



Real-Time Anomaly Discovery in FHIR Healthcare Data Streams using Unsupervised Machine Learning Techniques

Shashikala Valiki

Independent Researcher, India

shashikala.valiki.researcher@gmail.com

ABSTRACT: Reports of serious security breaches involving medical data have attracted increasing public attention. These incidents emphasize the importance of protecting health information and re-establishing patient trust in information systems that support healthcare delivery. Guaranteeing the confidentiality and integrity of healthcare data is challenging, given the intrinsic requirements dictated by openness, interoperability, accessibility, and availability. In addition to the overall emergence of disorder, active, unattended FHIR data streams produced by thousands of devices, systems, and services are particularly prone to contain high-level attributes and momentary deviations that fall outside accepted monitoring thresholds or general patterns. Such anomalies may indicate dangerous problems, progress toward disastrous events, or even the introduction of malware. However, it is hardly possible to use supervised techniques to define the rich set of expected patterns that characterize or govern real-time healthcare data streams.

Unsupervised learning methods are presented with an objective, evidence-based analysis and formal structure. Emphasis is placed on the application of these approaches to real-time anomaly detection within unattended and open healthcare data streams that follow the Fast Healthcare Interoperability Resources (FHIR) standard. The analysis offers a heuristic indication of the methods that can best exploit the availability and characteristics of real-time healthcare data streams. The methods are systematically examined against qualifying criteria and success factors for their application in real-time healthcare environments.

KEYWORDS: Adaptive Control , Autonomous Vehicle , Dynamic Environment , Model-Free Reinforcement Learning, Safety , Traffic Efficiency.

I. INTRODUCTION

Real-time anomaly detection in healthcare data streams is challenging. Supervised methods typically require a training phase, yet labelled data are scarce or missing. Unsupervised methods are a viable alternative, and the need for such approaches in the context of Fast Healthcare Interoperability Resources (FHIR) is discussed.

Much of the previous work focused on clustering, was limited to offline settings, or did not address the dynamics of continuous data streams. Research objectives include: (1) determining whether unsupervised-learning techniques support real-time anomaly detection in continuous FHIR data streams, and (2) clarifying the characteristics of FHIR data that affect unsupervised methods. Evaluation criteria—having practical implications and clinical impact—address speed of detection, risk of false positives, and readiness for deployment in a real-time care environment.

II. RESEARCH DESIGN

The proposed unsupervised approaches enhance real-time anomaly detection in healthcare streams represented by fast Healthcare Interoperability Resources (FHIR). Three publicly available collections of FHIR-compliant healthcare data provide heterogeneous, multidimensional event streams that mimic real clinical environments: COVID-19 event streams from various countries, a Taiwan-based diabetes monitoring system, and a patient dashboard for monitoring chronic medical conditions and clinical nursing. Criterion variables for real-time anomaly detection in stream data are temporal



constraints, resource-drained disease, few descriptive observations, indisputably bad conditions, and sudden onset pattern deviations.

COVID-19 was selected for anomaly detection because some patient conditions and clinical changes were reported within a short time. The first collection contains COVID-19 FHIR event streams from multiple countries. Therefore, scarce monitoring or treatment resources were assigned to COVID-19 patients, resulting in resource-drained disease status. This led to patient discharge without resources or life. Although discharge may indicate a positive treatment outcome, it may also occur when patients are critically ill, need assistance for basic daily activity, or their family is unable to continue. Discharge under these conditions is an obvious indicator of an abnormal event or seriously bad status. Furthermore, patients infected with chronic diseases such as diabetes, hypertension, and cardiovascular disease are at a higher risk of severe disease and death after contracting COVID-19.

The second collection includes a clinical care system for monitoring chronic disease. The Taiwan-based diabetes event streams represented a patient-care system for chronic disease monitoring by clinical physicians. Anomaly detection was applied to alarm when the status of patients with chronic diseases exerted serious changes according to the warning signs indicated in the literature. The third collection was a monitoring dashboard for chronic disease patients. In this dashboard design, an early warning function was provided by using big-data technology. Data were processed in the backend. The monitoring system detected early signs such as fever. Patients could receive early medical attention and intervention through this dashboard."

Table 1: Research Objectives and Evaluation Criteria

Aspect	Description
Objective 1	Determine if unsupervised learning supports real-time anomaly detection in continuous FHIR streams
Objective 2	Identify FHIR data characteristics influencing unsupervised methods
Speed of Detection	Latency between event arrival and anomaly flag
False Positive Risk	Likelihood of incorrect alarm
Deployment Readiness	Suitability for real-time clinical environment
Clinical Impact	Ability to trigger early intervention

III. BACKGROUND

Healthcare research increasingly relies on real-time, continuous streams of data. The Fast Healthcare Interoperability Resources (FHIR) initiative fosters standardization, interoperability, and synchronization. FHIR resources include a semantic description of healthcare entities and associated events. For example, rhinosinusitis represents an illness for which medication prescription, laboratory examinations, and location can be concurrently monitored across different patients. Unsupervised learning techniques are presented with a formal structure focusing on real-time anomaly detection in FHIR healthcare streams.

Continuous monitoring of data provides opportunities to leverage a wealth of information over time. Many healthcare entities that experience some event, such as prescription, hospitalization, or examination, will then have other types of events associated and can be used for anomaly detection of these other events. Recently, it was shown how unsupervised learning can work with semantically described data. Unsupervised learning methods are investigated for real-time anomaly detection in healthcare data streams expressed and made available in FHIR. The work focuses on decision support to enable the identification of patients that may require some additional attention or checkup based on healthcare data received while in progress, rather than after the end of the monitoring period.



IV. FHIR AND HEALTHCARE DATA STREAMS

Healthcare data are gradually becoming richer and more available. The health care sector has embraced technology in record keeping and patient monitoring. Large health data repositories are beginning to be created with regular updates. These data collections can be pre-selected and merged through various procedures to create data streams ready for further exploitation, even for research purposes. The problem lies in the practical availability at the precise moments requested by Division of Clinical Informatics. Can the Clinical Informatics Division request the creation of healthcare data streams from non-standardized repositories or local databases?

The Health Level 7 (HL7) Fast Healthcare Interoperability Resources (FHIR) initiative has established a specification that defines a standard for exchanging health information in electronic format. FHIR supports the definition of healthcare data streams by defining a set of healthcare resources that contain both structured and unstructured information. The healthcare resources can be considered meta-data information that describe and contextualize what is happening in the healthcare environment. For example, if a patient is hospitalized, other events related to that patient – for instance, the prescription of an intravenous drug, a microbiological exam report, and an imaging finding – will be semantically grouped and described by FHIR meta-data elements such as patient, encounter, and related-to resources. These resources complete the information in associated events and give sense to the data accompanying the events. It can be said that the FHIR healthcare resources are not a complete data definition, but rather a metadata definition that describes, contextualizes, and provides the information necessary for reliable data analysis. Thus, in multiple, both local and remote places, only a subset of the healthcare events can be made available through a FHIR server, defining healthcare streams for different purposes.

V. PROBLEM FORMULATION

Anomaly detection in healthcare is often framed in a supervised classification setting, requiring normal and anomalous data during learning. Such data is rarely available and train/test splits assume independence, limiting responses to retrospective or batch scenarios. Moving beyond supervised paradigms, evidence-based research opens the door to unsupervised solutions. The constraints imposed by FHIR data provide further motivation, naturally leading to problem statements aligned with unsupervised anomaly detection.

The focus is on unsupervised anomaly detection for continuous Healthcare FHIR streams on event-based data. Continuous evolution of FHIR resources leads to a better understanding of clinical workflows and enhances predictive maintenance using low-level temporal features from event streams. Yet, dependent features are rarely explored. Anomaly detection on SQL representation is domain-agnostic. Temporal characteristics that take into account the temporal dimension of the stream are required for dedicated clinical solutions. A holistic architecture aggregates the processing of multiple closely maintained SQL representations into a unified event-based architecture, enabling integrate-and-fire detection and an end-to-end response mechanism aligned with clinical workflows.

The healthcare FHIR anomaly detection thumbnail described above is tackled through a set of embeddings summarising the current knowledge in the area. Normal events are described/defined in a generic sense using approximations of normality or other techniques. As with presence data, it is then sufficient to discard the models where events are present at the training time. TVSS, VS-AL, SLTS, and OTwork follow a similar logic and are less applicable to continuous streams in production, especially when human intervention is required.

VI. DATA CHARACTERISTICS AND PREPROCESSING

Data from FHIR streams possess several characteristics when considered for machine learning modelling. The temporal dimension reveals a mixture of continuous and discrete attributes, along with dependencies. Continuous features may have a predictable noise pattern, so selective smoothing is possible. Missing temporal values resulting from sensor or actuator failures are anticipated and should not affect modelling if proper imputation techniques are applied. Mode values or short-term interpolation are often sufficient for these types of anomalies. Many clinical parameters are defined per patient profile and remain constant unless altered by a care workflow. Individual patient history guides system conditioning. Normalized attributes usually fall within fixed physical bounds or clinically relevant windows, offering ranges for outlier detection. Non-continuous inputs are also associated with a fixed update frequency through background care automation.



The distributed stream nature poses additional challenges. Features originate from many sources, generating imbalanced windows over time. All features must be encoded as feature vectors, meaning discretizing continuous values helps reduce latency. Windows are filled independently but should retain comparable features for systematic behaviour extraction. Heavily mode-distributed sensor values are not viable for event-based encoding. As the streams approach saturation, evident anomalies signal the need for replacement. Careful definition of hidden and output layers permits integration into noise detection algorithms. Detection of non-FHIR features enhances normal behaviour by mitigating blind states and stating ongoing activity, a requirement for proposal integration.

VII. METHODOLOGICAL FRAMEWORK

The methodological framework for real-time anomaly detection in healthcare streams is organized along four binary dimensions: (1) families of unsupervised model types, (2) learning strategy—either batch or incremental with explicit support for labeled exceptions, (3) evaluation approach—using retrospective data for anomaly discovery or for monitoring in a continuous setting, and (4) criteria for assessing results in a streaming context.

Considered methods are clustering, density-based, isolation-based, and representation-learning models, together with incremental model versions in two cases—one designed for detecting known anomalies and the other explicitly evaluating their success in supervised settings.

Table 2: Healthcare Data Collections Used

Dataset	Domain	Stream Type	Purpose of Anomaly Detection
COVID-19 FHIR Streams	Infectious disease	Multinational event streams	Detect abnormal discharge, rapid deterioration
Taiwan Diabetes Monitoring System	Chronic disease	Physiological & clinical events	Alert serious patient status changes
Chronic Disease Patient Dashboard	Chronic care	Dashboard event streams	Early warning (fever, vitals, patterns)

Feature Extraction from FHIR Streams

When applying unsupervised learning methods to raw data, the general assumption is that the data contains exploitable patterns relevant to the application context. Feature extraction is often a necessary step in the pipeline leading to those methods. Data drawn from clinically relevant FHIR Healthcare Event Streams contain a wealth of attributes and information offered by resources, interoperability and the semantics of the events. Any combination of the resources and their corresponding data types can be treated as part of a pattern to be learned, since the FHIR Specification provides a normative description of the resources for authoring a pattern. However, the latest resources do not have a complete set of attributes and data types. Patterns formed by the available information can be quite common in the presence of these deficient resources.

In continuous streams, feature extraction operates over a sliding window. Events that can be matched to previous patterns are used to refine the model. Any suitable encoding can be adopted, based on the model family in use. There are well-known temporal features such as Inter-Event Time (IET), Inter-Arrival Time (IAT), Inter-Event Frequency (IEF), and higher-order statistics (central moments) that compose the temporal dimension of pieces of patterns. Resources that are in higher demand due to the clinical context may induce resources-level encodings with counts, entropy or auto-correlation as higher-order statistics. Windowed statistics may also incorporate domain knowledge indicators. For example, in Intensive Care Unit (ICU) events, source codes and associated drugs have been shown to be useful indicators of alarms during drug infusion.



VIII. SYSTEM ARCHITECTURE

The described system comprises three main components. The input streams, drawn from the healthcare domain and Azure (Health Data Service), present specialized data semantics and a lower operational maturity than common datasets from Kaggle, UCI Machine Learning Repository, and OpenML. This affects governance procedures, such as data policies, associated with the supporting cloud infrastructure. Nevertheless, the goal is to guarantee a low-latency execution path capable of supporting the application of the proposed models for real-time anomaly detection.

The system architecture is built on top of Microsoft Azure and is divided into three major layers: Data Ingestion, Stream Processing, and Data Storage. Data Ingestion takes care of receiving data from the FHIR streams and sending them downstream in a different message format to support subsequent stream processing. Stream Processing is a topology built with Apache Kafka and Kafka Streams capable of routing, performing simple transformations, applying windowing, controlling backpressure, and scaling.

Data Ingestion and Stream Processing Pipeline

The proposed solution incorporates a message broker, a stream processing framework, and a message format tailored to FHIR data. The high incidence of network and processing failures in real-world data acquisition systems necessitates a resilient design. The selected message broker, Apache Kafka, can persist data during ingestion and support stream processing through Kafka Streams or Apache Flink. Because the target anomaly-detection models operate directly on normalized and encoded FHIR event streams, these event streams must be synthesized, managed, and stored in Kafka.

The stream-processing pipeline is implemented as a page-structured, window-oriented, backpressure-aware topology, with customizable window types, window sizes, and sizes of state stores. To accommodate the target anomaly-detection models, all encoded event streams are persisted at low latency. Non-windowed streams that connect several SAPs are securely synchronized by introducing an appropriate back-pressure mechanism.

IX. CONCLUSION

The proposed use of unsupervised-learning-based techniques for anomaly detection in healthcare streams represented by FHIR messages is justified and supported by preliminary results. The defined method family successfully meets the adaptation constraints established for the problem statements. Further effects related to clinical assumptions and low-latency demand of the task are under investigation. Reliable training and normal-defense windows may be established by using a suitable set of FHIR event streams belonging to risk-free or normal clinical states.

The research design establishes the need for unsupervised techniques and delineates the procedure with a contrasting classification baseline. Results are reproducible by any external research peer. The publicly available method orthogonally complements other streams in the real-time domain. The focus on heterogeneous, rarely normal data and the absence of request-response synchronising signals, noise control, normal class level conditioning and certified healthy-risk temporal knowledge restrict the direct adaptation of supervised models. Four interrelated emerging trends are anticipated. Adaptive anomaly detection in healthcare requires continuous model learning directly from the incoming data. Detection results should be interpretable to decision makers and clinicians.

X. EMERGING TRENDS

Adaptation of models to the evolving nature of healthcare data streams will certainly remain an active area of investigation: recent works suggest a reduction of the time window needed to indicate concept drifts, complementing the existing literature that focuses on detection. This should further enhance the integration with inductive methods that are independent of a fully specified temporal order among events, such as the streaming of adversarial genetic representations for domain generalization. Another relevant area of ongoing research addresses the difficulty of modelling real-time flows reflecting interdependent multi-dimensional data with a mixed temporal behaviour, such as FHIR resources that project the time order of events and, simultaneously, capture the concurrency of a clinical workflow via the relevant nested structure.



Spatial and spatio-temporal extensions also deserve more attention. Some recent works propose the application of unsupervised anomaly detection methods on data originating from a fixed number of spatially distributed traffic sensors. A natural extension is to deal with a variable number of spatially distributed or mobility-related sensors, at the cost of integrating more complex representations of spatial relationships among embedded space-time points, such as spatio-temporal geometry. Another relevant avenue of research aims at exploring explainable unsupervised anomaly detection methods, enhancing interpretability and trustworthiness, and enabling non-expert users to better understand the instructions for an adequate treatment of detected anomalies. Further applications of unsupervised methods in healthcare data streams include approaches that protect the privacy of patients, using federated or differential privacy paradigms for model learning, and integrating anomaly detection techniques with support systems for clinical decision making, alerting medical experts to non-normal behaviours in patient follow-up data streams.

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