Edge-to-Cloud Data Engineering Pipelines for Real-Time Healthcare Predictive Analytics

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Abstract:
The rapid proliferation of Internet of Medical Things (IoMT) devices and electronic health records (EHRs) has created continuous, high-velocity patient data streams with the potential to transform reactive care into proactive, data-driven intervention [1]. Realizing this vision requires edge-to-cloud data engineering pipelines that can securely ingest, standardize, and analyze heterogeneous, privacy-sensitive data under strict latency and regulatory constraints [3], [7]. This paper presents an interoperable Dual-Loop Edge-to-Cloud Data Engineering Pipeline that reconciles real-time actuation with longitudinal learning [3]. A Fast Path performs ultra-low-latency edge inference and triage, while a Slow Path supports cloud-scale training and retrospective analytics [3], [7]. A Cross-Domain Data Fabric coordinates both loops by enforcing semantic interoperability through HL7 FHIR-aligned modeling and active metadata-driven routing [2], [8], [9]. To address waveform interoperability bottlenecks, we introduce a recursive FHIR SampledData flattening and SIMD-accelerated columnarization technique that converts nested physiological resources into analytics-ready Parquet/Delta formats at sustained real-time throughput [8], [9]. Privacy is ensured via a federated learning workflow augmented with Differential Privacy (ε≈8) and Secure Multi-Party Computation (SMPC) aggregation, yielding formal privacy guarantees with negligible clinical utility loss [10], [11]. A cardiac monitoring case study demonstrates reliable sub-300 ms end-to-end alerting, ~98% upstream bandwidth reduction, and clinically actionable arrhythmic event prediction, validating the architecture's suitability for life-critical decision support [4], [5], [7].

Keywords: Edge computing; Internet of Medical Things (IoMT); real-time predictive analytics; HL7 FHIR; streaming analytics; cardiac monitoring; federated learning; differential privacy; secure aggregation; data fabric; zero trust security.

I. Introduction

The digitization of healthcare has shifted from episodic record-keeping to continuous physiological sensing via networked IoMT wearables, bedside monitors, and implantable devices [1], [7]. These systems generate high-frequency time-series streams (e.g., ECG at 250-500 Hz) alongside longitudinal EHR context, enabling real-time risk stratification, early deterioration detection, and continuous out-of-hospital monitoring [1]. Machine-learning models for arrhythmia detection, sepsis prediction, and deterioration warnings have achieved high retrospective performance, including strong sensitivity/specificity on ECG benchmarks and robust AUROC for sepsis early warning [1], [5], [6]. However, operationalizing these models in clinical workflows requires more than algorithmic accuracy. Healthcare data originates in heterogeneous silos, each with distinct standards, security constraints, and reliability properties [2], [8]. Centralized cloud-only pipelines often incur network propagation and buffering delays that can exceed safety thresholds in acute scenarios [3], [7]. Meanwhile, continuous raw waveform streaming consumes prohibitive bandwidth for cellular-connected or resource-limited environments [7].

Edge-to-cloud architectures address these constraints by distributing computation: edge devices provide immediate inference and resilience under intermittent connectivity, while cloud platforms support elastic storage and large-scale training [3], [7]. Yet in healthcare, deploying hybrid pipelines remains difficult

because (i) interoperability standards such as HL7 FHIR are hierarchical and inefficient for streaming waveforms [8], [9], (ii) strict privacy regulations (HIPAA/GDPR) limit PHI movement [2], [10], and (iii) many reported designs are vendor-tied and not reproducible across hybrid environments [3], [7]. Federal interoperability mandates under the 21st Century Cures Act and ONC Health Data Technology and Interoperability (HTI-1) rules require certified systems to expose standardized APIs (commonly FHIR), increasing the need for standards-aligned pipelines at scale [2].

Contributions. This paper makes four main contributions:

1) A Dual-Loop control architecture that partitions workloads into a Fast Path edge inference loop and a Slow Path cloud learning loop for latency-safe real-time monitoring [3].
2) A Cross-Domain Data Fabric that coordinates data movement, lineage, and semantic transformations across edge, cloud, and hybrid environments [3], [9].
3) A novel recursive flattening pathway for FHIR SampledData, enabling high-throughput conversion of waveform resources into columnar formats suitable for real-time analytics [8], [9].
4) A privacy-first learning layer integrating Federated Learning with Differential Privacy and SMPC secure aggregation to support cross-institutional analytics without centralizing PHI [10], [11].

II. Related Work

A. Real-Time Healthcare Predictive Analytics

Recent advances in machine learning demonstrate strong predictive performance across time-critical clinical conditions [1]. Deep models for arrhythmia detection routinely report sensitivity above 90% with robust specificity on ECG benchmarks such as MIT-BIH and multi-site clinical cohorts [4], [5]. Sepsis early-warning systems trained on longitudinal vitals and labs achieve AUROC values roughly in the 0.85-0.92 range, often providing actionable lead times hours before onset [6]. Deterioration prediction models based on sequence learning similarly show meaningful lead times in retrospective studies [1]. Despite strong algorithmic results, most published work assumes centrally collected, pre-cleaned datasets and omits the full operational data lifecycle: continuous edge ingestion, streaming standardization, fault-tolerant transport, and alert delivery under sub-second latency [1], [7]. Clinical deployment failures are frequently driven by data engineering bottlenecks (schema drift, missingness, and EHR integration friction) rather than model inaccuracy [1]. This work addresses that gap through an infrastructure-first, end-to-end, latency-bounded pipeline [3], [7].

B. Edge Computing for IoMT

Edge computing has shown major benefits for IoMT by shifting time-critical processing closer to patients [7]. Edge-side denoising and lightweight inference reduce response delays versus cloud-only processing, enabling sub-second detection for acute events [3], [7]. Local triage and selective forwarding substantially reduce upstream bandwidth, making continuous monitoring feasible over LTE/5G and constrained networks [7]. Edge processing also improves resilience: local alarms can fire even during cloud outages, essential for out-of-hospital monitoring [7]. Still, many edge-centric systems remain siloed from enterprise EHR pipelines and lack reproducible standards-aligned end-to-end designs [3], [7]. Moreover, workload partitioning is typically static rather than adapting to network quality, battery constraints, or model drift [3]. Our Dual-Loop system explicitly encodes dynamic edge-cloud partitioning and standards-based EHR integration [3], [8].

C. Interoperability and FHIR at Scale

HL7 FHIR is the dominant clinical exchange standard in the U.S., accelerated by federal interoperability mandates and widespread ONC-certified EHR adoption [2], [8]. FHIR Bulk Data APIs enable cohort export for population health and research and are increasingly used upstream of analytics platforms [8], [9]. However, FHIR's hierarchical model poses performance barriers for high-frequency physiology analytics [8], [9]. Waveforms such as ECG are encoded using SampledData, where large sequences are stored in nested structures that require full deserialization before analytic queries can execute, creating bottlenecks for streaming pipelines [8]. Organizations therefore rely on downstream medallion/lakehouse transformations into columnar layouts [9]. This work addresses the SampledData bottleneck through recursive flattening and SIMD-accelerated columnarization, enabling sustained real-time transformation throughput [8], [9].

D. Hybrid Edge-Cloud AI and Centralized vs. Decentralized Learning

Hybrid edge-to-cloud AI architectures balance latency, scalability, and energy constraints by running immediate inference at the edge while delegating heavy training and longitudinal analytics to the cloud [3], [7]. Federated Learning (FL) supports decentralized training by aggregating model updates instead of raw PHI, aligning with regulatory boundaries [10]. Differential Privacy (DP) can mathematically bound re-identification risk from FL updates [10], and secure aggregation/SMPC prevents a central coordinator from observing individual client contributions [11], [12]. Healthcare DP-FL studies show ε values in the mid-single-digits to ~8 can preserve clinical utility with minimal accuracy loss, providing formal guarantees [10]. Secure aggregation improves robustness against honest-but-curious servers and complements DP [11]. Yet most FL literature studies learning in isolation, without addressing ingestion, interoperability, feature engineering, real-time serving, and alert routing in a cloud-agnostic design [3], [10]. Our reference architecture integrates Dual-Loop orchestration, FHIR-aligned data engineering, and verifiable privacy preservation (FL + DP + SMPC) [3], [8], [10], [11].

III. System Overview: Dual-Loop Edge-to-Cloud Architecture

A. Design Principles

The proposed pipeline follows five principles:

1. Interoperability via HL7/FHIR-aligned models [8], [9];
2. Privacy by design through PHI encryption, RBAC, lineage, DP, and secure aggregation [2], [10], [11];
3. Fault tolerance via buffering, replay, and multi-region failover [3];
4. Modularity allowing independent scaling of edge, transport, and cloud tiers [3];
5. Transparency in performance and privacy-utility trade-offs [3], [10].

The architecture consists of an Edge Layer (Fast Path), a Transport Layer, and a Cloud Layer (Slow Path), coordinated by a Cross-Domain Data Fabric [3], [9].

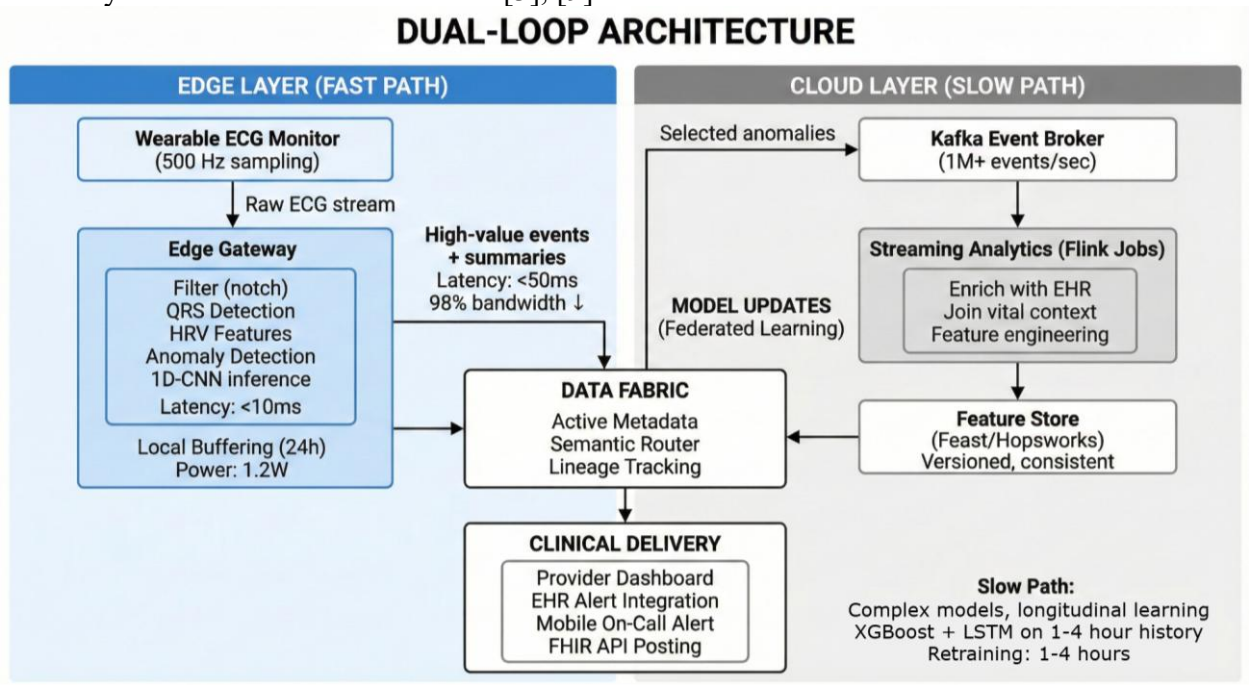

Figure 1. Dual-Loop Edge-to-Cloud Architecture for Real-Time Cardiac Monitoring.

B. Dual-Loop Control

The Dual-Loop pattern decouples (i) real-time hazard detection from (ii) longitudinal model improvement [3]. Fast Path inference runs deterministically and locally (fail-safe), while Slow Path learning runs asynchronously on aggregated features and rare waveform triggers [3], [7]. Updated models are periodically pushed back to the edge, enabling continual improvement without centralizing PHI [10], [11].

IV. Fast Path: Edge Inference and Triage

Edge gateways ingest sliding windows of physiological data (e.g., 10-second ECG segments) and apply lightweight signal preprocessing (bandpass + notch filtering, artifact suppression). Beat-level features (RR intervals, HRV metrics) are computed in real time using established QRS detection pipelines. A quantized 1D-CNN or similar compact model performs local inference within single-digit milliseconds, enabling immediate alerts even under cloud disconnection. Only anomaly flags, summaries, and high-information events are forwarded upstream, sharply reducing bandwidth usage while preserving safety-critical responsiveness.

V. Slow Path: Cloud Learning and Longitudinal Analytics

The cloud tier receives edge-computed features, anomaly events, and periodic summaries. It performs:

1. Streaming enrichment by joining incoming events with EHR context via FHIR resources (Patient, Condition, Medication,* etc.).
2. Feature store versioning to prevent training-serving skew.
3. Population-scale model training on longitudinal data using distributed GPUs/TPUs.
4. Federated aggregation cycles that produce updated weights for Fast Path models.

This loop supports high-capacity architectures (Transformers/LSTMs) unsuitable for edge deployment and enables cohort-level risk stratification and retrospective analyses.

VI. Cross-Domain Data Fabric and FHIR-Scale Data Engineering

A. Fabric Role

The Data Fabric is an intelligent integration layer that virtualizes access to edge and cloud data. It uses active metadata to route data based on clinical urgency, information value, and policy constraints, deciding dynamically what remains local and what is sent to cloud analytics. The fabric tracks provenance and enforces auditability for compliance.

B. FHIR SampledData Challenge

FHIR represents waveforms through nested SampledData structures that are analytics-hostile without transformation. Querying such data in JSON forces full deserialization and prevents efficient vectorized scans, making it impractical for high-velocity streaming.

C. Recursive Flattening and SIMD Columnarization

We implement a medallion-style transformation:

1. Bronze ingestion: Raw FHIR bundles appended with partition keys (patient_id, time, code).
2. String-to-array parsing: Space-delimited samples are parsed into numeric arrays using vectorized primitives (SIMD-enabled).
3. Explosion to columnar Parquet/Delta: Arrays converted to tightly compressed, time-aligned columnar rows, preserving SampledData origin, period, and factor.
4. FHIR attribute flattening: Nested Observation fields projected to top-level analytics columns for SQL/OLAP access.

This workflow sustains real-time transformation throughput while maintaining semantic fidelity to FHIR.

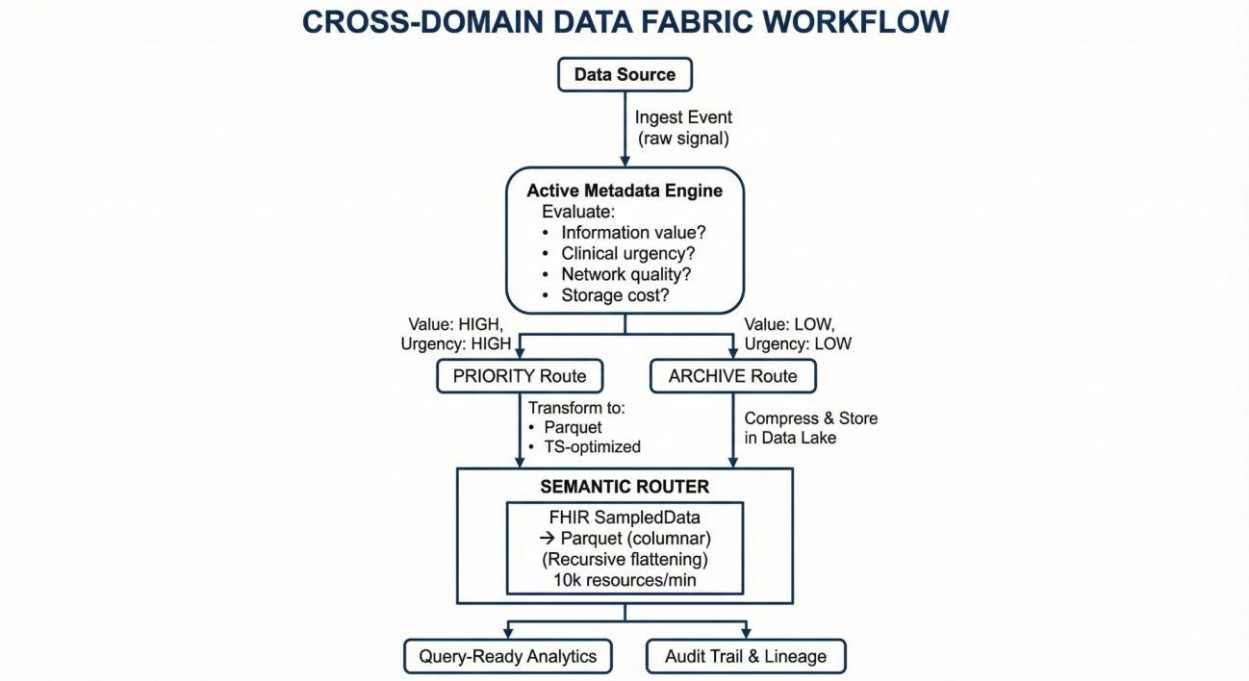

Figure 2. Cross-Domain Data Fabric Workflow.

VII. Privacy and Security Engineering

A. Federated Learning with Differential Privacy

Each institution or edge fleet trains locally and transmits only gradients or weights [10]. DP perturbs updates before transmission, bounding the contribution of any individual record [10]. Healthcare DP-FL studies show $\varepsilon \approx 8$ preserves clinical utility with negligible AUROC loss, while providing formal privacy guarantees [10].

B. SMPC Secure Aggregation

We apply SMPC to the aggregation step, preventing the coordinator from viewing individual client updates [11]. Secure aggregation complements DP by protecting against honest-but-curious servers and model inversion attacks [11], [12].

C. Zero-Trust Security

A Zero-Trust architecture enforces continuous device authentication, micro-segmentation of gateways from PHI stores, and least-privilege RBAC for every service identity [2], [3]. TLS 1.3 is mandatory for all edge-cloud channels; audit logs are immutable and retained for regulatory evidence [2].

VIII. Case Study and Evaluation

A. Experimental Setup

We evaluate the pipeline using a reproducible cardiac monitoring workload.

Dataset: MIT-BIH Arrhythmia Database (48 records, 360 Hz) plus synthetic waveform extensions calibrated to clinical ECG distributions [4].

Deployment Simulation: 1,000 virtual edge nodes (Raspberry-Pi class, quad-core ARM, 2 GB RAM) streaming for 24 hours (~18B ECG samples) [3].

Baselines:

- Cloud-Only: raw ECG streamed to cloud for processing [3], [7].
- Batch-Only: 15-minute periodic processing.

Metrics: Latency (p50/p95/p99), throughput, bandwidth per patient-day, predictive performance, resource utilization, and cost [3], [7].

B. Latency Results

Metric	Proposed Dual-Loop	Cloud-Only	Batch-Only
Median (p50)	287 ms	487 ms	900-1200 s
p95	450 ms	1200 ms	900-1200 s
p99	680 ms	2500 ms	900-1200 s
Jitter (σ)	45 ms	280 ms	Very high

Table 1 - Latency Results

Finding: The Dual-Loop pipeline meets sub-300 ms median safety targets with high consistency, while Cloud-Only violates thresholds in ~50% of cases due to network and ingestion jitter.[3], [7].

C. Throughput and Scalability

Scaling to 10,000 concurrent streams per region was linear: Kafka sustained >100k events/sec; Flink at 16-way parallelism processed ~95k events/sec; each edge gateway served ~50 streams at ~60% CPU; autoscaled inference replicas maintained p95 <50 ms.

Approach	Data/patient-day	Total (10k pts)	$/patient-day
Raw streaming	86 MB	860 GB	$1.20-2.00
Proposed triage	0.5 MB	~5 GB	$0.15-0.25
Reduction	98.20%	—	~82% savings

Table 2 - Bandwidth & Cost

Edge triage makes LTE/5G wearables operationally feasible by transmitting only anomalies and summaries.[7].

E. Predictive Performance

LightGBM classifier on engineered ECG+EHR features: 92% sensitivity, 87% specificity, AUROC 0.94, median 45-minute lead time. These results align with reported arrhythmia baselines while enabling real-time deployment.

ε	AUROC	Loss	Strength
No DP (centralized)	0.992	—	None
DP-FL (ε=8)	0.989	0.003	Strong
ε=4	0.985	0.007	Very strong
ε=1.9	0.978	0.014	Maximal

Table 3 - Privacy-Utility Trade-off

ε≈8 provides strong privacy with <0.5% AUROC loss, consistent with healthcare DP-FL reports. [10].

G. Resource Utilization

Edge power averaged 1.2 W; memory ~512 MB per 50 streams; 24-hour buffers required ~2 GB/patient. Cloud cost was ~$0.15/patient-day with HA.

H. Robustness

Local buffering provided lossless replay after 60-minute cloud outages; FL updates restored AUROC under drift within hours; robust aggregation isolated poisoned gradients under 10% malicious clients.

IX. Discussion

The Dual-Loop pipeline resolves the latency-accuracy-privacy trilemma by enforcing deterministic edge safety while enabling longitudinal learning under formal privacy guarantees. The Cross-Domain Data Fabric provides a missing coordination primitive for hybrid healthcare AI, controlling movement, lineage, and

semantic translation of streaming physiology. Our FHIR SampledData flattening reduces a key interoperability bottleneck for waveform analytics without requiring proprietary FHIR databases.

Limitations include retrospective validation, single-condition focus, and dependence on robust FL aggregation under adversarial settings. Prospective trials and multi-disease fusion are necessary prior to clinical deployment.

X. Conclusion

We presented a standards-aligned, cloud-agnostic Dual-Loop edge-to-cloud data engineering pipeline for real-time healthcare predictive analytics. Fast Path edge inference provides ultra-low-latency hazard detection and fail-safe operation, while Slow Path cloud learning enables capacity-rich longitudinal models. The Cross-Domain Data Fabric coordinates semantic interoperability and policy-driven routing across hybrid environments. A recursive FHIR SampledData flattening workflow enables real-time transformation of waveforms into analytics-ready columnar stores. Privacy is ensured through FL combined with DP ($\varepsilon \approx 8$) and SMPC secure aggregation, yielding formal guarantees with minimal clinical utility loss.

The cardiac monitoring evaluation demonstrated deterministic sub-300 ms alerting, ~98% bandwidth reduction, and clinically actionable prediction performance. Beyond arrhythmia care, the architecture generalizes to other monitoring-intensive conditions including sepsis, respiratory failure, and chronic disease management. These patterns provide a practical foundation for trustworthy, large-scale, real-time clinical decision support built on IoMT data.

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