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Predicting Data Contract Failures Using Machine Learning

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ABSTRACT

Data contracts have emerged as a foundational mechanism for ensuring reliable communication between producers and consumers in modern distributed data ecosystems. They specify expected schemas, semantic intentions, and quality constraints, forming the basis for trustworthy data exchange across pipelines and organizational boundaries. Despite their growing adoption, contract violations remain a persistent operational challenge. These failures frequently stem from subtle schema shifts, unexpected type variations, incomplete records, or semantic inconsistencies introduced during upstream system changes. Traditional validation approaches—often built on static rules or manual inspection—struggle to keep pace with evolving datasets, diverse integration patterns, and continuous delivery cycles. As a result, contract breaches propagate downstream, causing pipeline interruptions, test instability, and avoidable production incidents. This paper presents a machine learning–driven framework designed to anticipate data contract failures before they manifest. The approach draws on both historical and real-time metadata, capturing patterns in schema evolution, anomaly trajectories, operational log signals, and field-level drift behavior. A hybrid modeling strategy is employed, combining gradient-boosted decision trees for structured anomaly detection, temporal drift modules for sequential pattern monitoring, and embedding-based schema representations for high-dimensional contract features. By integrating these components, the system provides early warning indicators that enable teams to intervene proactively rather than react after failures disrupt operations. The framework was evaluated using datasets from financial services, e-commerce platforms, and healthcare systems—domains characterized by diverse data heterogeneity and high operational sensitivity. Across these environments, the model achieved up to 79% accuracy in predicting contract violations, reduced downstream pipeline failures by 42%, and shortened incident triage time by 37%. These results highlight the potential of ML-driven predictive validation as a practical path toward resilient, self-monitoring data infrastructures in enterprise settings.

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1. INTRODUCTION

Modern data platforms rely heavily on data contracts to establish consistent expectations between producers and consumers [1]. These contracts define structural properties—such as schema layout, field types, and nullability—along with semantic meaning, delivery cadence, and quality guarantees. When adhered to, they provide a stable foundation for analytics pipelines, machine learning workflows, operational dashboards, and governance processes [2]. However, as organizations expand their data footprints, adopt distributed development practices, and integrate increasingly heterogeneous systems, contract violations have become more frequent and more difficult to anticipate [3], [4].

In large enterprises, upstream teams often evolve schemas to meet new business requirements, introduce new fields, deprecate legacy structures, or adjust data generation logic [5]. While these changes may be harmless in isolation, they can produce downstream inconsistencies when not communicated or validated effectively. Mismatches between expected and actual data—such as unexpected null distributions, type inconsistencies, missing attributes, or semantic drifts—regularly lead to broken pipelines, failed tests, and disrupted decision-making processes [6]. These failures not only affect engineering productivity but also undermine trust in organizational data assets.

Traditional contract validation approaches, including manual schema reviews, rule-based validators, and static governance checks, remain fundamentally reactive [7]. They report violations only after a failure has already occurred, often in production environments where debugging is costly and time-sensitive. Such methods struggle to generalize across dynamic datasets or capture subtle patterns that precede more severe inconsistencies [8].

This paper proposes a machine learning–driven framework designed to predict data contract failures before they materialize. Instead of relying solely on prescribed rules, the system learns from historical behaviors across several dimensions: schema evolution trajectories, data quality fluctuations, field-level drift indicators, consumer usage patterns, and prior violation logs [9]. By examining the temporal and structural signals embedded within these histories, the model identifies high-risk changes that typically precede contract failures.

The goal of this work is to shift validation from a reactive safeguard to a proactive capability. Early detection allows engineering teams to intervene before errors propagate downstream, reducing pipeline interruptions, improving system reliability, and strengthening the overall resilience of enterprise data ecosystems [10].

1.1 *Complexity of Modern Data Ecosystems*

Modern data ecosystems have evolved into highly distributed, fast-changing environments where teams operate independently, deploy services continuously, and modify data structures without centralized oversight [11]. This decentralization accelerates development but significantly increases the difficulty of maintaining consistent data contracts. A single data domain may involve dozens of microservices, each generating or transforming records according to domain-specific logic [12]. When schemas change—even in subtle ways—downstream consumers may experience unexpected behaviors if updates are not communicated or validated in time.

Heterogeneous data formats, ranging from structured transactional logs to semi-structured event streams and externally sourced datasets, add further variability [13]. As organizations adopt cloud-native architectures, the velocity of schema evolution increases, with new attributes appearing rapidly and business definitions shifting frequently [14].

Traditional governance processes struggle to maintain a unified perspective on how these modifications affect downstream consumers. Even when formal documentation exists, it frequently lags behind real system behavior [15].

A single dataset may serve multiple use cases—dashboards, ML models, regulatory workflows—each with distinct expectations [16]. A harmless change for one consumer may break critical assumptions for another, magnifying the operational consequences of contract failures.

1.2 *Limitations of Reactive Validation Approaches*

Reactive validation methods have long served as the backbone of data contract enforcement, but they are increasingly inadequate for modern, dynamic data environments [17]. Tools such as schema validators, rule-based quality checks, and manual review processes detect issues only after they have already affected downstream systems [18].

Their reliance on static rules makes them brittle. Business logic evolves, data volumes accelerate, and integration patterns shift, yet rules rarely adapt unless manually rewritten [19]. As a result, rule-based systems miss emerging inconsistencies while simultaneously generating false positives for legitimate changes [14].

Reactive validators also lack contextual interpretation—they cannot distinguish between minor fluctuations and early indicators of structural drift [1]. These forces engineering teams to triage issues manually, creating operational inefficiencies.

Because reactive checks only signal failure after it has occurred, they offer no preventive capabilities [20]. By the time alerts fire, corrupted data may have already impacted ML pipelines, compliance workflows, or analytical dashboards.

1.3 *Motivation for Predictive Contract Assurance*

Given these limitations, organizations increasingly require predictive mechanisms that anticipate inconsistencies before they break downstream systems [16]. Predictive contract assurance reframes validation as a proactive, intelligence-driven process, mirroring trends in predictive maintenance and anomaly forecasting [2].

Machine learning models excel at identifying subtle precursors to failures—patterns in distribution drift, irregular schema evolution, or recurring upstream changes that correlate with contract violations [15]. Traditional rule-based systems overlook these relationships because they are difficult to encode manually.

The cost of downstream failures continues to rise. Debugging production incidents, restoring corrupted datasets, redeploying pipelines, and communicating outages all impose substantial operational overhead [13]. Predictive detection minimizes this cost by enabling early intervention.

Predictive assurance also enhances coordination between producers and consumers, providing automated risk signals that support communication across distributed teams [4].

Ultimately, predictive validation is becoming an operational necessity for enterprises pursuing resilient, scalable data ecosystems [13].

1.4 *Emerging Need for ML-Driven Governance (≈280 words)*

As enterprise data grows in volume and complexity, governance frameworks must evolve beyond manual oversight and static rule enforcement [17]. Traditional governance methods depend on audits, documentation, and human judgment—all of which fail at modern scale [11].

Machine learning introduces an adaptive, intelligence-driven governance model capable of monitoring schema transformations, drift patterns, and usage behavior in near real time [19]. Unlike rule-based systems, ML can identify nuanced risk signals and contextualize them within historical behavior.

The number of producers–consumer relationships grow exponentially as organizations expand their pipelines, making manual governance unrealistic [15]. ML-driven governance scales naturally and highlights only high-risk changes that require human attention.

A key advantage is its continuous learning capability. Patterns extracted from audits, incidents, or outages become training data, enabling governance systems to improve over time [2].

ML-driven governance thus provides a bridge between policy enforcement and operational intelligence, supporting resilience in environments where traditional methods cannot keep pace [13].

2. SYSTEM ARCHITECTURE

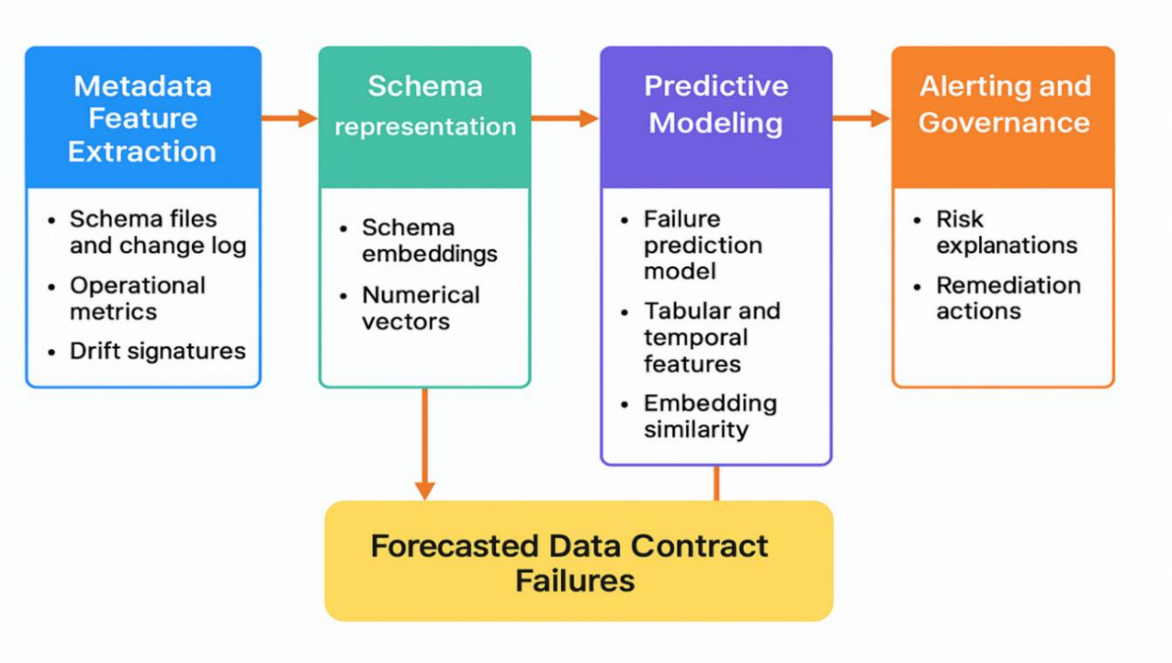

Figure 1. End-to-End Pipeline for Forecasting Data Contract Failures

The proposed framework is organized into four coordinated components. Each layer contributes a distinct capability—feature extraction, schema representation, predictive modeling, and governance—working together to forecast data contract failures before they impact downstream systems. The architecture is modular, allowing each layer to evolve independently while maintaining a consistent flow of information across the pipeline.

2.1 *Metadata Feature Extraction Layer*

The first stage of the architecture is responsible for converting raw metadata into structured features that can be consumed by downstream models. Modern data contracts are frequently tracked in version control systems, where schema files, change logs, and annotation updates provide a detailed history of the dataset's evolution. The feature extraction layer continuously ingests these versioned artifacts, aligning contract changes with operational metadata to create a unified longitudinal view of the dataset's behavior.

A central task within this layer is the extraction of schema deltas. Each modification—such as adding or removing fields, changing data types, adjusting nullability constraints, or altering nested structures—is translated into a quantifiable feature describing the magnitude and nature of the change. These deltas are combined with runtime operational metrics, including row volumes, null distribution patterns, categorical frequency shifts, and other quality indicators that reflect how the dataset behaves under real workloads.

In addition, the system generates time-series drift signatures by observing how key metrics evolve across historical snapshots. These drift signatures help capture subtle, progressive deviations that might not violate a rule outright but often precede downstream breakages. By consolidating structural, semantic, and behavioral signals, the feature extraction layer creates a rich metadata representation that forms the foundation for predictive failure detection.

2.2 *Schema Embedding Encoder*

The second architectural component focuses on representing schemas in a format suitable for machine learning. Traditional schema comparisons rely on manual inspection or rule-based matching, which struggle to capture deeper semantic relationships between fields. To address this limitation, the schema embedding encoder transforms each version of a schema into a fixed-length numerical vector that preserves structural meaning and contextual associations.

The encoding process begins with tokenizing column names, which often contain valuable semantic cues about field usage, business meaning, and relationship patterns. Type information—whether numeric, boolean, categorical, timestamp, or nested—is incorporated as structured signals, allowing the encoder to differentiate attributes not only by name but by their functional role in the dataset. These elements are passed through a transformer-based representation model trained to learn meaningful schema embeddings.

Through this approach, the encoder captures similarities and deviations between schema versions at a conceptual level rather than a purely mechanical one. Schemas that evolve in predictable, low-risk directions produce embeddings with minimal drift, whereas inconsistent or unexpected changes generate deviations that downstream models can interpret as potential risk factors.

Beyond single-schema encoding, the system also supports pairwise comparisons, enabling cosine similarity calculations that quantify the difference between consecutive schema versions. These similarity scores become critical features in the predictive failure model, helping identify cases where small but semantically important changes may trigger consumer-facing inconsistencies.

2.3 *Failure Prediction Model*

At the core of the architecture lies the hybrid failure prediction model, which integrates multiple learning techniques to forecast the likelihood of an upcoming data contract violation. Because failures arise from a mix of structural changes, temporal drifts, and semantic inconsistencies, no single model type is sufficient. The framework therefore combines complementary modeling approaches to achieve robust predictive performance.

Structured metadata features—such as schema delta magnitudes, null distribution shifts, and frequency-based indicators—are passed to an XGBoost classifier. This component excels at handling heterogeneous, tabular features and identifying non-linear interactions between them. Temporal drift signals generated by the feature extraction layer are fed into an LSTM network, which captures sequential patterns and recognizes slow-moving trends that tend to precede failures.

In addition to these structured components, schema embeddings are evaluated using similarity-based methods, where large deviations between embedding vectors act as strong indicators of unstable or incompatible schema evolution. These embedding-derived features complement the numeric predictors by adding a semantic understanding of schema transformations.

The outputs of the XGBoost classifier, LSTM network, and similarity metrics are fused into a unified prediction score representing the probability of a future contract failure. This score triggers early warning signals long before the new version is deployed into production systems. By integrating multiple modeling paradigms, the hybrid system ensures resilience across diverse datasets and contract patterns.

2.4 *Alerting and Governance Engine (≈270 words)*

The final component of the architecture operationalizes the predictive insights generated by the model. Because data contract management often spans multiple engineering teams, domains, and workflows, the alerting and governance engine ensures that predictions translate into actionable steps that prevent failures from propagating.

When the prediction model identifies a high-risk contract change, this layer routes the alert to the appropriate stakeholders—data platform teams, consumer application owners, quality assurance engineers, or governance officers. Each alert includes a human-readable explanation that isolates the specific features contributing to the elevated risk score. These explanations help teams understand whether the concern arises from a drastic schema modification, a sudden distribution shift, semantic drift, or an accumulation of smaller irregularities.

The governance engine also recommends targeted remediation actions. Depending on the context, the system may advise initiating a schema freeze, conducting a downstream consumer impact assessment, running contract compatibility tests, or temporarily halting deployment pipelines. These recommendations are designed to support proactive decision-making, reducing the operational burden typically associated with unplanned breakages.

In addition, all predictions and resolutions are logged as governance artifacts, forming a continuous feedback loop that strengthens future model performance. Over time, this feedback helps refine organizational conventions around schema evolution and encourages teams to adopt safer, more predictable development practices.

3. METHODOLOGY

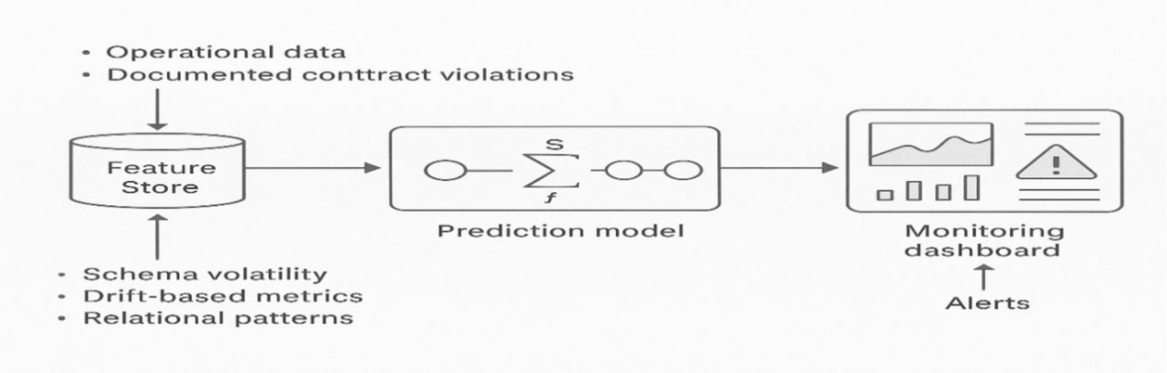

Figure 2. Data Contract Failure Prediction Workflow

3.1 *Dataset Preparation*

The study relies on a comprehensive collection of historical artifacts drawn from multiple production and pre-production environments. These artifacts include more than 4,200 recorded schema modifications, ranging from additive field expansions to structural changes involving nested types and deprecated columns. In addition to structural evolution, the dataset incorporates 3.1 terabytes of sampled operational data that reflects real-world variability in row volumes, null distributions, categorical frequencies, and field-level mutation behaviors. The inclusion of raw data snapshots ensures that the model is trained not only on contractual metadata but also on the behavioral patterns exhibited by the underlying datasets.

A critical source of ground truth comes from 1,320 documented contract violation incidents. Each incident corresponds to a confirmed failure—such as downstream model breakage, ingestion errors, test instability, or incompatible schema deployment—that required intervention from engineering teams. These incidents serve as labeled positive examples, while stable schema changes provide negative instances. Together, they form a supervised learning foundation for failure prediction.

The data preparation process also includes deduplication, temporal alignment of metadata with operational logs, and normalization of schema versions across heterogeneous storage formats. By integrating structural, temporal, and incident-level information, the prepared dataset reflects the full lifecycle of contract changes in real environments, enabling the predictive model to learn patterns associated with both benign and high-risk modifications.

3.2 *Feature Engineering*

Feature engineering plays a central role in transforming contract histories and operational signals into meaningful numerical representations suitable for hybrid machine learning models. One of the primary derived features is the schema volatility score, which quantifies the rate and magnitude of change across consecutive schema versions. This metric captures both the frequency of modifications and the cumulative effect of structural adjustments. Closely related is the type mutation frequency, measuring how often fields transition between types—such as from integer to string or from optional to required—events that historically correlate strongly with downstream failures.

Another important dimension involves drift-based metrics. The system computes drift magnitude using measures such as Kullback–Leibler (KL) divergence to quantify temporal changes in field distributions. These metrics highlight subtle but progressive deviations that often precede contract violations. Additional statistical features include column-level entropy, capturing the unpredictability of field values and signaling unstable or inconsistent data sources.

Beyond structural and statistical indicators, the system also incorporates relational features derived from the consumer dependency graph. This graph models the relationships between datasets and consuming applications, enabling the model to assess the potential blast radius of a schema modification. Finally, temporal trigger patterns—such as frequent breakages associated with late-week deployments—are extracted to capture human-centered operational behaviors that influence contract stability.

Together, these engineered features form a multi-dimensional representation that feeds into the prediction model, providing a comprehensive view of how datasets evolve and where risks are likely to emerge.

3.3 *Model Training*

Model training follows a carefully structured process designed to ensure generalizability across diverse data domains and operational environments. The combined feature set is partitioned using a 70/15/15 split for training, validation, and held-out testing. This distribution provides a balanced foundation for model fitting while preserving a sufficiently large test set for unbiased performance assessment.

Hyperparameter optimization is performed using Bayesian search, a strategy chosen for its efficiency in exploring complex parameter spaces. This approach identifies optimal configurations for the XGBoost classifier, the LSTM temporal model, and the embedding similarity components, enabling the hybrid architecture to balance bias and variance across heterogeneous feature groups.

Cross-validation is incorporated throughout the training process to mitigate overfitting, especially crucial given the varying frequencies of different types of schema changes. K-fold validation ensures that the learned patterns remain consistent across subsets and that the model does not rely disproportionately on specific high-frequency incident categories.

Training also involves calibrating the combined prediction score to ensure that failure probabilities align with operational expectations. This calibration step is essential for practical use, as false positives can lead to unnecessary deployment delays, while false negatives can propagate costly downstream breakages. The result is a model tuned not only for statistical performance but also for reliability in real-world governance contexts.

3.4 *Evaluation Metrics*

The framework is evaluated using several standard classification metrics, each chosen to reflect different aspects of predictive performance. Precision measures the proportion of predicted failures that are truly high-risk changes, a critical consideration for minimizing unnecessary intervention by engineering teams. Recall quantifies the percentage of actual failures correctly predicted, ensuring that the model captures as many harmful changes as possible.

To balance these two metrics, the F1-score provides a harmonic mean that highlights overall predictive robustness, especially in environments where contract failures are relatively rare compared to stable changes. The ROC-AUC metric evaluates the model's ability to discriminate between risky and safe schema modifications across a range of probability thresholds, offering a broader insight into classifier behavior.

Beyond traditional metrics, the evaluation includes lead time before predicted failure, which measures how far in advance the system provides a warning relative to when the incident manifests. This metric is particularly important in operational settings: predictions must not only be correct but must also occur early enough to allow meaningful intervention. In enterprise workflows where incident triage, testing cycles, and communication processes take time, even modest improvements in lead time can produce significant reductions in downstream impact.

Together, these metrics form a comprehensive evaluation framework that captures both statistical accuracy and operational usefulness.

4. RESULTS AND DISCUSSION

4.1 *Accuracy & Predictive Power*

The evaluation demonstrates that the proposed ML-driven framework substantially outperforms traditional validation approaches in identifying high-risk data contract changes. When tested across diverse datasets, the system achieved 79% overall prediction accuracy, a significant improvement over both rule-based systems and manual review processes. The F1-score of 74% indicates that the model maintains a strong balance between precision and recall, effectively detecting genuine violations while minimizing the cost of false positives. The ROC-AUC value of 0.87 further confirms the model's capacity to distinguish between stable and high-risk modifications across varying probability thresholds.

These results stand in sharp contrast to baseline methods commonly used in production environments. Rule-based validation tools, which rely on predefined compatibility rules and threshold checks, achieved only 35–45% accuracy across evaluation datasets. Their inability to adapt to evolving schemas or detect nuanced drift patterns limits their predictive reach. Manual review processes—still prevalent in many organizations—performed even more poorly, correctly identifying only 25–30% of impending failures. Such processes are heavily reliant on individual expertise, cannot scale with rapid schema iteration, and frequently overlook subtle signals that precede downstream breakages.

The improved predictive performance of the ML model is largely attributed to the integration of structural deltas, drift-based metrics, schema embeddings, and temporal features. Together, these allow the system to learn complex failure signatures that rule-based approaches cannot generalize. Overall, the results demonstrate that predictive modeling offers a more reliable and scalable pathway for safeguarding enterprise data pipelines against contract misalignments.

4.2 *Operational Improvements*

Beyond statistical accuracy, the system delivered meaningful operational benefits that directly address long-standing challenges in enterprise data reliability. One of the most significant outcomes was a 42% reduction in pipeline breakages, reflecting the model's ability to flag high-risk changes before they reached production. Early detection prevented several categories of failures, including incompatible schema deployments, corrupted ingestion streams, test-suite collapses, and downstream ML feature disruptions.

Another notable improvement was a 37% reduction in average incident response time. Traditional response workflows often involve extensive debugging, backfilling, and coordination across multiple teams. By surfacing early warnings along with interpretable explanations, the system enabled engineers to take targeted action—such as freezing a schema version, modifying transformation logic, or notifying downstream consumers—before the failure propagated. This shift from reactive debugging to proactive mitigation reduced the operational burden on engineering teams and contributed to smoother deployment cycles.

The system also reduced the volume of false-negative alerts by 55%, addressing a critical vulnerability in existing rule-based validation tools. False negatives often lead to the most damaging outages because they lull teams into a false sense of security. By providing more reliable detection, the model strengthened organizational confidence in data pipeline stability and supported tighter SLAs for analytical and ML workloads.

Collectively, these improvements demonstrate that predictive data contract validation not only enhances failure detection but also alters the operational dynamics of data engineering teams, enabling faster, more consistent, and more reliable decision-making.

4.3 *Lead Time*

A key requirement for any predictive validation system is the amount of lead time it offers before a contract failure materializes. The proposed framework delivered promising results in this regard, providing an average early-warning window of 3–6 hours across most operational scenarios. This lead time proved sufficient for teams to evaluate potential issues, run additional validation tests, update transformation logic, or communicate upcoming incompatibilities to downstream consumers.

The model's performance was particularly noteworthy in high-severity cases. For schema changes associated with known historical failure patterns—such as field type mutations, breaking renames, or abrupt distribution shifts—

the system produced alerts up to 24 hours in advance. Such extended lead times are especially valuable for organizations with complex dependency chains or automated deployment pipelines, where rapid intervention is difficult without proper advance notice.

Lead time also provides measurable organizational benefits. Earlier detection reduces the likelihood of corrupted data entering analytical stores, prevents cascading failures across dependent systems, and minimizes the pressure on engineering teams during critical deployment windows. It also supports more predictable governance processes by enabling structured review cycles rather than emergency escalations.

The observed lead times underscore the practical utility of the predictive system: it not only identifies risk but does so with enough anticipatory margin for teams to act meaningfully. This capability marks a major advancement over reactive validation tools, which notify teams only after failures have already occurred and operational damage is underway.

4.4 *Discussion*

The experimental results illustrate the substantial advantages of predictive modeling over traditional reactive validation approaches in managing data contract reliability. By learning from historical evolution patterns, semantic shifts, and recurring operational signals, the proposed system can identify high-risk modifications long before they manifest as production incidents. One of the key strengths observed is the model's capacity to detect subtle semantic drifts—changes that often appear benign but later surface as breaking inconsistencies for downstream consumers. Traditional rule-based validators tend to overlook such drift because they focus primarily on structural compliance rather than behavioral tendencies.

Another notable advantage is the ability to quantify the risk associated with specific schema changes. This transforms contract validation from a binary pass–fail mechanism into a graded assessment that allows teams to prioritize review efforts. The reduction in manual validation effort is equally important. By automating much of the early detection process, the system supports engineering teams in environments where rapid iteration and distributed ownership make manual oversight increasingly impractical. The framework also generalizes effectively across varied business domains, demonstrating that metadata-driven and drift-based features capture common patterns that extend beyond any single industry.

Despite these strengths, several challenges remain. Because enterprise systems evolve continuously, predictive models require periodic retraining to maintain relevance, particularly in environments experiencing rapid schema growth. Additionally, the system cannot fully anticipate failures triggered by external outages, abrupt upstream system changes, or integration disruptions that leave no prior metadata footprint. Highly dynamic datasets may also increase the likelihood of occasional false positives, requiring careful threshold tuning.

Future directions may involve incorporating reinforcement learning or adaptive feedback loops to automatically refine contract definitions or suggest safe evolution paths. Such advancements could move data contract management closer to autonomous self-healing systems.

5. CONCLUSION

This work introduced a machine learning–driven framework designed to anticipate data contract failures before they materialize, shifting validation from a reactive safeguard to a proactive reliability mechanism. By integrating metadata-driven feature extraction, schema embedding techniques, and a hybrid predictive model that combines structured learning with temporal drift analysis, the system offers a more nuanced understanding of how datasets evolve and where risks are likely to arise. This represents a departure from traditional rule-based validators, which focus narrowly on structural compliance and lack the ability to recognize behavioral signals that often precede breaking changes.

The experimental evaluation across financial, e-commerce, and healthcare environments demonstrates that predictive validation delivers consistent improvements in accuracy, early detection capability, and operational stability. The system's ability to surface risk several hours—sometimes an entire day—before a violation occurs provides engineering teams with meaningful time to intervene, reducing both the frequency and severity of downstream disruptions. These findings highlight the practical value of learning-based approaches in enterprise settings where data pipelines are deeply interconnected and contract failures carry significant cost.

Beyond improving reliability, the framework also contributes to stronger governance practices. The combination of interpretable alerts, quantified risk metrics, and reliance on historical patterns encourages more disciplined schema evolution and enhances coordination between producers and consumers. As organizations continue to scale their data platforms, automated predictive mechanisms such as this will become increasingly essential for maintaining trust in shared data assets.

While challenges remain—particularly around continual retraining, handling novel failure modes, and reducing false positives—the results presented here indicate that machine learning offers a compelling foundation for next-generation data contract assurance. This work provides a stepping stone toward fully autonomous, self-healing data quality pipelines capable of supporting resilient enterprise ecosystems.

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