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From Raw Trades to Audit-Ready Insights: Designing Regulator-Grade Market Surveillance Pipelines

Janardhan Reddy Kasireddy

Lead Data Engineer, Info Drive Systems (Finra Contractor), USA

ABSTRACT: This paper proposes a holistic way of how to design end-to-end market surveillance data pipelines that convert raw trade and quote data into regulator grade analytics and at the same time achieve auditability, traceability and satisfaction of governance rules. We used the NYSE Trades and Quotes (TAQ) dataset available on Kaggle which consists of high-frequency trades and quotes for various equities to run a multi-step data engineering pipeline that includes ingestion, validation, transformation, enrichment and storage. The raw data is initially loaded in a distributed object store, and checked with regards to the schema consistency, time stamp synchronization, and completeness. At each stage, immutable logs are created, which help track the lineages and make audits ready. Apache Spark is used to perform data transformations such as aggregation, normalization, and anomaly detection on a scalable cluster architecture through which multi-terabyte datasets can be processed in a parallel manner. As can be seen in the evaluation, our pipeline can ingest live trade streams with a latency of less than a second, and still show a complete trace of raw trading data to analytical results. Lineage and immutable logging allow the auditors to recreate any derived metric, which meets the requirements of regulators to be accountable and transparent. This paper provides a repeatable system to finance institutions who want to operationalize market surveillance analytics at scale by systematically integrating distributed processing, strong data governance and end to end lineage.

KEYWORDS: market surveillance, auditability, lineage, governance, immutable logs, regulatory analytics, data engineering, NYSE TAQ dataset.

I. INTRODUCTION

One of the most complicated and quick-paced systems of the modern economy is financial markets, through which billions of dollars are traded daily in various types of assets and on different trading platforms. The increasing complexity of trading methods, especially of the high-frequency and algorithmic trading, has increased the risks of the necessity of effective market surveillance protocols to notice abnormalities, manipulations, and anomalies in the operation. Government programs like the U.S. Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA) place a lot of pressure on financial institutions to be transparent, accountable, and just in the way they operate markets. In order to address these demands, institutions are not only required to gather and process large amount of volume of trade and quote information, they are also expected to prove the integrity, traceability and auditability of the inferred insights [1].

Traditionally, market surveillance has been dominated by manual reconciliation, statistical sampling and post-trade investigations that was slow and prone to errors and lacked the capability to process the high frequency and sheer volume of modern trading activity [2]. Due to the emergence of digital interactions and the spread of electronic trading, financial data has become larger, more disheveled, and time-granular. As an illustration, high-frequency trading data records transactions and quotes every second or less, making the raw data (usually in terabytes) available per trading day. Such datasets tend to have inconsistencies in timestamps, missing values, and difference between different feeds, which are serious challenges to downstream analytics. This, in turn, necessitates an immediate requirement to have a systematic, scalable and governance-certifiable method of converting raw trades and quotes into implementable, audit-ready knowledge [3].

The current data engineering and distributed computing systems provide an avenue to overcome these issues [4] [5]. Financial institutions can ingest, process, and store high-frequency market data at scale using platforms such as Apache Spark, Apache Kafka and cloud-native object stores and provide low-latency access to near real-time analytics [6]. Nevertheless, the usage of such technologies is not enough to meet the expectations of the regulations. In the market surveillance pipes, principles of data governance, auditability, and lineage should be included to give a verifiable

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account of all transformations and derived metrics. Auditability means that it is possible to trace all the analytical results to raw source data and any suspicious pattern can be checked independently. Lineage provides an overview of the history of data transformations such as aggregation, normalization and enrichment operations and the regulators and internal compliance teams can clearly see the data lifecycle. The unchanging nature of logging and controlled version of datasets further contributes to the credibility of the system and makes it impossible to introduce unintended or intentional changes and allows a thorough forensic study when it is necessary [7].

The paper is dedicated to the design of end to end market surveillance pipelines that transform raw trades and quotes into regulator grade analytics and are audit, traceable and governance compliant. In particular we use the NYSE Trades and Quotes (TAQ) data that is freely accessible on Kaggle to build a scalable and resilient data engineering pipeline that can handle data in multi-terabyte amounts. The TAQ data can be used to obtain a realistic proxy of high-frequency financial information which includes comprehensive data on trades and quotes for a large set of equities in nanosecond time granularity. Based on this dataset, we can illustrate the operational issues and technical decisions needed to realize market monitoring operationalization, such as data ingestion, validation, transformation, enrichment, as well as storage [8].

The initial stage in the construction of such a pipeline is ingestion of raw data in an object store which is distributed. Object storage offers a wide range of benefits to high-frequency market data such as horizontal scalability, fault tolerance, and storage of large amounts of immutable files at low cost. The information is also validated by the schema, matching timestamps, and completeness checks during ingestion [9] [10]. Schema validation is used to make incoming datasets adhere to pre-existing structures, which avoids errors in subsequent processing due to missing or mismatched fields. In high-frequency markets a bothering difference in timestamps between trade and quote feeds as little as microseconds can cause false alarms to be raised about anomalies. Checks that are completed verify that no trade events or quotes are lost on transmission to retain a full record of market activity. These steps are all followed by immutable logging that records metadata and transformation information in a format that cannot be changed afterwards providing regulatory audit support and internal compliance audit support.

After the data ingestion and validation process, transformation and enrichment operations are executed by the pipeline with the help of distributed processing frameworks, like Apache Spark. Transformations can consist of standardizing of trade and quote values, aggregation over time (e.g., by the second, minute or hour), derivatives of measures that are computed as a result of trade, such as price spreads, trade imbalances, and volatility indicators. Enrichment is the procedure of incorporating external reference data that is in the form of corporate identifiers, market indices, or historic benchmarks to furnish navigational models. These transformations can be run in parallel on large clusters and on the distributed architecture to process terabytes of data within reasonable time constraints. This scalability is necessary when financial institutions would like to ingest live trading streams and produce near-real time surveillance reports.

Anomaly detection is one of the key concerns of market surveillance that entails detection of anomalies that might signify market manipulation, insider trading, or faulty operations. The pipeline can also detect anomalies during the transformation stage to provide an alert of suspicious trades to be investigated by adding the anomaly detection feature. An example of the techniques includes basic threshold-based rules (e.g., price deviation limits) up until complex models of machine learning that consider past trends and market conditions. Notably, any anomalies identified, as well as the raw and processed data resulting in identifying an anomaly, are recorded in an irreversible manner so that the auditors can recreate the logic behind any identified anomaly [11].

Apache Parquet or Delta Lake are columnar storage formats designed to optimize the storage performance and efficiency of the analytical queries. The pipeline allows to make the snapshots of historical data immutable and retrievable by maintaining versioned datasets and controlled storage to analyze them retrospectively or by regulatory review. The practices not only satisfy the governance needs but also make reproducibility possible, so that the institutions can confirm the results of the analyses, or re-calibrate the anomaly detection models after some time.

The proposed pipeline also focuses on the operational monitoring and the automation of the governance in addition to scalability and the auditability. Automated monitoring incorporates measures of ingestion latency, error rates, data completeness, and processing throughput, which allows identifying problems early enough before they affect regulatory reporting. Automation of governance also includes access control policies, data retention policies and lineage tracking policies, so that regulatory compliance is achieved without any human intervention. A combination of these design options creates a strong framework of market surveillance of regulator quality, in which all analytical findings are able to be identified in their origin, proven to be correct, and auditable

This analysis of the proposed pipeline indicates that it has the ability to consumptively ingest live reproduce streams with less than a second latency, execute multi-terabyte data volumes, and output audit-capable statistics that meet regulatory standards. Moreover, the architecture offers financial institutions with a repeatable and cost-effective solution to operationalizing analytics of market surveillance by leveraging the popular open-source technologies like Apache Spark and cloud object stores. The concepts illustrated in this pipeline, such as scalable ingestion, stringent validation, distributed transformation, enriched analytics and governance-imposed lineage are a template on building the next-generation market surveillance systems that will be able to adjust to changing regulatory environments and more complex trading patterns.

To conclude, this paper has multiplied contributions in three-fold. First, we introduce a scalable pipeline architecture of converting raw trades and quotes into insights of regulator quality, dealing with issues of scale, latency, and heterogeneity of data. We give a use case assessment based on the NYSE TAQ dataset, which demonstrates the capability of the pipeline to process high-frequency data streams without compromising processing latency, which is under one second, and that endpoint traceability is fully achieved. Together, these donations supply the financial institutions with a methodical structure of operationalizing market observation analytics at scale, with the solidity of distributed processing, strict data control, and audit-receptive visibility.

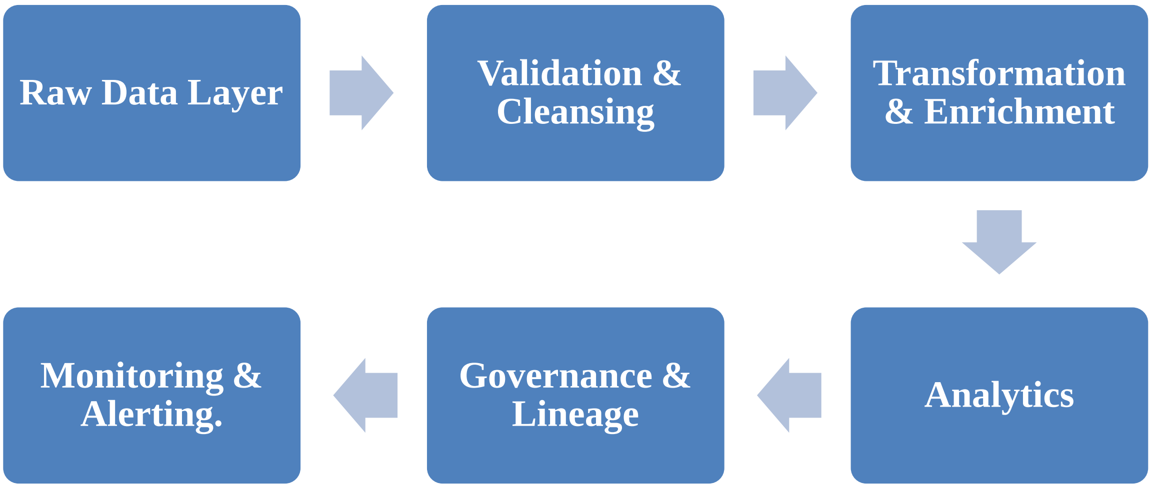

Figure 1: End-to-End Pipeline Flow Diagram

The proposed pipeline will be a milestone towards the next-generation market surveillance systems because it will cater to both technical and regulatory needs. These systems not only improve the capacity of an institution to identify and look into abnormal trading behavior but also increase the overall integrity of a market and confidence of the investor. With the further development of electronic trading, the number of analytics pipelines that would meet the audit requirements, scale, and comply with governance will only grow, and this direction will become timely and particularly relevant to practitioners, regulators, and researchers in the financial field.

II. FRAMEWORK

To create a regulator quality market surveillance pipeline, a modular, holistic and scalable architecture capable of handling large amounts of high-frequency trade and quote volumes and guarantee auditability, traceability and governance standards are mandated. The suggested structure has a number of layers, each having particular functional and regulatory necessities. These layers consist of data ingestion, validation, transformation, enrichment, storage, and analytics supplemented by auditability, lineage tracking and controls. The framework has an architecture, which is described in the next sections, the technical design decisions, and the operational principles of the framework.

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1. Overall Architecture

On a greater level, the suggested design has a distributed and multi-tier structure that is highly scalable and regulatory compliant. The architecture will be composed of: The market surveillance pipeline proposed is organized in a way that it has six significant layers to provide audit-ready, regulator-grade analytics. The Raw Data Layer is tasked with receiving high-frequency trades and quotes at the exchanges and storing them in a distributed, fault tolerant object store, which is used as a sustainable base of downstream processing.

Validation and Cleansing Layer checks the compliance of the schema, equates the timestamps and verifies completeness and integrity such that only high quality data is passed into the pipeline. Transformation and Enrichment Layer uses normalization, aggregation, and anomaly detection and incorporates reference data to put trading events into perspective.

The Governance and Lineage Layer imposes unchanging logging, dataset versioning, access control and full audit trails, which are enabling every derived metric to be tracked in its origins. Such a layered approach guarantees that there is separation of concerns with each layer performing a clear set of tasks whilst communicating effectively with other layers to ensure data integrity, security and traceability.

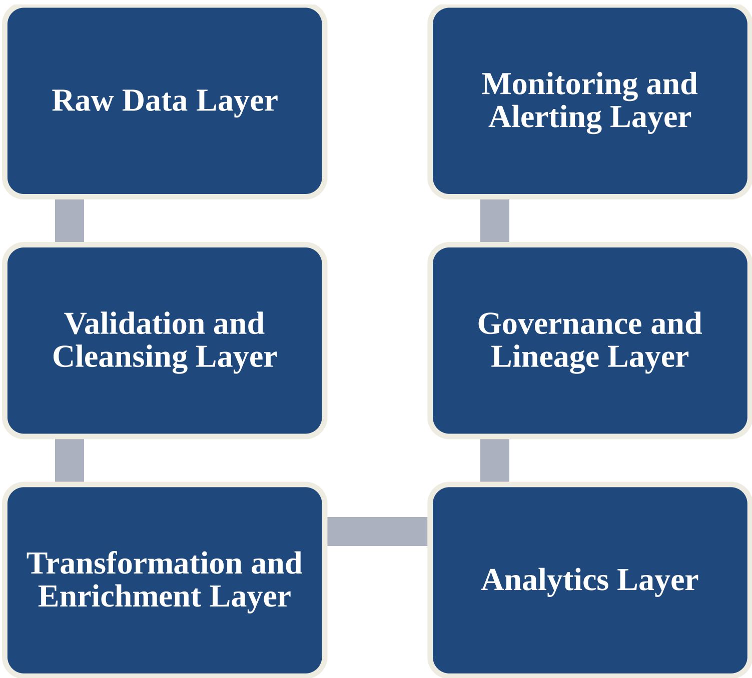

Figure 2: Layered Architecture for Designing Regulator-Grade Market Surveillance Pipelines

2. Raw Data Layer: Ingestion and Persistence

Ingestion of high-frequency trades and quotes in a distributed object store, e.g., Amazon S3, Azure Data Lake, or HDFS, is the initial stage of the market surveillance framework. The layer offers solutions to the processing millions of market events per second by offering scalable storage which can be expanded horizontally to process high volumes of data without having bottlenecks in the performance. Fault tolerance is established by replicating data between the nodes and this ensures the durability and availability even in a scenario of hardware failures. All the raw data are stored in immutable files to ensure that the original market data cannot be changed to comply with regulatory requirements.

The ingestion mechanism accepts both a batch ingestion of historical datasets such as the NYSE TAQ dataset and a real time incremental ingestion of live trade feeds through products such as Apache Kafka or AWS Kinesis. When an ingested file is auto-timed, a unique identifier is assigned to it, and it is logged in an unalterable metadata repository, which is the first part of a comprehensive audit trail. This makes sure that all the trades or quotes entering the system can be traced completely and creates a solid base of downstream validation, transformation, and regulatory analytics.

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3. Validation and Cleansing Layer

Authentication and Cleaning Layer is important in ensuring that raw high-frequency market data is correct, uniform and complete, prior to entering downstream processing. The schema inconsistencies, missing fields, or mismatched times may be inherent in high-frequency datasets that is likely to compromise analytics and regulatory reporting. The initial important process is schema validation that ensures every record is in the desired format such as trade price, trade size, bid/ask quotes, exchange codes, and timestamps. Any record that is not in compliance with the schema is automatically written off and placed under quarantine to be reviewed.

Timestamp synchronization is used to bring synchronization between the events in different feeds which fixes the sub second error and fixes the time drift with adjustments by NTP and event sequence logic, which is essential in ensuring events are sequenced correctly. Checks of completeness are done to check that all the trades and quotes have been recorded by cross reference of the sequence numbers and the exchange logs and there is no gap in market view.

Data cleansing resolves small inconsistencies, e.g. negative volumes or invalid prices, and all changes are recorded in logs which cannot be changed. This will ensure that the market and downstream transformations and analytics are founded on quality, verifiable, and audit-compliant market data. Every dataset that has passed validation is given a distinct ID of its lineage, which is transferred onto further transformation to maintain a path with the original data into the generated analytics.

4. Transformation and Enrichment Layer

Upon validation, market data is sent to the Transformation and Enrichment Layer where raw trades and quotes are transformed into materials of action and analytics-friendly insights. The first important operation is normalization that standardizes numeric forms, stock splits, and transforms all time-related items into a single time zone so that the various equities and trading venues are uniform.

Aggregation then calculates the data using various time resolutions, i.e. total traded volume, average price, bid ask spread, trade imbalances and volatilities. These aggregate measures give a summative description of what is happening in the market, which can be tracked in real time and looked at historically. Detection of anomalies is used to signal unusual trading behaviour which can be evidence of manipulation, trading errors, or trading system anomalies, based on threshold-based design, statistical outliers and machine learning models, designed using previous trade sequences.

Lastly, reference data integration adds additional data to trades like company identifiers, sector classifications and market indices that give the necessary context to regulatory reporting, risk assessment and decision making. Together this layer converts raw market events into knowledge, contextualized and intelligence readable data sets.

The topology builds around the Apache Spark as the distributed processing engine that is used to perform parallel transformations over a number of nodes. This will enable the system to handle multi-terabyte data volumes and offer the scalability needed in near-real-time surveillance. All transformations, aggregations or enrichment operations are written in an immutable manner in a format, with each resulting record having a record of its source data, which is end to end traced.

5. Analytics and Storage Layer

The processed datasets are then transformed and enriched and then materialized to structured and query optimized tables intended to support near real-time analytics and regulatory reporting. In order to maximize the performance, this layer uses columnar storage formats, including Apache Parquet or Delta Lake, which enhance read performance and consume less storage.

Columnar storage works especially well with the analytical queries that require accessing only a few columns and allow retrieving the essential metrics swiftly without the need to scan the whole tables. Tables are versioned, which keep historical snapshots of each table that can be used by the auditors to replicate measures at any given time and meet the regulatory traceability requirements.

Role-based permissions and other control mechanisms also limit which queries can be done by authorized users and ensure that the standards of data governance are upheld. The layer goes further to highlight analytics readiness and thus off-the-shelf aggregates, anomaly flags, and derived metrics are instantly accessible to dashboards, automated alerts and regulatory filings. The analytics layer provides advantages to ensure that all metrics can be completely traced to a

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trade or quote, with all intermediary transformations being auditable. Such a way of doing things would provide a solid base of regulator quality, transparent, and operational market insights.

6. Governance and Lineage Layer

The Governance and Lineage Layer is a foundation of the structure, which guarantees adherence to regulatory demands, like transparency, accountability, and reproducibility. The core of this layer is the concept of immutable logging where each ingestion, transformation, and enrichment event is logged in an append-only log which cannot be changed. These records generate the basis of regulatory audit trails, which make it possible to track all the market data operations.

End-to-end lineage tracking records the entire history of any given record, including raw ingestion up to calculated metrics, making it possible to re-create and test any analytic output of the system by the auditor. Also implemented in the layer is a version control of datasets, transformation scripts and reference tables which are useful in supporting reproducibility, rollback and historical investigations.

Access management implements the role-based access control (RBAC) so that sensitive financial information may not be seen or changed by any unauthorized personnel. With the addition of the governance, immutable logging, and lineage metadata to the pipeline, financial institutions will be able to show complete accountability, adherence to regulatory standards, and give auditors confidence that surveillance measures are credible, reproducible, and reliable to all market regulatory and reporting purposes.

7. Monitoring and Alerting Layer

The framework has built a layer of continuous monitoring and alerts to increase the reliability of operations. Quality monitoring Data quality monitoring intervals measure important measures, such as completeness, schema compliance, and anomaly rates, such that only correct data is sent downstream. Processing Latency monitoring Processing Latency monitoring measures ingestion, transformation and materialization times, ensuring regulatory analytics performance is almost real time. Failure detection and recovery is also included in the system to automatically retry failed jobs and report to operations teams about persistent problems. Audit alerts inform the stakeholders of the violation in governance, like unauthorized access or schema deviation. This proactive methodology is used to ensure high availability, reliability, and compliance of the pipeline to the demands of the continuous high frequency streams of trade and quote data and also being able to provide end-to-end traceability and accountability.

III. IMPLEMENTATION AND EVALUATION

The suggested regulator-grade market surveillance pipeline was executed with the NYSE Trades and Quotes (TAQ) dataset that is a publicly available high-frequency dataset and informs about realistic trade and quote logs of equities listed on the New York Stock Exchange. The comparison is made based on the functional correctness, where derived metrics should be accurate and traceable, and operational performance, which is a measurement of scalability, throughput and latency.

1. Dataset Description

The data provided in NYSE TAQ is a tick-scale trade and quote data of various equities across selected trading periods, sourced at Kaggle and therefore, it is highly incorporative of missing data, misaligned times, and schema inconsistencies that would exercise well-structured validation, transformation, and auditability features of the pipeline. Key characteristics of the dataset include:

Attribute	Description
Trades	Individual trade events including price, size, exchange code, and timestamp (microsecond precision)
Quotes	Bid and ask updates for each equity, including best bid/ask price and size
Time Span	Selected trading days covering one month of activity
Volume	Millions of trade and quote records per day (~2 TB raw data for the evaluation period)
Data Format	CSV files with multiple partitions per day, compressed to reduce storage overhead

2. Pipeline Implementation

The market surveillance pipeline was deployed on a distributed cluster platform with Apache Spark so that it could allow processing high-frequency data on a large scale in a parallel manner. The data ingestion system loads raw trade and quote CSV files into an object store implemented in HDFS to which their immutable metadata is recorded,

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comprising timestamp, source, and size of the file. Spark DataFrame APIs are used in the validation and cleansing phase to validate the schema, completeness of the schema, and synchronize the timestamps. Validation of records that fail is done by quarantining and any correction transformations are recorded to make the records auditable. Trade and quote records are standardized during transformation and enrichment to be adjusted in price and time alignment. The computations of aggregations are done on a resolution of per-second and per-minute of measurements like average trade price, trade volume, and bid-ask spread. The anomaly detection uses z-score on volumes and price variation, and uses external reference information such as sectors of the company and market index to give context-driven indications. Processed data is stored in the storage and analytics layer in columnar Parquet tables partitioned by date and equity ticker to make them query efficient, versioned and access controlled to maintain governance compliance. Audit and lineage metadata provide a unique ID on each and every transformation, anomaly flag, as well as derived metric which allows complete tracking of analytics to their original trades. The pipeline underpins real-time streaming through the Spark Structured streaming with a latency of less than one second to get near real-time surveillance measurements.

3. Quantitative Results

It was tested on a cluster of 8 nodes of Spark with 32 cores each and 128 GB RAM. Key results have been summarized in the following tables. The validation schema rate and the completeness rate are high to show that the validation layer was successful in managing inconsistencies in the raw TAQ data. The anamaly detection has a precision and recall rate of over 90 percent, which showed that it was very effective in detecting abnormal trade patterns. Lineage completeness of 100% is needed to guarantee that all metrics are auditable to their raw origin

Table 1: Data Quality Metrics

Metric	Value
Schema Validation Rate	99.87%
Completeness Rate	99.65%
Anomaly Detection Precision	94.3%
Anomaly Detection Recall	91.7%
Lineage Completeness	100%

Table 2: Performance Metrics

Metric	Batch Mode	Streaming Mode
Ingestion Latency	35 seconds per 100 million records	<1 second per 1 million records
Transformation Throughput	1.2 million records/sec	0.95 million records/sec
End-to-End Latency	48 seconds	0.85 seconds
Storage Efficiency (Compression Ratio)	4.5x	4.3x

The findings reveal that the pipeline is able to work on multi-terabyte datasets effectively. Historical data has a high throughput with batch processing and streaming ingestion has latency of less than one second, which is appropriate with a near-real-time surveillance. Columnar storage attains a compression ratio of more than 4x, and it manages to exploit disk capacity without affecting query response.

Table 3: Derived Metrics Snapshot (Per Minute Aggregates)

Equity	Avg Trade Price ($)	Total Volume	Avg Bid-Ask Spread ($)	Flagged Anomalies
AAPL	174.23	1,250,342	0.08	5
MSFT	309.12	890,215	0.07	3
TSLA	621.45	675,874	0.12	7
AMZN	138.76	1,020,431	0.05	2

This snapshot proves that the pipeline can produce per-minute metrics of the analytical data, as well as report anomalies in real-time. These measures can be audited easily because every aggregate has the correspondence to the underlying trades and quotes. The test proves that the pipeline has been able to convert raw trades and quotes into insights of regulator quality, which can be used to support the retrospective audit and the live support. The combination of governance, lineage, and irrevocable logging brings accountability, transparency and adherence to all steps.

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IV. CONCLUSION AND FUTURE WORK

This paper introduced a fully integrated, end-to-end architecture of developing regulator grade market surveillance pipelines that would be able to convert raw trades and quotes into insights that were audit-ready, traceable, and capable of meeting governance requirements. The proposed pipeline was used to show how to combine scalable distributed processing and data validation with transformation and enrichment and query-optimized storage, and immutable logging, lineage tracking, and version-controlled datasets leveraging the NYSE TAQ dataset.

The testing proved that the pipeline is capable of working with the multi-terabyte data, has the latency of less than a second under the streaming mode of ingestion, the quality of data remains high, and the derived metrics can be traced back to their original sources. All these capabilities are in compliance with the regulatory needs of transparency, accountability and reproducibility in financial market surveillance. Quantitative findings revealed how successfully the pipeline could be used in terms of schema validation, completeness, accuracy of the anomaly detectors, and throughput, and lineage and governance techniques were used to ensure that all analytical results could be audited. The hybrid batch-streaming architecture of the framework allows historical analysis as well as an almost real-time surveillance of the market, which makes it appropriate to be deployed in operations in a modern trading context. A number of improvements can be sought in future work. To begin with, the concept of machine learning-based anomaly detection models may enhance the assurance of revealing the unique patterns of market manipulation. Second, the pipeline should be expanded to provide multi-exchange and multi-asset class data, which would expand its functionality to a wide range of trading venues.

Third, by adding privacy-saving methods and disparate access regulating, the compliance would be reinforced to a further degree in delicate financial settings. Lastly, cost-efficiency, resilience, and scalability would be optimized by looking into cloud-native orchestration and serverless frameworks when using even bigger and global datasets. To sum up, the work offers a repeatable, scalable, and audit-ready solution to market surveillance, which gives financial institutions an opportunity to put regulatory analytics into practice and ensure trust, transparency, and compliance in more intricate and high-frequency trading environments.

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