Agile-Driven Machine Learning Pipeline : Framework for Mitigating Concept Drift

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***Abstract*—In an era where data streams move at breakneck speeds, deploying a static Machine Learning (ML) model is a bit like trying to navigate a new city with an old paper map. It might work for a day or two, but eventually, you're going to drive into a river. This phenomenon—where the real world evolves while your model stays frozen—is known as concept drift, and in high-stakes fields like financial fraud or healthcare, that degradation isn't just an inconvenience; it's a security risk.**

This research presents a blueprint for an Agile-driven MLOps Pipeline that stops treating retraining as a manual, quarterly chore and starts treating it like a continuous software process. By taking and mixing up principles from DevOps with statistical monitoring (specifically using the Kolmogorov–Smirnov test), we propose a framework that detects drift in real-time and automatically triggers a retraining cycle—no human intervention required.

To prove this actually works, we simulated a financial fraud environment that gets hit with both sudden shocks and slow, creeping changes in transaction behavior. We pitted our automated pipeline against the traditional "train-it-and-leave-it" approach. The results were pretty definitive: the agile pipeline cut the "Mean Time to Restore" (MTTR) performance by up to 85 percent and kept F1-scores above 0.90, even when the data was going haywire (All data under regularized environment). It effectively turns ML models from fragile artifacts into self healing almost resilient products that can heal themselves.

***Index Terms*—MLOps, Agile Methodology, Concept Drift, Continuous Training (CT), DevOps Metrics, Real-time Deployment, Kolmogorov - Smirnov Test , Automated Retraining .**

I. Introduction

The integration of Machine Learning (ML) into critical enterprise and consumer applications—ranging from financial fraud detection and click-through rate prediction to autonomous driving and healthcare triage—has exposed a sharp misalignment between conventional software engineering practices and ML engineering. Traditional software artifacts are largely deterministic; barring external failures, the same input will produce the same output indefinitely. The underlying code does not "rot" merely due to the passage of time.

Machine learning systems, in contrast, are inherently stochastic and data-dependent. A model that performs optimally at deployment may gradually or abruptly degrade as the underlying data-generating process evolves. This phenomenon, captured under the umbrella term *concept drift*, arises when the joint distribution $P(X, y)$ or its components $P(X)$ and $P(y|X)$ change over time [1], [3]. As a result, static ML deployments increasingly diverge from the environments they are intended to model.

Beyond statistical concerns, maintaining ML systems in production introduces substantial technical debt. Sculley et al. [2] argue that the training code represents only a small fraction of a production ML system; the surrounding infrastructure—data pipelines, feature stores, monitoring mechanisms, and deployment tooling—accumulates long-lived dependencies. Left unmanaged, this complexity results in brittle systems, silent failures, and escalating operational costs.

Conventional ML workflows often follow a quasi-waterfall pattern. A dataset is extracted, a model is trained in isolation, and the resulting artifact is handed off to engineering teams for deployment. Retraining is treated as an occasional, manually triggered activity, typically initiated only after noticeable performance degradation. This approach introduces long feedback loops and a critical *Retraining Latency Gap* between drift onset and corrective action.

In parallel, Agile methodologies and DevOps practices have transformed software delivery through short sprints, CI/CD pipelines, and automated testing. MLOps extends these principles to ML systems [3], [5]. However, fully automated, drift-aware pipelines remain relatively immature in practice.

This paper explores how Agile and DevOps principles can be systematically integrated with statistical drift detection to construct an Agile-driven ML pipeline capable of real-time adaptation. We design, implement, and evaluate a microservices-based architecture that couples continuous monitoring with KS-test-based drift detection to automatically trigger retraining and deployment when model performance is threatened by concept drift.

The key contributions of this work are:

- A formal problem formulation capturing retraining latency, training–serving skew, and operational bottlenecks in conventional ML pipelines.
- A statistically grounded drift detection layer embedded within an Agile MLOps architecture.
- A simulation-based evaluation using a synthetic financial fraud dataset with controlled drift injection.

- Empirical DevOps-style metrics demonstrating substantial improvements in MTTR, deployment frequency, and operational robustness.

II. Theoretical Background

A. Concept Drift and Drift Typology

Concept drift refers to changes in the statistical properties of data over time that alter the predictive relationship learned by a model [1], [3]. Let $X \in \mathbb{R}^d$ denote the feature vector and y the target label. Concept drift can be decomposed into covariate shift, prior probability shift, and real concept drift, depending on which components of the data distribution change.

Drift may also be classified temporally as sudden, incremental, or recurring, reflecting the rate and recurrence of distributional change.

B. Drift Detection Methods

Several families of drift detection techniques have been proposed [1], [7], [8], including statistical distribution tests, error-rate monitoring methods, and ensemble-based approaches. In this work, we prioritize distributional tests due to their interpretability, model-agnostic nature, and suitability for streaming data using sliding windows.

C. Agile, DevOps, and MLOps

Agile methodologies emphasize iterative development, continuous feedback, and frequent delivery. DevOps extends these principles through automation and collaboration across development and operations [10]. MLOps introduces additional concerns such as data versioning, model reproducibility, online monitoring, and automated rollback [3], [6]. According to Google's MLOps maturity model [3], the proposed system targets Level 2, characterized by full CI/CD with continuous training and monitoring. *event-driven retraining* coupled to drift detection.

III. Problem Statement

The operationalization of ML models in dynamic environments suffers from three primary inefficiencies.

A. Retraining Latency Gap

Model deterioration is often detected ex post facto, typically after stakeholders observe anomalies in downstream business metrics. The subsequent remediation process—data curation, retraining, and offline evaluation—can take days or weeks. During this interval, the model continues to generate suboptimal predictions. We define the *Retraining Latency Gap* as the time between drift onset and the restoration of acceptable predictive performance.

B. Training–Serving Skew

Training–serving skew arises when the data transformations or feature engineering logic used during training diverge from those applied in production [6]. Such inconsistencies may stem from stale configurations, missing logic in the serving stack, or duplicated preprocessing code. Even with drift monitoring, unnoticed skew can cause silent failures or severe inaccuracies.

C. Manual Bottleneck in Agile Contexts

Agile principles emphasize rapid responsiveness to change. In ML systems, however, changes occur not only in requirements but also in the data distribution itself. If retraining pipelines rely on manual validation and ad-hoc approval gates, genuine agility becomes unattainable. These manual processes form a structural bottleneck that prevents ML systems from matching modern DevOps velocity.

D. Additional Operational Challenges

Additional challenges include enforcing data freshness SLAs, balancing retraining frequency against infrastructure cost, and maintaining clean model lineage as versions evolve rapidly. Addressing these issues holistically requires tightly coupled monitoring, drift detection, retraining, and deployment.

IV. Objectives

The primary objectives of this research are:

1) To design and implement an end-to-end automated MLOps pipeline.
2) To integrate a statistical drift detection module using KS-test-based metrics as an event-driven retraining trigger.
3) To construct a controllable synthetic financial fraud dataset with injected drift scenarios.
4) To quantify predictive and operational performance using ML and DevOps metrics.
5) To compare static, periodic, and event-driven retraining strategies.

V. Literature Review

A. Evolution of MLOps

Gama et al. [1] and Lu et al. [3] highlight that concept drift is ubiquitous in real-world data streams, yet early ML systems were rarely designed with continuous adaptation in mind. Initial operational practices focused on reproducible training environments and version control for data and code. Tools such as DVC and MLflow emerged to track experiments and artifacts, but did not in themselves guarantee robust production behavior.

Google's MLOps guidance [4] and Sculley et al. [2] emphasize that ML systems incur unique forms of technical debt, including *entanglement* between features, undeclared consumers, and configuration debt. Later work on MLOps maturity models [3] introduced the notion of automated pipelines, including continuous training and deployment.

B. Concept Drift Adaptation Techniques

Gama et al. [1] and Lu et al. [3] provide comprehensive surveys of concept drift techniques. Statistical tests are widely used to detect covariate shift, while error-based methods such as DDM (Drift Detection Method) [7] and ADWIN (Adaptive Windowing) [8] monitor the evolution of prediction error on streaming data. Ensemble methods maintain multiple models with different temporal scopes and dynamically adjust weights or replace stale components.

While these approaches are well-studied in academic streaming contexts, their integration with production-grade MLOps infrastructures is less well documented. Production systems must operate under resource constraints, adhere to SLAs, and align with organizational DevOps practices.

C. Agile and Continuous Delivery in ML

Sato et al. [5] articulate *Continuous Delivery for Machine Learning* (CD4ML) as an extension of CI/CD into the ML domain. They argue that ML teams must conceptualize models as evolving artifacts updated through automated pipelines. Amershi et al. [9] discuss the broader spectrum of software engineering practices required for ML, including data management, experimentation, and monitoring.

Forsgren et al. [10] identify four key DevOps metrics—deployment frequency, lead time for changes, change failure rate, and MTTR—that correlate strongly with organizational performance. Mapping these metrics onto ML systems provides a useful lens for evaluating MLOps maturity. Our work explicitly incorporates such metrics into the evaluation of an Agile-driven ML pipeline.

D. Data Quality and ML Testing

Breck et al. [6] propose the ML Test Score, a rubric for evaluating the production readiness of ML systems, emphasizing data validation, feature monitoring, and canary analysis. Their work motivates our integration of data validation and monitoring components before drift detection and retraining.

E. Summary of Literature Gaps

Existing work provides:

- theoretical drift models and detection algorithms,
- generalized guidance on MLOps and CD4ML, and
- checklists for ML production readiness.

However, there is limited end-to-end empirical evaluation of *Agile, drift-aware* pipelines that join statistical drift detection with DevOps metrics in a unified architecture. This paper addresses that gap.

VI. Literature Review

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VII. Comparative Analysis of Related Work

VIII. Research Methodology

A. Simulation Design

Access to real-world, labeled, streaming financial data is often constrained by privacy and regulatory requirements. Therefore, we adopt a simulation-based methodology. A synthetic

data generator is used to emulate a high-velocity stream of transactions, producing both legitimate and fraudulent samples with controllable distributions.

The simulation supports:

- injection of sudden and incremental drift events,
- manipulation of class priors to simulate shocks (e.g., sudden surges in fraud volume).

IX. Dataset Description

A. Feature Composition

The artificial data is composed of 50,000 samples and 10. features II. Additional has properties such as categorical encoding of device type, mer- chant risk score, and user tenure. Gaussian mixtures and Approximation to realistic data is done using categorical distributions. patterns.

B. Drift Injection Scenarios

There are several drift scenarios that we define:

Sudden Drift at T = 20,000: The generation of fraud mechanism abruptly changes. First, high value transactions. are committed most in late-night hours. After drift, the most of the fraud is low-value, high-frequency. daytime transactions, acting as a change of adversarial. strategy.

1) Incremental Drift from $T = 30{,}000$ to $T = 40{,}000$: The mean amount of the transactions among the legitimate users is raised. gradually, simulation of inflation or modification of customer spend- ing habits. This overlaps with the fraud distribution, Raising the classification challenge.

2) Recurring Drift: is simulated by a recurrent pattern. which are introduced higher rates of fraud when weekends are involved. in each constant number of time steps. This tests the ability of the mechanism to sustain the performance under seasonal trends.

C. Visualizing Covariate Shift

Fig. 1 illustrates an example of covariate shift for a single feature.Visualizing Covariate Shift Visualization can also be used to detect covariate shift

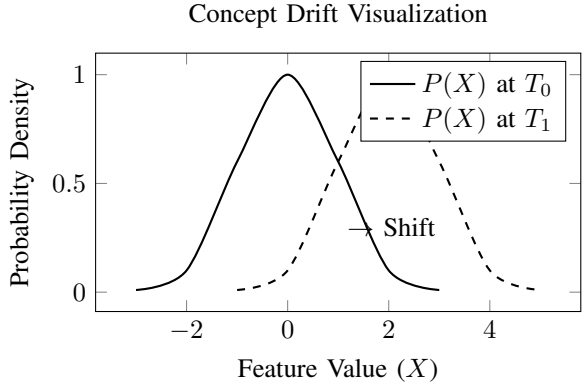

Fig. 1. Illustration of covariate shift where the input distribution changes over time.

X. Proposed Model Architecture

A. Microservices-Based MLOps System

A. MLOps System based on microservices. The suggested solution adheres to a microservices model of. scalability, fault isolation and modularity. Major components include: Streaming: Transactions to a message. broker into the magazine shop. • **Data Validation Service**: Imposes schema and distribu- tion checks. • **Drift Detection Service**: Calculates KS statistics and auxiliary metrics. Training Service: Organizes the extraction of features, model. training, and evaluation. • **Model Registry**: Stores versioned models and related. metadata. • **Serving Service**: Hosts the existing model of production and exposes prediction APIs. • **Monitoring Service**: Tracks model performance, latency, and drift statistics. The high-level architecture is represented in Fig. 2

Fig. 2 the high-level architecture.

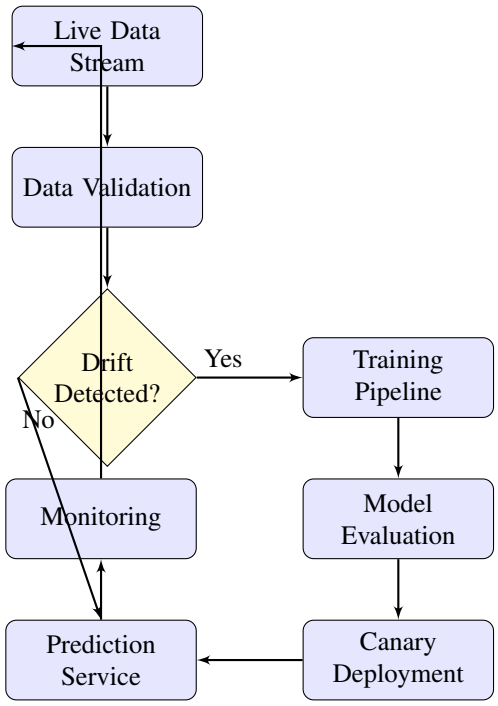

Fig. 2. Agile MLOps architecture with automated retraining loop.

B. Drift Detection Algorithm: Kolmogorov–Smirnov Test

We use the KolmogorovSmirnova (KS) test, which is a non-test. parametric test of the empirical cumulative distribu- tion -functions (ECDFs) of a reference window R and a current. inference window I. The KS statistic may be defined as the mathematical relation fro above is

$$D_{\text{KS}} = \sup_x \left| F_R(x) - F_I(x) \right|. \tag{1}$$

The null hypothesis H 0 supposes that R and I are selected out of. the same distribution. At a significance level , when

$$D_{\text{KS}} > c(\alpha) \sqrt{\frac{n_R + n_I}{n_R n_I}}, \tag{2}$$

TABLE I
DETAILED RESEARCH GAP ANALYSIS AND HOW THE PROPOSED FRAMEWORK ADDRESSES THEM

Research Dimension	**Gaps Identified in Prior Work**	**How the Proposed Agile MLOps Framework Addresses the Gap**
Drift Detection Integration in Production Systems	Most prior work treats drift algorithms (DDM, ADWIN, KS-test, PSI) in isolation, focusing on theory rather than deployment feasibility. Few studies link statistical drift detection directly to automated production retraining pipelines.	We tightly couple KS-test-based drift detection with Airflow-driven CI/CD workflows. Detected drift generates event-driven retraining signals that directly activate the training DAG, enabling real-time adaptation.
Real-Time vs. Periodic Retraining Trade-offs	Existing studies do not systematically compare static, periodic, and event-driven retraining strategies under identical conditions.	We conduct controlled comparisons between static, periodic, and KS-triggered retraining strategies using the same data streams, measuring recovery accuracy, responsiveness, and cost.
Microservices Architecture for Continuous ML Systems	Drift and MLOps research often lacks clear systems-level architecture or microservice decomposition addressing production constraints such as latency and scalability.	We present a complete microservices blueprint comprising ingestion, validation, drift detection, training, registry, monitoring, and serving services, coordinated through asynchronous messaging.
DevOps SLO/SLA-Aware Evaluation	Most literature evaluates ML systems primarily on predictive metrics, ignoring latency budgets and SLA-driven constraints.	Our pipeline incorporates SLO-aware triggers (p-value thresholds, performance degradation alerts), enforces data freshness constraints, and measures end-to-end pipeline latency.
Reproducibility and Model Lineage	Drift-retrained models often lack clear version lineage, complicating debugging and rollback.	All model versions, metrics, drift signals, datasets, and preprocessing artifacts are tracked in MLflow, ensuring reproducibility, auditability, and safe rollback.

TABLE II
DATASET FEATURE DESCRIPTION

Feature	**Type**	**Description**
`tx_amount`	Float	Normalised transaction as a float.
`tx_time`	Integer	Hour of day (0–23).
`merchant_cat`	Categorical	Merchant category (e.g., Grocery, Tech).
`user_dist`	Float	Distance from home location.
`device_type`	Categorical	Mobile, Web, POS.
`user_tenure`	Float	Months since account creation.
`risk_score`	Float	Precomputed heuristic risk signal.
`country_code`	Categorical	Country of the transaction.
`velocity_count`	Integer	Transactions in last 24 hours.
`is_fraud`	Binary	Target label (0: Normal, 1: Fraud).

we do not accept H0 and flag drift, nR and nI are sample sizes. and c(alpha) is a critical value that is dependent on alpha.

The KS test is applied feature-wise to numeric features. For categorical features, we use Chi-square tests and monitor changes in empirical category frequencies.

C. Automated Pipeline Steps

The automated retraining process is comprised of: **Ingestion**: Recent transactions are materialised off the feature store. **Checking**: Schema and range checks; missing values. and outliers are detected. **Preprocessing**: Scaling and one-hot encoding; transfor- The mations are represented in the form of pipelines that have serializable representations. **Training** A random forest classifier (hyperpa- rameters that are trained in cross-validation) is trained. **Evaluation** To test the candidate model, it is evaluated on a. hold-out validation set, and, optionally, shadow-deployed. (whilst original still exists online). **Promotion**: In case the candidate F1-score (and AUC) is less than it is at stage X. outperform those of the production model by a configurable margin, it is advanced to production.

XI. IMPLEMENTATION DETAILS

A. Technology Stack

The prototype pipeline is implemented using:

- **Python 3.x** Python 3x to process data and train models.
- **Apache Airflow** Apache Airflow as the orchestration framework of. DAG-based workflows.
- **Alibi-Detect** for drift detection utilities.
- **MLflow** as a model registry and experiment tracker.
- **Docker** for containerization of services.

B. Trigger Logic and Orchestration

The streaming streaming detects drifts on a continuous basis. statistics. In case the KS-based p-value of any of the monitored is. feature is below 0.05 and a DRIFTALERT event is produced. to a message queue. An Airflow(apache tool) sensor is a sensor that hearkens to. this action and causes the retraindag which performs the practising and assessment process(within a supervised setting). When the DAG is successful, a registry update is made. and canary deployment, optional.

XII. EVALUATION METRICS

A. Model-Centric Metrics

A set of standard classification metrics that we use are:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4}$$

We measure also AUC (Area Under the ROC Curve). ranking does not depend on a particular decision threshold.

B. Agile and DevOps Metrics

Following DevOps research [10], we track:

- **Deployment Frequency:** Successful model number. updates per simulated week.
- **Lead Time for Changes:**Time between the drift identification and deployment of a new model
- **Mean Time to Restore (MTTR):** Perfor to Restore Time. mance degradation to recovery beyond a target F1-score..
- **Change Failure Rate:** Percentage of deployment failures that weaken performance relative to the former version.

XIII. Results and Discussion

A. Static vs. Agile Performance Over Time

Fig. 3 We compare the F1-score curves. The static baseline, which has been perturbed by the first drift, is victimized by a long-lasting. deterioration out of which it never recovers. In sharp relief, there is a sawtooth mor- in the Agile pipeline. phology. When drift strikes, of course, performance goes down, however. the slump does not last long; the system quickly self-adjusts after- retraining.

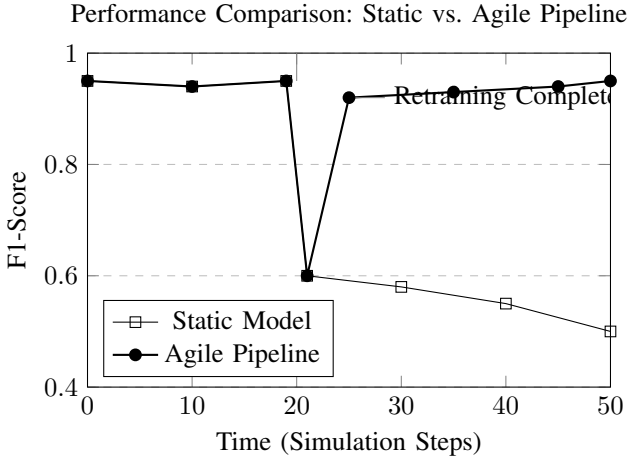

Fig. 3. Impact of automated retraining on model F1-score under drift.

B. Sensitivity to Magnitude of Drift.

We also change the drift magnitude (small, medium,¡—human—¿We also change the drift magnitude (small, medium, large) and post-retraining F1-score. Table III summarizes the observations.

TABLE III
Effects of Drift Magnitude on Agile Pipeline Recovery

Drift Magnitude	Min F1 During Drift	Post-Retrain F1
Small	0.88	0.94
Medium	0.72	0.92
Large	0.60	0.90

The Agile pipeline is able to recover to a even large drift. F1-score of around 0.90 which shows strength in changing environment.

C. Confusion Matrix Analysis

Table IV A confusion matrix (slight deviation) of is presented in Table VI. the Agile model following the initial drift incident.

TABLE IV
Confusion Matrix (Post-Drift Recovery)

		Predicted	
		Normal	Fraud
Actual	Normal	960 (TN)	40 (FP)
	Fraud	90 (FN)	910 (TP)

CONFUSION matrix (Post-drift recovery): This algorithm evaluates the classification rate of the evaluation data which has experienced drift. This is because the recall is high, which shows that the system is able to adapt. to fresh fraud patterns(constantly), as the accuracy is kept. acceptable.

D. Operational Efficiency

Table V i s a comparison of essential operational metrics by strate-gies.

TABLE V
Operational Metrics Comparison

Metric	Traditional	Agile Pipeline
Drift Detection Time	$>$ 24 hours	$<$ 5 minutes
Retraining Lead Time	3–5 days	45 minutes
Deployment Frequency	Monthly	On-demand
MTTR	Days	Under 1 hour
Change Failure Rate	Variable	Low (with canaries)

MTTR Days Under 1 hour Change Failure rate Variable Low (with canaries) Agile pipeline has an essential negative impact on the MTTR and in. increases frequency of deployment without high failure. rates that may occur generally in this type of work, coinciding. and high-performing DevOps characters [10].

XIV. Threats to Validity

A. Simulation vs. Real-World Complexity

The synthetic dataset is designed to estimate at the same time as the real dataset. realistic patterns of fraud, it is still an abstraction. It cannot completely model the adversarial behaviour, which is stochastic. or evolving regulations. The data of the real world is always sloppier. It shows noisy labels and business correlated shifts. by definition, processes that a generator simplifies.

B. Model and Algorithm Choices

Random Forest and KS-based detection were prioritised by us. at least in part because of interpretability. The logic is transparent. Of course, other forms can be used, such as gradient boost- –might, ing, deep neural networks, or detectors such as ADWIN. express varying adaptive behaviours. Our findings, therefore, but as a suggestive discovery of the framework, not. a claim of universality which is exhaustive.

C. Infrastructure Assumptions

The prototype is based on the assumption of reliable. orchestration. Message delivery is a given to us. In practice, but distributed systems are vulnerable to stochastic failure. A is required to implement on a production level. circuit sive architecture, using resilience mechanisms–circuit breakers, backoff strategies–to resist the inevitable infras- tructure instability

XV. Conclusion

This study proposes to integrate Agile mechanics with. MLOps is not a luxury to operate. In non-stationary en- it is an imperative, environments. By coupling KS-based drift the proposed pipeline is detection by retraining automatically. is able to counter concept drift. Our simulations within a financial fraud situate reveal the shortcomings of statical. approaches. Retraining that is event-driven does not simply correspond. base line performance; it is far much higher than that, sustaining compressing the Mean Time to Restore but with high F1-scores. (MTTR). Measures are not the only implication. Treating as a product that is in a state of evolution, machine learning models. fixed artifacts- makes organizations check technical debt. and are in line with the pace of the current software engineering.

XVI. Future Scope

Several promising directions remain for future work:

- **Unsupervised and Semi-Supervised Adaptation:** Invesmitigate domain adaptation and self-supervised methods.to refresh models in the event of delayed and missing labels.
- **Federated and Edge MLOps:**Take the pipeline to federal learning situations, drift is experienced across. data is restricted by heterogeneous devices and privacy issues. sharing..
- **Reinforcement Learning for Thresholding:** RL- drift thresholds are adjusted dynamically using based controllers. and re-training policies founded on cost-performance trade- offs.
- **Serverless and Cost-Aware Orchestration:** Discover. scaling training and inference with serverless architectures. capacity, elastically, latency and optimization.
- **Rich Multi-Modal Drift:** Epanding monitoring to multimodal data (text, images, graphs) where change manifests in more complex patterns.

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