution Latency, it was noted that this latency might be in the range 40 ms to 400 ms. Even though our system does not directly interact with an exchange, and therefore it is hard to get this latency, at least adding the possible range was decided to be useful for the user.

Round Trip Latency: This is the cumulative delay, the total latency, experienced by a user from data retrieval to order execution. This range is named as, Round-Trip Latency Range (RTLR) and is defined by (2).

RTLR = [API Response Latency + NL+ 40, API Response Latency + NL+ 400)] (2)

Our warning mechanism makes sure that the user is constantly aware about the possible latency.

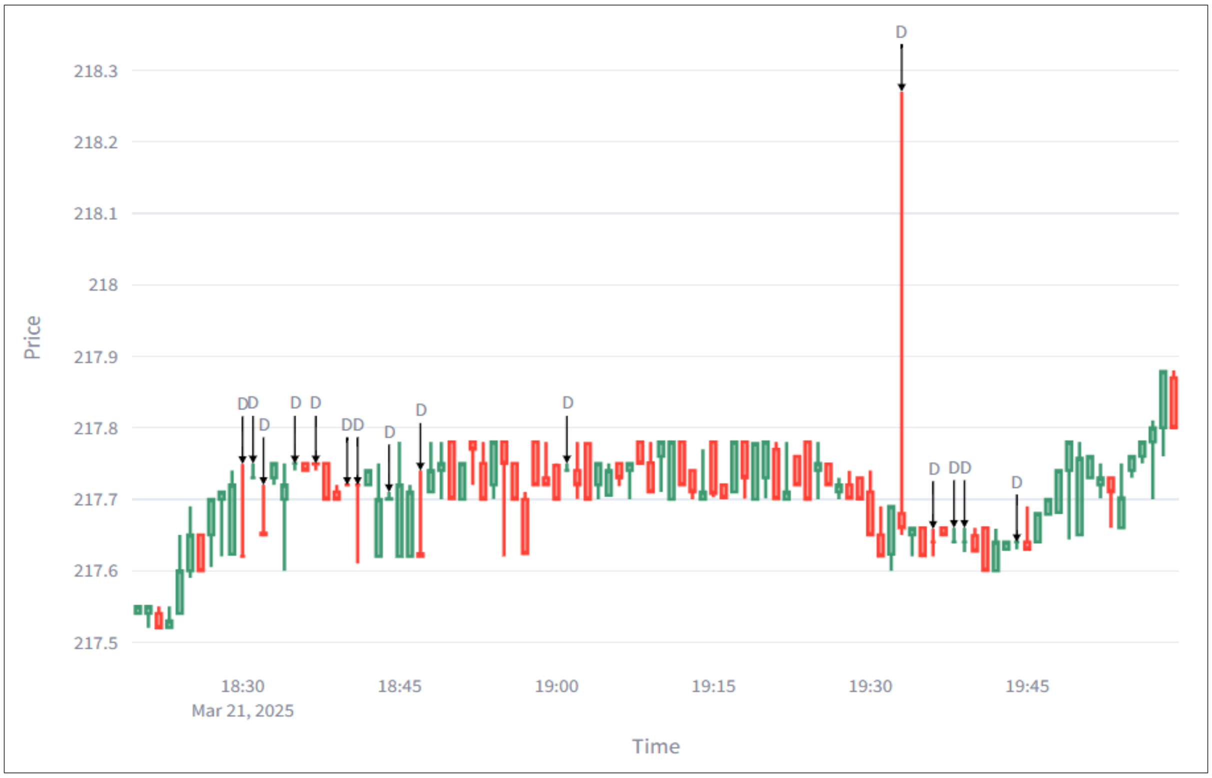
Results and Discussion

This segment evaluates our dashboard's responsiveness to the movements in real-time market and to changes in the behaviour of assets. This study employs three analytic tools, Candlestick Chart with Indexed Pattern Recognition, Change Point Analysis model and Latency Metrics.

Candlestick chart with indexed pattern recognition

The Candlestick chart with indexed pattern recognition model captures market sentiment in high frequency environments. It provides real-time candlestick charts with automated detection of single, double, triple, and complex patterns using intra-day data. Recognized patterns are directly overlaid on the charts and indexed with timestamps, helping users interpret signals at a glance. This was demonstrated using the AAPL stock on March 21, 2025, selecting only the Doji pattern (Fig. 1**)**. Ten Doji formations were identified between 18:40:00 and 19:44:00, marked with indexed arrows ("D"). Clustering between 18:30–19:00 hints at market indecision—often preceding minor reversals or consolidation. Notably, a Doji at 19:44:00 appears just before a brief upward breakout, aligning with conventional Doji interpretations. Next Doji, Hammer, and Bullish Engulfing are combined (Fig. 2). A key cluster was found between 19:38:00 and 19:57:00. Bullish Engulfing appeared seven times, often after Doji or Hammer patterns. Hammers at 19:49:00 and 19:57:00 signaled upward price action, while tight Doji clustering continued to indicate indecision.

Figure 1.
Doji detections on AAPL, March 21, 2025 (visual detection of DOJI).

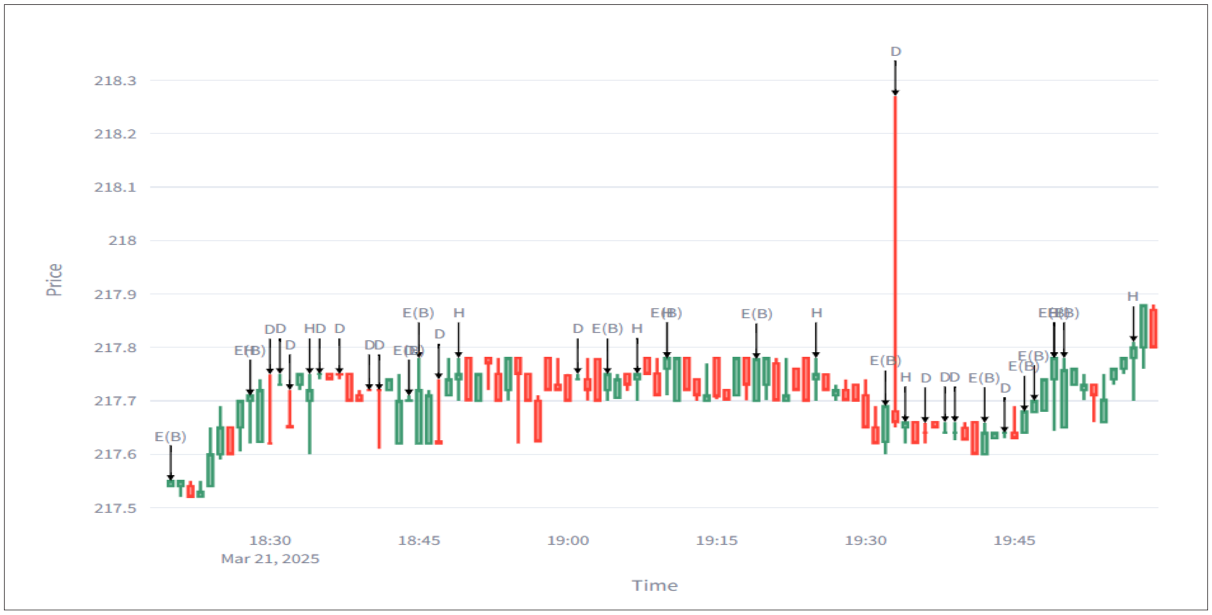


Detected Patterns

	Index	Pattern	Time	Meaning
0	D	Doji	2025-03-21 19:44:00	Market indecision, possible reversal.
1	D	Doji	2025-03-21 19:39:00	Market indecision, possible reversal.
2	D	Doji	2025-03-21 19:38:00	Market indecision, possible reversal.
3	D	Doji	2025-03-21 19:36:00	Market indecision, possible reversal.
4	D	Doji	2025-03-21 19:33:00	Market indecision, possible reversal.
5	D	Doji	2025-03-21 19:01:00	Market indecision, possible reversal.
6	D	Doji	2025-03-21 18:47:00	Market indecision, possible reversal.
7	D	Doji	2025-03-21 18:44:00	Market indecision, possible reversal.
8	D	Doji	2025-03-21 18:41:00	Market indecision, possible reversal.
9	D	Doji	2025-03-21 18:40:00	Market indecision, possible reversal.

Figure 2.

Doji, hammer, and bullish engulfing detections on AAPL, March 21, 20 (visual detection of combined patterns).



Detected Patterns

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

The convergence of all three patterns between 19:42:00–19:50:00 suggests a high reversal probability, confirmed by the price uptick post-19:50. This demonstrates the model's strength in capturing temporal proximity and pattern interplay, enabling richer interpretations beyond isolated detections.

Change point analysis (CPA)

Our CPA model detects statistically significant shifts in intraday price movement, helping traders identify regime changes, liquidity shocks, or sudden information releases. The model's sensitivity can be tuned via a *penalty* *slider*, which controls detection strictness, and a *streaming speed slider*, which adjusts the update rate (Fig. 3). Lower penalties yield more change points but risk detecting noise. Higher penalties highlight only major structural events. Similarly, faster streaming simulates high-frequency environments, while slower speeds make patterns easier to observe. This was illustrated using various settings (Fig. 4 & Fig. 6).

Figure 3.

Control panel of the change point analysis model.

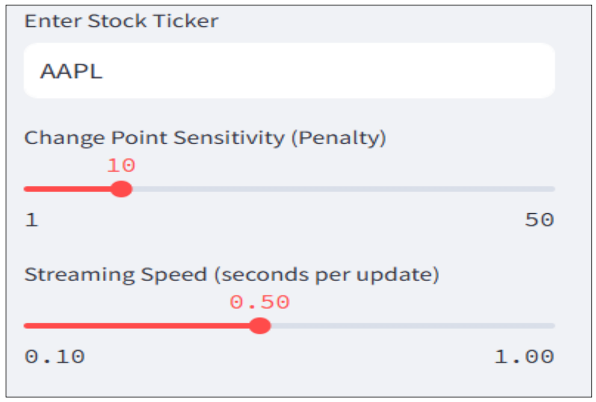
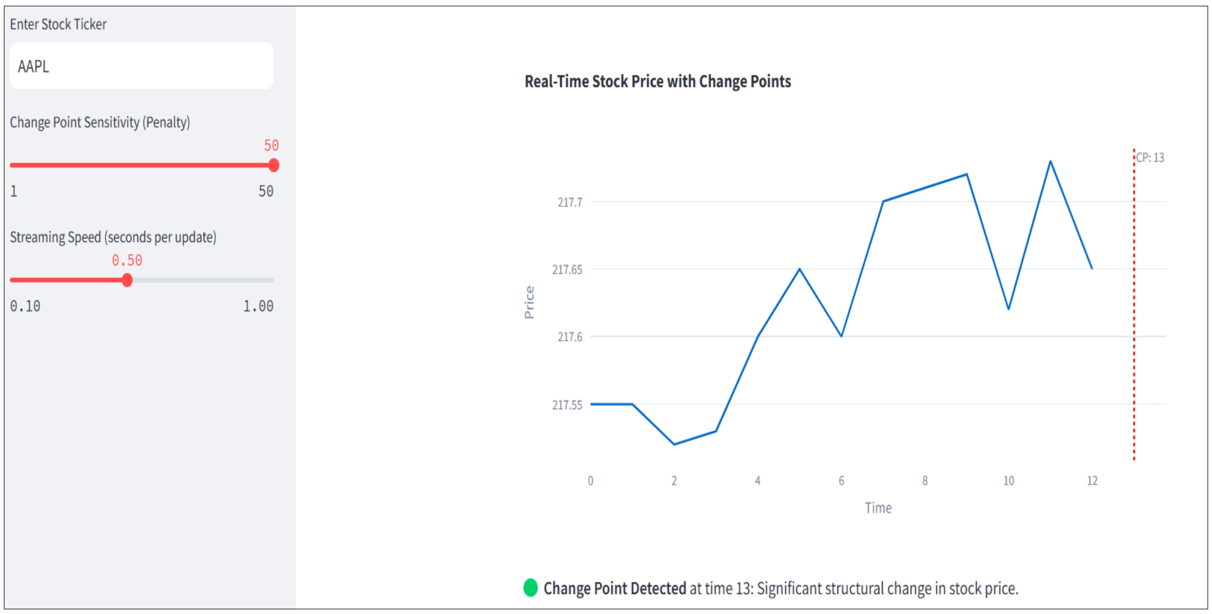
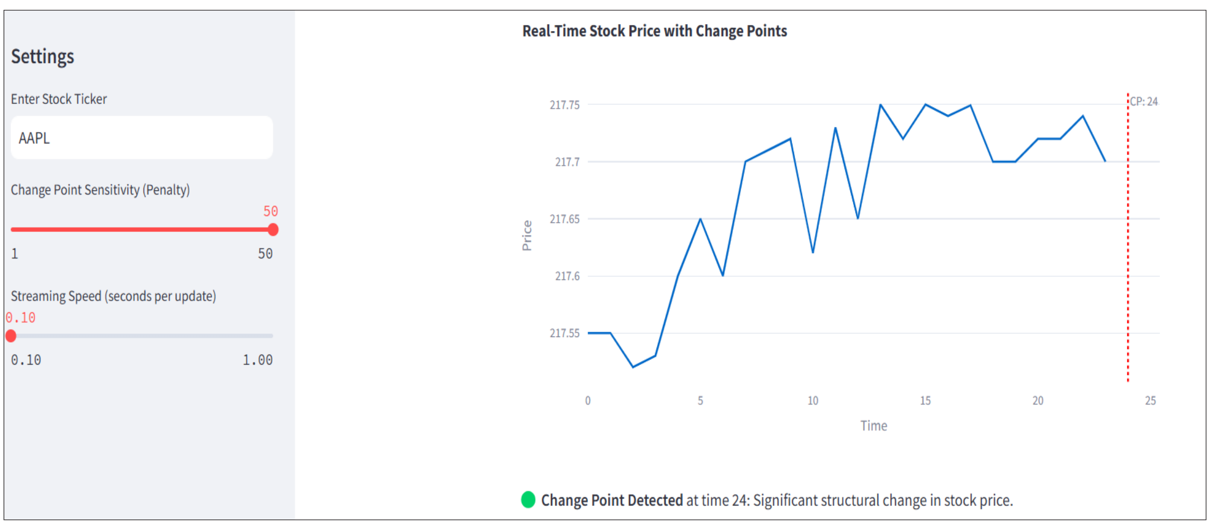


Figure 4.

High-penalty configurations highlighting only major shifts.



(a) Interface overview



(b) Penalty = 50, Speed = 0.10

It emphasizes regime-level shifts (Fig. 4 and Fig. 5). In contrast, minimizing the penalty to 1 makes the model highly sensitive. Multiple change points are flagged rapidly -even in stable conditions: capturing subtle fluctuations but risking overfitting (Fig. 6). This experiment highlights the trade-off between detection precision and signal frequency. A high penalty, low speed combo suits trending or stable markets. A low penalty, fast speed combo fits high frequency environments where swift adaptation to volatility or shocks is crucial.

Figure 5.
CPA with Penalty = 50, Streaming Speed = 1.00.

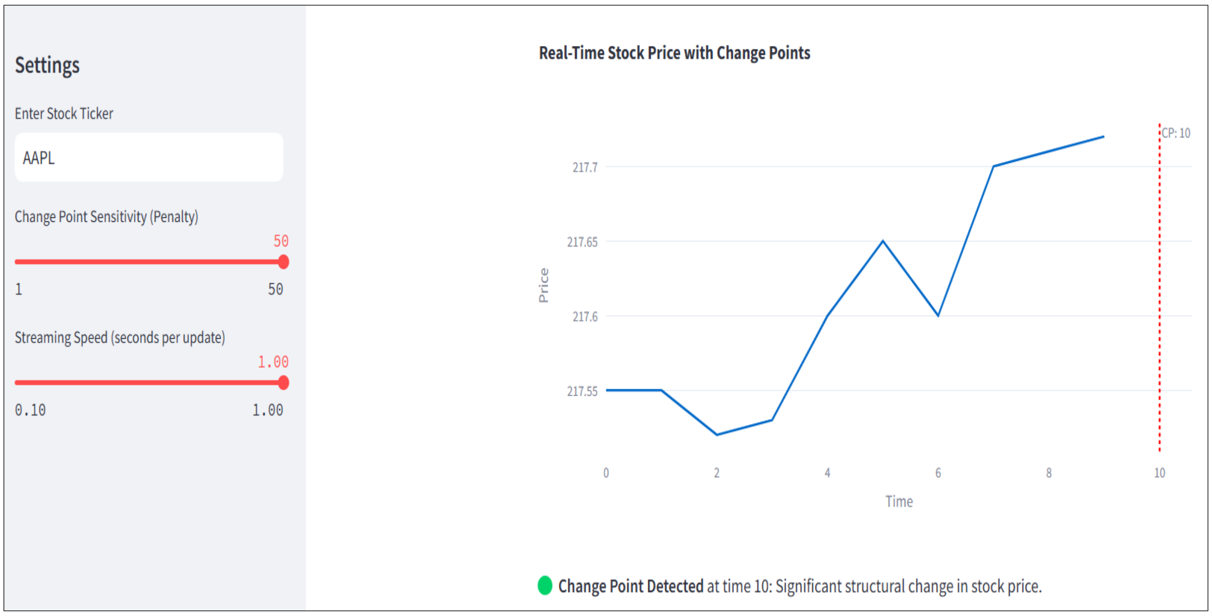
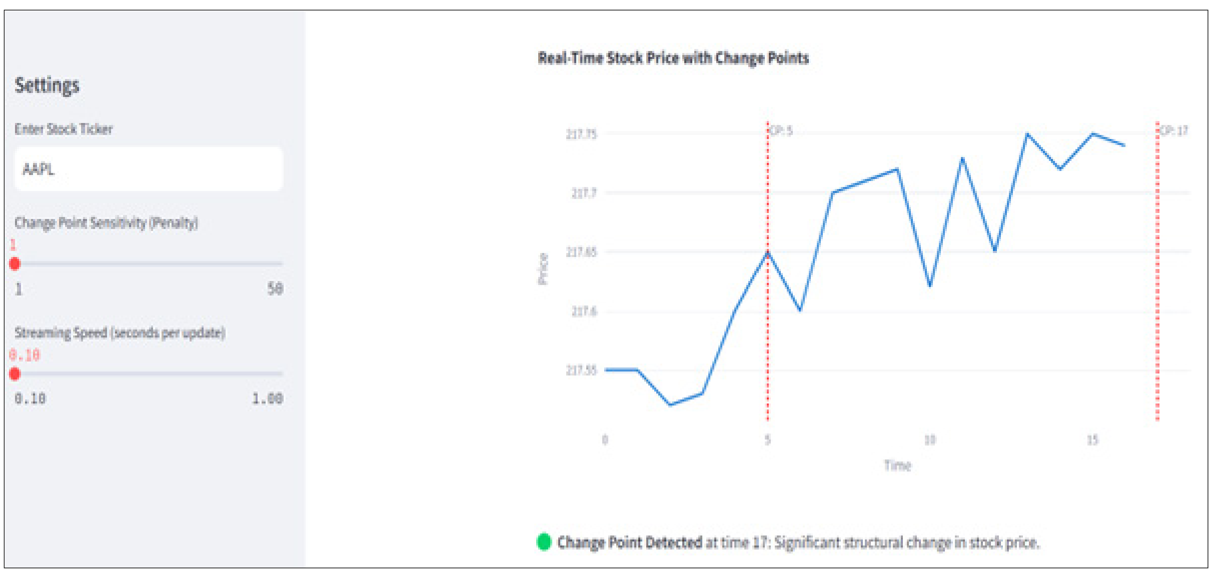
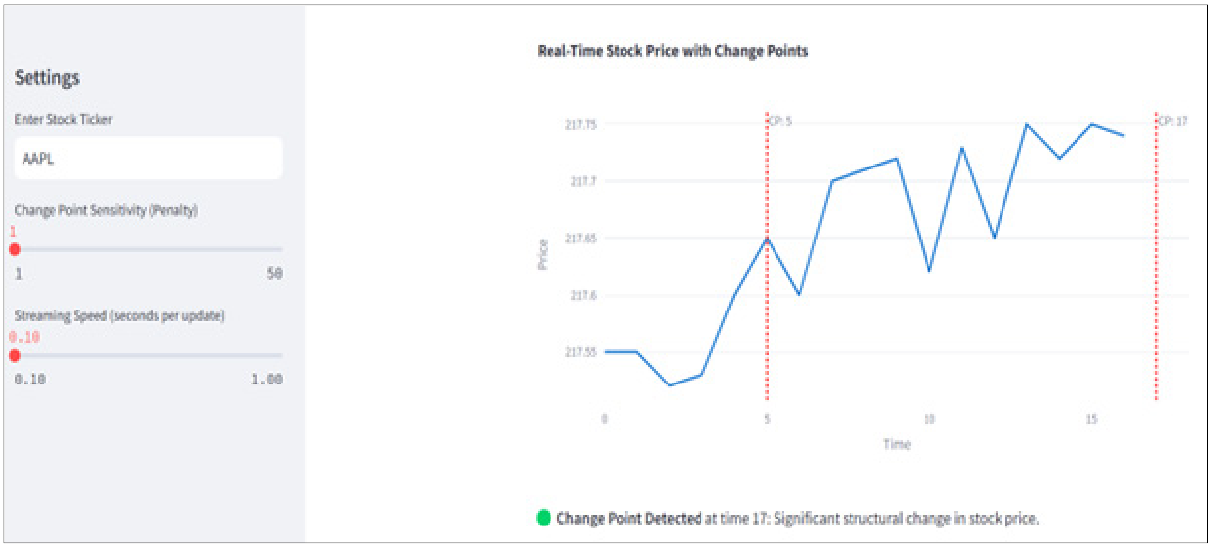


Figure 6.
Low-penalty configurations show dense signal clusters.



(a) Penalty = 1, Speed = 0.10



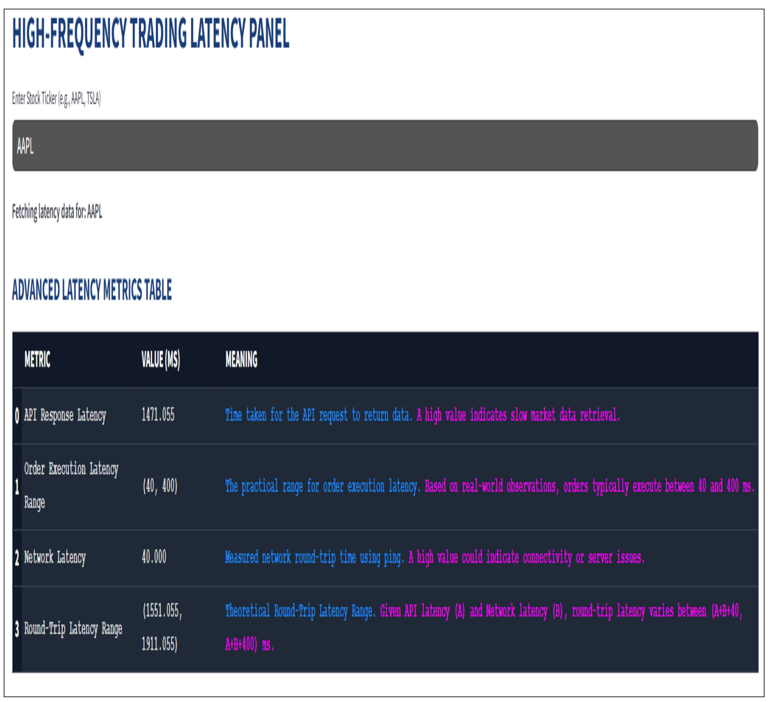
(b) Penalty = 1, Speed = 1.00

Latency metrics

The Latency metrics panel acts as warning tool, that warns the users of the extent of latency that can be experienced when using our dashboard. This helps the user understand how delayed we are in comparison to the real-time market. Especially when it comes to high frequency trading, the whole system is particularly sensitive to latency. In our dashboard, latency is broken down as API response latency, network latency, order execution latency range, and round-trip latency range (Fig. 7).

Figure 7.

A snapshot obtained from the latency panel of the dashboard.



	METRIC	VALUE (MS)	MEANING
0	API Response Latency	1471.055	Time taken for the API request to return data. A high value indicates slow market data retrieval.
1	Order Execution Latency Range	(40, 400)	The practical range for order execution latency. Based on real-world observations, orders typically execute between 40 and 400 ms.
2	Network Latency	40.000	Measured network round-trip time using ping. A high value could indicate connectivity or server issues.
3	Round-Trip Latency Range	(1551.055, 1911.055)	Theoretical Round-Trip Latency Range. Given API latency (A) and Network latency (B), round-trip latency varies between (A+B+40, A+B+400) ms.

In the latency table (Fig. 7), API response latency is given as 1471.055 ms. The API has responded quite slowly; this value gives the time taken from HTTP request to retrieve the stock data we want from Alpha Vantage. This is possibly due to server congestion, or high server load in Alpha Vantage. The order execution latency is a range, and in the early sections, we discussed how we obtained it. What this value says is, "the order executions could take anywhere from 40 ms to 400 ms". This value is only provided for the context; this value is not a measure of the dashboard performance.

The obtained network latency is 40.000 ms. This is taken between the dashboard and Alpha Vantage's server and is obtained using *ping* command. 40.000 ms is reasonably good value for network latency, this suggests great internet connectivity. But for high frequency trading, this value is slow. The possible round trip latency range is calculated as (1551.055 ms, 1911.055 ms). This speaks of the full cycle from retrieving the data to network transmission to possible order execution time. In our case, 1.55 to 1.91 seconds is slow for high frequency trading. The high API response latency is the latency that mainly contributes to this delay.

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 not only to observe market conditions but also to 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.

References

Adams, R. P., & MacKay, D. J. C. (2007). *Bayesian online changepoint detection*. arXiv preprint arXiv:0710.3742.

Aldridge, I. (2013). *High-frequency trading: A practical guide to algorithmic strategies and trading systems*. Wiley.

Caginalp, G., & Laurent, H. (1998). The predictive power of price patterns. *Applied Mathematical Finance, 5*(3–4), 181–205.

Hasbrouck, J., & Saar, G. (2013). Low-latency trading. *Journal of Financial Markets, 16*(4), 646–679.

Jackson, B., Scargle, J. D., Barnes, D., Arabhi, S., Alt, A., Gioumousis, P., Gwin, E., Sangtrakulcharoen, P., Tan, L., & Tsai, T. T. (2005). An algorithm for optimal partitioning of data on an interval. *IEEE Signal Processing Letters, 12*(2), 105–108.

Killick, R., Fearnhead, P., & Eckley, I. A. (2012). Optimal detection of changepoints with a linear computational cost. *Journal of the American Statistical Association, 107*(500), 1590–1598.

Nison, S. (2001). *Japanese candlestick charting techniques: A contemporary guide to the ancient investment techniques of the Far East*. Penguin.

Page, E. S. (1954). Continuous inspection schemes. *Biometrika, 41*(1–2), 100–115.

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review (2005–2019). *Applied Soft Computing, 90*, 106181.