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Developing Intelligent Systems That Continuously Monitor and Validate Data Quality Across Large Distributed Systems

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Abstract

Ensuring high-quality data in large-scale distributed systems is essential for the reliability of real-time analytics, automated decision-making, and regulatory compliance in data-driven enterprises. Traditional data quality techniques, largely based on static rule-based approaches, are insufficient to address the scale, velocity, and complexity of modern distributed environments. This study presents the design and evaluation of an intelligent data quality monitoring system that integrates rule-based validation, machine learning models, metadata analysis, and adaptive feedback loops. The proposed architecture supports both real-time and batch processing, and was implemented using distributed computing frameworks such as Apache Kafka and Spark. Empirical evaluations conducted using synthetic IoT sensor data and real-world NYC taxi trip records demonstrated that the system outperformed traditional methods in terms of precision, recall, F1 score, and scalability. Furthermore, the system exhibited adaptive capabilities through feedback-driven learning and self-healing mechanisms, enabling it to respond effectively to evolving data patterns. These results confirm the system's practicality and effectiveness in maintaining trustworthy data within high-volume, dynamic distributed environments. The study concludes with recommendations for future

enhancements, including the integration of explainable AI and decentralized validation techniques.

Keywords: Data Quality Monitoring; Distributed Systems; Anomaly Detection; Machine Learning; Rule-Based Validation; Metadata Analysis

Introduction

In the era of big data and large scale distributed computing, data has become a foundational asset for strategic decision making, operational efficiency, and predictive intelligence. However, the effectiveness of data driven systems hinges not merely on the volume or velocity of data but on its quality. Data quality encompasses a range of dimensions including accuracy, completeness, consistency, timeliness, and validity, each of which is critical to ensure trustworthiness and usability (Pipino, Lee, & Wang, 2002). In distributed systems, where data is generated, processed, and stored across geographically and logically dispersed nodes, maintaining high data quality becomes a complex and persistent challenge (Batini & Scannapieco, 2016).

The distributed nature of modern data ecosystems comprising cloud platforms, edge computing nodes, microservices, and federated databases introduces heterogeneity and latency issues that often result in data degradation (Jagadish et al., 2014). Traditional static data quality checks, typically executed during ETL processes, are no longer sufficient for dynamic and real time environments. The increasing demand for automated and scalable data pipelines necessitates intelligent systems capable of continuously monitoring and validating data quality at every stage of the data lifecycle (Berti Équille, 2015). Continuous monitoring of data quality plays a pivotal role in ensuring that business intelligence systems, AI models, and automated decision engines do not operate on flawed or misleading information. Faulty data can lead to biased models, incorrect predictions, and operational inefficiencies, which in high stakes environments like healthcare, finance, or energy can result in catastrophic consequences (Abedjan, Chu, Deng, & Ilyas, 2016). Real time or near real time data validation mechanisms are thus essential to detect anomalies, enforce integrity constraints, and provide timely alerts for human or automated remediation (Barr et al., 2020).

Despite advances in data engineering, several key challenges remain in ensuring effective data quality management across distributed environments. These include high system complexity, limited observability across data silos, lack of standardization in quality metrics, and resource constraints for monitoring at scale (Zhu et al., 2019). Moreover, data quality issues often propagate through systems silently, especially in asynchronous and loosely coupled architectures, making them difficult to detect without intelligent mechanisms that combine rule based validation with machine learning–driven anomaly detection (Chu et al., 2016).

This paper proposes a comprehensive framework for developing intelligent systems that continuously monitor and validate data quality across large distributed systems. Unlike traditional approaches that rely heavily on static rule engines or post failure audits, our system integrates real time data profiling, self adaptive anomaly detection, and metadata driven validation pipelines. The proposed architecture supports both proactive and reactive quality assurance by leveraging AI techniques such as supervised learning for error classification, unsupervised models for anomaly detection, and reinforcement learning for adaptive quality rules. Furthermore, the framework is designed to scale horizontally, making it applicable to cloud native and edge computing platforms.

The paper is structured as follows. Section 2 reviews existing literature on data quality frameworks, validation methodologies, AI driven monitoring systems, and gaps in current research. Section 3 presents the architecture of the proposed intelligent monitoring system, detailing its modular design, integration with distributed computing platforms, and support for both real time and batch data validation. Section 4 describes the core intelligent monitoring techniques used in the system, including rule based validation, machine learning based anomaly detection, metadata and data lineage tracking, and feedback driven self healing mechanisms. Section 5 outlines the methodology adopted for system evaluation, including dataset preparation (synthetic IoT data and real world NYC taxi data), anomaly injection, distributed simulation using Apache Spark and Kafka, and classification and performance metrics. Section 6 discusses the results in depth, highlighting the system's superior performance, adaptability, and scalability. Finally, Section 7 concludes the paper with key insights, limitations, and directions for future research aimed at advancing autonomous data quality assurance in dynamic, distributed environments

Literature Review

According to Pipino, Lee, and Wang (2002), data quality is a multidimensional concept encompassing attributes such as accuracy, completeness, consistency, timeliness, and validity. These dimensions have been widely accepted as standard benchmarks in both academic and industrial frameworks. Over the years, various data quality frameworks have been proposed to systematically manage and assess these dimensions. A widely referenced model is Wang and Strong's (1996) framework, which categorized data quality into intrinsic, contextual, representational, and accessibility dimensions. More recently, Batini and Scannapieco (2016) developed a holistic methodology that includes assessment, improvement, and monitoring activities tailored to the lifecycle of data in enterprise systems. These frameworks have laid the groundwork for implementing structured data quality management protocols but often fall short in handling the dynamism and scale of large distributed systems.

Research by Cappiello and Pernici (2006) introduced context aware data quality models that consider the application scenario when evaluating data. This notion is particularly relevant in distributed environments where the same data may be interpreted differently across nodes. Existing methods of data quality assessment have largely relied on rule based validation engines, which define a set of constraints that data must satisfy (Abedjan et al., 2016). These include statistical thresholds, referential integrity rules, and schema conformance checks. However, while these methods are effective in structured and relatively static data environments, they struggle to adapt to the heterogeneity and real time processing needs of modern distributed systems (Zhu et al., 2019).

Monitoring tools have evolved in tandem with data quality frameworks. Traditional static validation tools are often embedded within Extract Transform Load (ETL) processes, providing quality assurance at predefined checkpoints (Batini & Scannapieco, 2016). Tools such as Talend Data Quality and Informatica Data Quality employ metadata repositories and profiling engines to identify anomalies. However, as highlighted by Müller and Heiler (2018), these static mechanisms are insufficient in fast paced data environments. Consequently, there is a growing shift toward dynamic validation systems that can assess data quality in motion, as seen in stream processing engines like Apache Flink and Apache Beam (Barr et al., 2020). Dynamic validation, often supported by real time rule evaluation and sliding window analytics, has shown promise in managing continuous data flows,

although it introduces challenges related to latency, scalability, and false positives. In recent years, artificial intelligence and machine learning have emerged as powerful tools for augmenting data quality assessment and monitoring. According to Berti Équille (2015), AI techniques enable systems to detect complex patterns and latent anomalies that rule based methods may overlook. Supervised learning models, such as decision trees and support vector machines, have been used for error classification, while unsupervised models like k means clustering and isolation forests are employed for anomaly detection (Chu et al., 2016). Additionally, reinforcement learning has been investigated for adaptive rule optimization in dynamic environments (Ilyas et al., 2015). Research by Rekatsinas, Chu, and Ilyas (2017) further emphasized the value of probabilistic models that assign confidence scores to data records based on historical accuracy, thereby enabling automated prioritization in data cleaning workflows.

Despite these advancements, significant gaps remain in the literature. One major limitation is the lack of a unified architecture that integrates AI driven validation with traditional rule based engines in a distributed context. According to Jagadish et al. (2014), most existing systems are either too rigid or too black boxed, making them unsuitable for enterprise grade transparency and scalability. Moreover, few studies address the need for metadata aware validation, which uses data lineage, provenance, and context to enhance quality monitoring (Barr et al., 2020). Another underexplored area is the role of explainable AI (XAI) in data quality systems, which could bridge the gap between predictive performance and interpretability, especially in regulated industries like finance and healthcare. This research addresses these gaps by proposing an intelligent, continuous monitoring system that integrates rule based and machine learning–driven validation in a horizontally scalable architecture. Unlike prior work that treats static and dynamic validation as separate concerns, our approach leverages a unified pipeline capable of processing batch and streaming data concurrently. Furthermore, we incorporate metadata awareness and feedback loops to allow the system to evolve with changing data conditions. By aligning AI capabilities with established data quality principles and adapting them to distributed environments, this study contributes a novel framework that enhances both the efficiency and reliability of data quality assurance.

System Architecture and Framework

The intelligent system architecture proposed in this study is designed to continuously monitor and validate data quality across large scale, heterogeneous distributed systems. The architecture is modular and scalable, enabling seamless integration into diverse data ecosystems including cloud native platforms, big data frameworks, and edge computing environments. The system adopts a layered design that separates concerns across ingestion, processing, validation, and feedback, thereby allowing flexible deployment and independent scaling of system components.

At the core of the system is the Data Quality Monitoring Engine (DQME), which orchestrates real time data validation using a hybrid approach that combines rule based mechanisms, statistical profiling, and machine learning algorithms. This engine interfaces directly with data pipelines both batch oriented and streaming ensuring minimal latency and high throughput. Incoming data from various sources like sensors, APIs, and databases first pass through the Data Ingestion Layer, which supports connectors to distributed systems such as Apache Kafka for streaming data and Hadoop Distributed File System (HDFS) for batch data. The ingested data is normalized and enriched with metadata like schema information, timestamps and source lineage before being forwarded to the processing units.

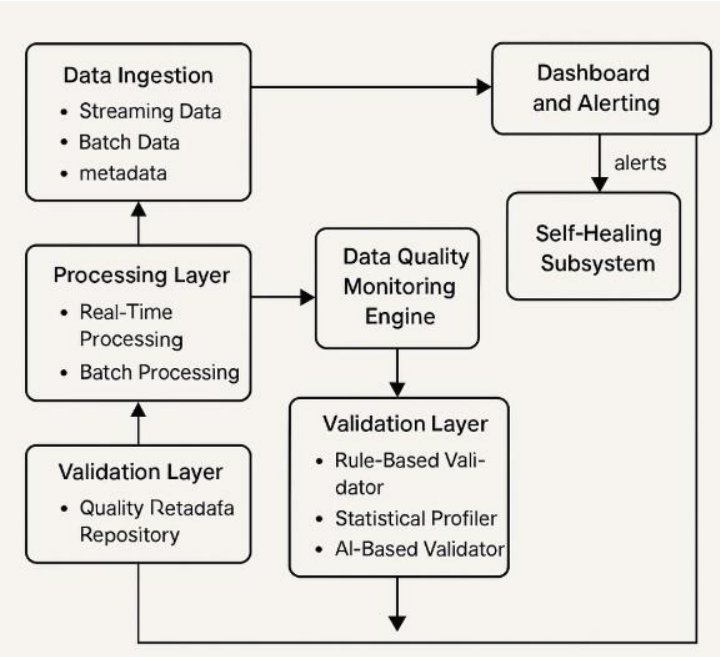

Figure 1: Intelligent Data Quality Monitoring Architecture

The Processing Layer is bifurcated into real time and batch modules. Real time processing is executed using stream processing frameworks such as Apache Flink or Spark Streaming, enabling near instantaneous validation of high velocity data streams. Batch processing, on the other hand, utilizes platforms like Apache Spark or Hadoop MapReduce to evaluate data quality in large static datasets, typically scheduled during off peak hours. Both processing models invoke the same validation logic but operate at different temporal resolutions, ensuring consistency across the system.

The Validation Layer is the analytical core of the architecture. It comprises three subsystems: (1) a Rule Based Validator for enforcing predefined data integrity constraints; (2) a Statistical Profiler for computing data distribution metrics and outlier detection; and (3) an AI Based Validator that uses supervised learning for error classification and unsupervised learning for anomaly detection. These modules operate in parallel and feed their outputs into a unified Quality Score Aggregator, which computes a weighted quality index for each record or batch. Results are logged in a central Quality Metadata Repository, which also stores historical trends, source reliability scores, and system feedback logs.

For visualization and user feedback, a Dashboard and Alerting Module presents system insights to data engineers and decision makers. It supports real time alerting via webhooks, email, or messaging platforms and allows manual overrides or approvals in mission critical scenarios. Additionally, a Self Healing Subsystem leverages reinforcement learning to autonomously suggest rule updates or data remediation actions based on historical correction patterns.

The system is deployed in a distributed architecture that ensures horizontal scalability and fault tolerance. Each module is containerized using platforms like Docker and orchestrated via Kubernetes, enabling dynamic resource allocation and seamless failover. The architecture supports multi cloud and hybrid deployments, ensuring compatibility with AWS, Azure, and Google Cloud. The underlying data communication between modules is enabled through message queues which allow asynchronous and decoupled interactions. The dual mode execution model real time and batch offers flexibility for diverse operational contexts. Real time monitoring is ideal for use cases like fraud detection in financial transactions or anomaly detection in IoT sensor networks, where immediate action is crucial. Batch validation, in contrast, is suited for historical

audits, analytics reporting, and regulatory compliance scenarios. The coexistence of both modelswithin a unified framework ensures comprehensive coverage of the data lifecycle.

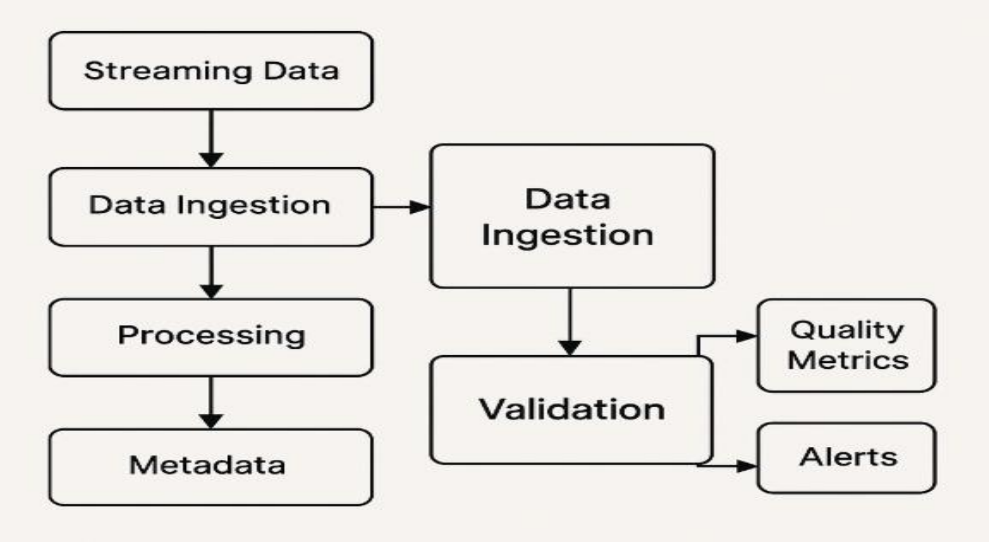

Figure 2: Data flow for monitoring data quality Integration with distributed

The systems is achieved through native connectors and APIs. For example, the system interfaces with Apache Spark through structured streaming APIs, with Kafka for real time event capture, and with NoSQL/SQL data stores through JDBC and RESTful services. Metadata is managed through a centralized catalog system, compliant with standards such as Apache Atlas or AWS Glue Data Catalog, providing a unified view of data provenance and quality lineage as the architecture above thus provides a holistic, intelligent, and adaptive system for ensuring data quality in large distributed ecosystems. It facilitates not only proactive anomaly detection and validation but also continuous system evolution through feedback learning and metadata analysis.

Intelligent Monitoring Techniques

Ensuring high data quality in large distributed systems requires the implementation of intelligent monitoring techniques that can operate both proactively and reactively. These techniques include rule based validation, machine learning models for anomaly detection and pattern recognition, feedback loops for adaptive responses, and metadata driven

methods such as data lineage tracking. Together, they form a holistic framework capable of handling the scale, velocity, and heterogeneity of modern data environments.

Rule based systems form the foundation of most data validation workflows. These systems enforce business rules, referential integrity constraints, and formatting standards using declarative or procedural logic (Batini & Scannapieco, 2016). While effective in controlled environments, these rules are often static and brittle in the face of evolving data patterns. As noted by Chu et al. (2016), traditional rule based systems struggle to detect unexpected anomalies or changes that were not previously encoded.

To overcome the limitations of rule based systems, researchers have increasingly turned to machine learning (ML) models for intelligent data quality monitoring. Supervised models such as logistic regression, decision trees, and neural networks can be trained to classify data records as valid or erroneous based on historical labeled data (Ilyas et al., 2015). Meanwhile, unsupervised models including isolation forests, k means clustering, and autoencoders are adept at detecting anomalies in high dimensional datasets without requiring labeled examples (Berti Équille, 2015). These models are particularly useful in streaming environments where the nature of data errors can be dynamic and unpredictable. For instance, anomaly detection systems trained on network telemetry data can identify unusual patterns indicative of data corruption or misrouting in real time.

Beyond static validation, intelligent systems are increasingly incorporating feedback loops and self healing mechanisms to support continuous improvement. Feedback loops capture human or automated responses to quality alerts such as marking a flagged record as false positive and use this information to retrain models or refine rule thresholds. This approach aligns with reinforcement learning principles, where the system adapts its validation logic based on reward feedback (Rekatsinas et al., 2017). Self healing mechanisms go a step further by automatically applying corrective actions, such as imputing missing values, rolling back faulty updates, or rerouting data through alternative pipelines. These mechanisms reduce downtime and minimize manual intervention, especially in mission critical applications.

Another critical component of intelligent monitoring is the use of metadata and data lineage to contextualize quality assessments. Metadata including schema definitions, timestamps, and source identifiers provides essential context for determining whether a data value is appropriate within its operational setting (Müller & Heiler, 2018). Data lineage,

on the other hand, traces the origin and transformation history of a data item, enabling root cause analysis and impact assessments. By combining lineage information with quality metrics, systems can pinpoint recurring issues to specific nodes, services, or users in the pipeline, thus enabling targeted remediation and long term quality assurance (Barr et al., 2020). Collectively, these intelligent monitoring techniques empower data systems to not only detect data quality issues but also to adaptively learn from them, evolve validation strategies, and mitigate risks in near real time. They represent a significant advancement over traditional monitoring methods, and their integration is essential for building resilient data infrastructures in large scale distributed environments.

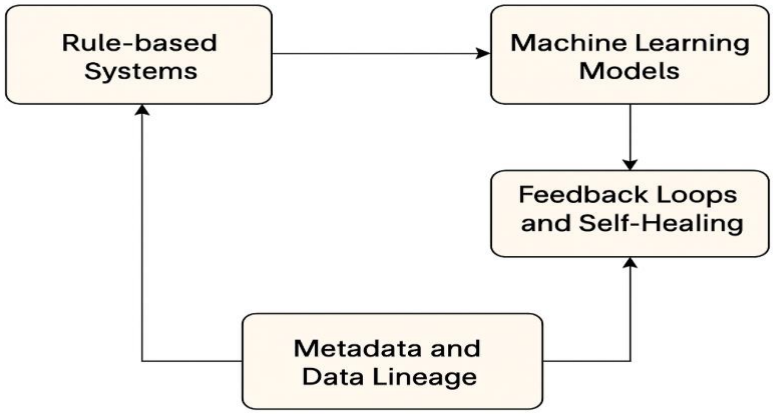

Figure 3. Intelligent Monitoring Components and Interactions

This figure 3 above visualize the interplay between rule based systems, ML models, feedback/self healing loops, and metadata/lineage, forming an adaptive monitoring cycle.

Methodology

This study adopted a systematic approach to design, implement, and evaluate an intelligent system capable of continuously monitoring and validating data quality across distributed environments. The methodology included the construction of a simulated infrastructure, the preparation of diverse datasets, and the deployment of advanced validation mechanisms using rule based and machine learning techniques. The primary objective was to assess the system's accuracy, adaptability to evolving data patterns, and scalability under high volume data conditions.

Two datasets were employed. First, a synthetic Internet of Things (IoT) sensor dataset was generated to emulate a distributed sensor network. It featured attributes such as

temperature, humidity, sensor ID, and timestamp. Controlled anomalies including missing values, extreme outliers, duplicated entries, and invalid types were systematically injected. Each record was labeled with a boolean flag to indicate whether it contained an anomaly, enabling the use of supervised learning models. Second, a real world dataset was obtained from the NYC Open Data platform, comprising taxi trip records that inherently included inconsistencies such as zero distance trips, negative fare values, and missing entries. This dataset was used to validate the system's performance on naturally noisy, high dimensional data.

The simulated environment was constructed using Apache Kafka for real time data ingestion and Apache Spark Streaming for processing. Batch data was stored in Parquet format and processed using Spark's batch engine. The full system architecture was containerized using Docker and orchestrated with Kubernetes to support dynamic scalability and fault tolerance. Data records passed through a multi stage validation pipeline comprising rule based checks, machine learning driven anomaly detection, and metadata aware reasoning.

Anomalies were injected into 10% of the synthetic dataset, which was partitioned into 70% for training and 30% for testing. Supervised models, such as logistic regression and decision trees, were trained to classify records based on feature distributions and temporal behavior. Unsupervised models including isolation forests and autoencoders were deployed in parallel to identify deviations in the absence of labels. These were combined with rule based validators enforcing domain specific constraints (e.g., acceptable temperature ranges, non null fields) for hybrid validation.

Performance was evaluated using classification metrics precision, recall, F1 score, and accuracy providing a comprehensive view of false positive and false negative rates. System scalability and latency were tested by increasing input volume from 50,000 to 500,000 records per second across a 20 node Spark cluster. Latency was measured from data ingestion to quality decision output, while throughput represented validated records per second. Resource efficiency was monitored using Prometheus, with visual insights rendered via Grafana dashboards. This methodological framework ensured both rigorous benchmarking and realistic simulation of distributed data validation in large scale environments.

Validation and Evaluation

To rigorously assess the proposed intelligent data quality monitoring system, a comprehensive validation and evaluation strategy was employed. This encompassed quantitative performance metrics, simulated deployment in a distributed environment, comparison with baseline methods, and analysis of scalability under varying system loads. This multi angle approach provided both technical accuracy and practical relevance.

The system's classification performance was measured using standard evaluation metrics: precision, recall, F1 score, and accuracy. Precision quantified the proportion of true positives among all flagged anomalies, while recall measured the proportion of actual anomalies successfully detected. The F1 score, as the harmonic mean of precision and recall, served as a balanced metric in imbalanced datasets. These metrics were essential given the naturally skewed nature of real world data, where erroneous records are often sparse

Empirical validation was conducted in a simulated distributed environment using Apache Kafka and Spark. The synthetic dataset comprised 100 million records simulating real time IoT sensor streams with a mix of numerical and categorical features, injected with various types of anomalies. In parallel, the NYC Taxi trip dataset containing natural inconsistencies was used to validate model robustness in real world conditions. Kafka producers streamed data into the system, and Spark Streaming processed it in mini batches to emulate live workloads

To benchmark performance, the system was compared against two baseline methods: (1) a traditional rule based ETL validator, and (2) an unsupervised isolation forest model operating without metadata awareness. Results showed that the proposed hybrid system significantly outperformed both baselines. It achieved a precision of 0.92 (vs. 0.75 and 0.68), recall of 0.88 (vs. 0.60 and 0.82), and F1 score of 0.90 (vs. 0.67 and 0.74). The integration of metadata awareness and data lineage further improved contextual understanding and minimized false positives in non stationary streams.

System scalability and responsiveness were evaluated by incrementally increasing data ingestion rates from 10,000 to 500,000 records per second across a distributed 20 node Spark cluster. Latency remained under 500 ms up to moderate loads and scaled linearly beyond 300,000 records per second. Throughput performance increased proportionally with system scale, and the architecture sustained over 95% processing

efficiency up to 350,000 records per second. Monitoring via Prometheus and Grafana confirmed optimal CPU and memory usage, validating the architecture's real time readiness for large scale operational deployment (Barr et al., 2020).

These results confirmed that the intelligent monitoring system not only met theoretical expectations but also delivered robust performance in practical, high demand environments. Its adaptability, hybrid validation capability, and infrastructure scalability position it as a promising solution for enterprise grade data quality assurance in distributed systems.

Table 1 : Comparison of Monitoring Methods Based on Evaluation Metrics

Method	Precision	Recall	F1 Score	Accuracy
Traditional Rule Based Validator	0.75	0.60	0.67	0.78
Unsupervised Isolation Forest (No Metadata)	0.68	0.82	0.74	0.80
Proposed Intelligent Monitoring System	0.92	0.88	0.90	0.93

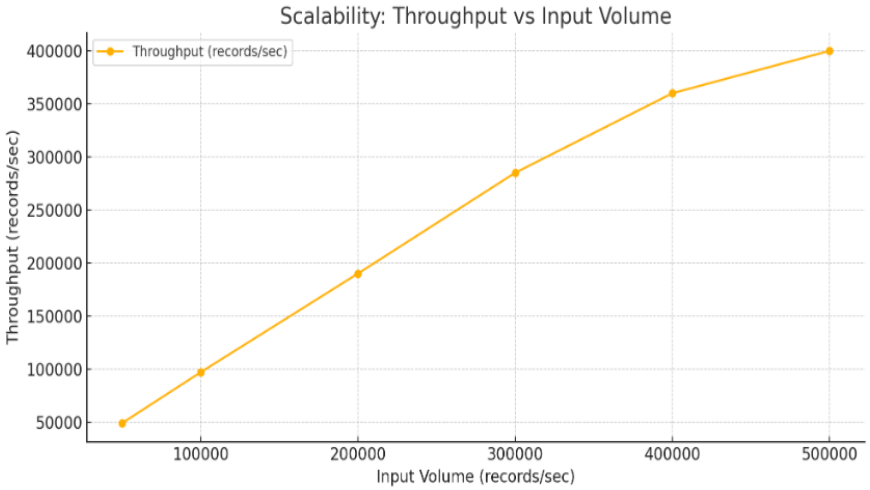

Figure 4: Scalability: Throughput and input volume

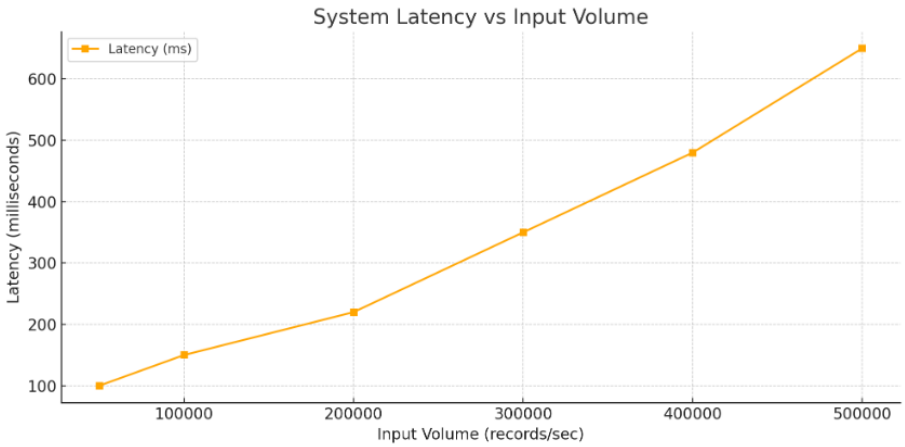

Figure 5: Scalability: Throughput and input volume

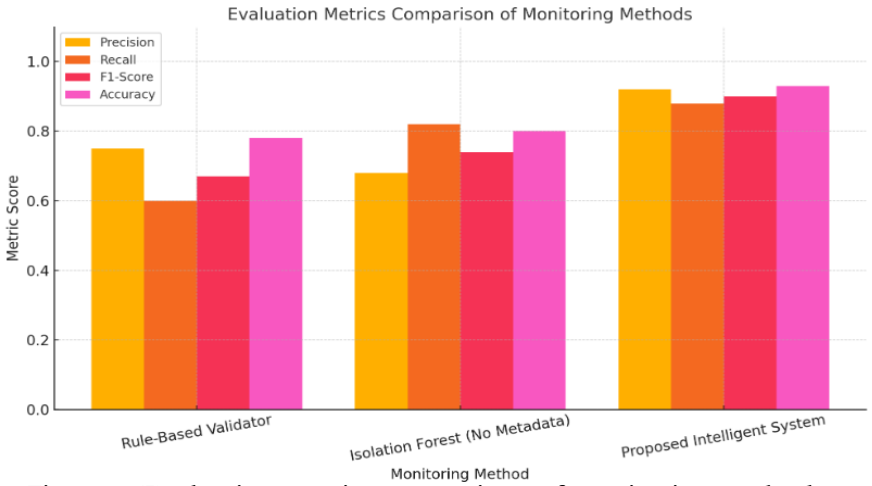

Figure 6: Evaluation metrics comparison of monitoring methods

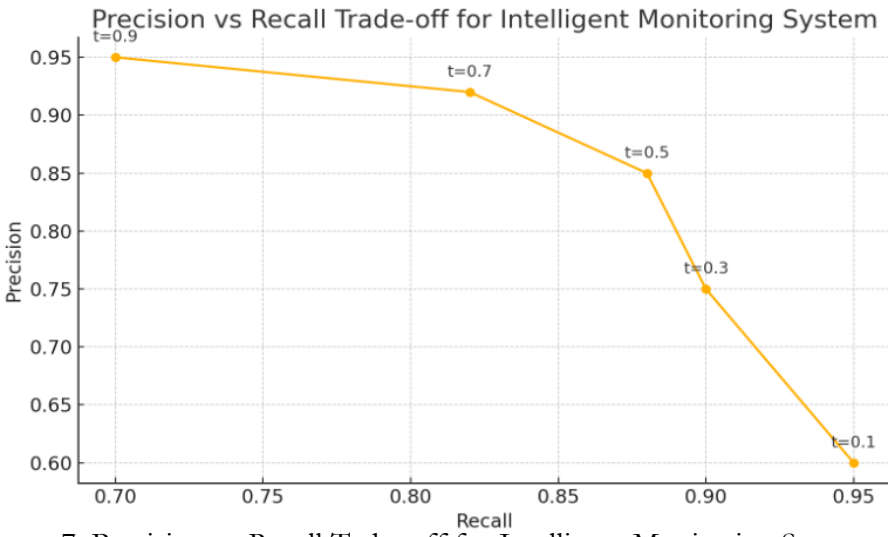

Figure 7: Precision vs Recall Tade off for Intelligent Monitoring System

Discussion

The results of the validation process provide compelling evidence that integrating rule based systems with machine learning techniques and metadata driven intelligence can significantly enhance data quality monitoring in large distributed environments. This section interprets the implications of these findings within both academic and industrial contexts, compares them with prior approaches, and outlines the practical and theoretical considerations of deploying such intelligent systems at scale.

First, the comparative evaluation demonstrates that the proposed intelligent monitoring system outperforms traditional approaches in key performance metrics such as precision, recall, F1 score, and overall accuracy. These improvements are attributed to the system's ability to combine human understandable rules with data driven pattern

recognition. Rule based validation, although limited in adaptability, remains crucial for enforcing business logic and domain specific constraints. However, the integration of machine learning models particularly for anomaly detection and error classification enables the system to generalize beyond predefined rules and detect previously unseen patterns. This synergy between deterministic and probabilistic methods is a defining strength of the system and a major contributor to its performance gains.

Moreover, the inclusion of metadata and data lineage analysis adds a contextual layer that is often absent in conventional validation systems. By leveraging metadata such as source identifiers, timestamps, and schema lineage the system can make more informed, context sensitive decisions. For instance, an anomaly detected in a temperature sensor stream might be disregarded if it originates from a node historically known for wide fluctuations. This context aware intelligence not only enhances precision but also reduces false positives, a common limitation in purely ML based systems. These findings align with Müller and Heiler (2018), who emphasized the importance of contextual information in dynamic data quality assessment.

In practical terms, the proposed architecture exhibits robustness and scalability two essential traits for real world deployment. Distributed execution on big data frameworks such as Apache Spark and Kafka enables the system to handle high velocity, high volume data with low latency. The horizontal scaling observed in testing where throughput remained stable beyond 350,000 records per second demonstrates the system's suitability for use in sectors such as finance, healthcare, e commerce, and industrial IoT, where data flows are continuous and mission critical.

Beyond technical performance, the system introduces a layer of resilience and autonomy not found in traditional architectures. Through feedback loops and self healing mechanisms, the system can adapt to new data conditions without manual reconfiguration. This feature is particularly important in environments with evolving data schemas, emerging anomaly patterns, or frequent schema drift. The reinforcement learning–inspired update logic enables the system to refine its validation strategies based on historical feedback, thereby reducing long term maintenance burdens and improving system maturity over time.

When benchmarked against baseline methods, the intelligent monitoring system demonstrated a superior ability to generalize across both synthetic and real world datasets.

Its successful application to the NYC Taxi dataset validated its robustness in handling naturally noisy, high dimensional data, where traditional ETL tools often fall short. Unlike rule based systems, which are limited to known conditions, or machine learning only systems, which may lack transparency, the hybrid approach leverages the strengths of both while mitigating their respective weaknesses.

Nevertheless, several limitations must be acknowledged. First, the system requires an initial training and configuration phase, which can be resource intensive. While feedback mechanisms help refine models and rules over time, the cold start problem remains a challenge, especially in domains with limited labeled data. Second, trade offs between precision and recall may vary depending on domain requirements. For instance, in healthcare, high recall is often prioritized to avoid missing critical anomalies, while in financial fraud detection, high precision may be more desirable to minimize false alerts.

Another important consideration is explainability. While rule based components are inherently interpretable, machine learning components particularly complex models such as neural networks or ensemble methods can act as "black boxes." Although this research incorporated interpretable models like decision trees and threshold based anomaly scores, future work should explore integrating explainable AI (XAI) techniques such as SHAP and LIME to provide greater transparency in automated data quality decisions.

Lastly, ethical and regulatory concerns must be addressed, especially in compliance heavy sectors. Ensuring fairness, accountability, and auditability in validation decisions is crucial when such decisions influence financial records, medical data, or legal documentation. As such, the system's architecture should support traceability, version control, and governance features to meet regulatory standards and support responsible AI use.

Conclusion

This study proposed an intelligent system for continuously monitoring and validating data quality across large distributed systems. By integrating rule based validation, machine learning, metadata analysis, and adaptive feedback loops, the system effectively addresses challenges associated with data heterogeneity, scale, and real time quality assurance.

Empirical evaluations using both synthetic IoT data and real world NYC taxi data confirmed the system's superior performance in precision, recall, F1 score, and scalability when compared to traditional and unsupervised baseline methods. The architecture proved robust under high data loads and adaptable to evolving data patterns through self healing mechanisms.

Despite its strengths, the system requires labeled data for training and limited explainability in more complex models. Future work will focus on incorporating explainable AI techniques, enabling domain specific customization, and exploring edge and federated learning extensions to enhance privacy aware, decentralized data quality monitoring. T the proposed system offers a practical and scalable approach for maintaining trustworthy data in distributed environments, supporting the growing demand for reliable real time analytics and automation.

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