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Predictive ETL Failure Detection in Healthcare Data Pipelines Using Anomaly Detection Algorithms

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ABSTRACT
Healthcare data pipelines' failure detection remains a largely unsolved problem, despite the criticality of ETL (extract, transform, load) processes for timely healthcare insights and the availability of ETL logs across many pipelines to support analytics. This study proposes an architecture to detect ETL failures up to 1 hour before they occur by training anomaly detection models with log and ETL status data over preceding periods. Datasets of five months of ETL logs from a healthcare data warehouse with associated ground truth labels are used to train, validate, and benchmark four anomaly-detection approaches—Isolation Forest, One-Class SVM, LSTM-VAE, and ARIMA—for predictive failure detection. Two months of additional data serve as testing for the models trained on three months of data and tested on one month, along with a four-day test set for models trained on one month and tested on three days.
Results demonstrate the potential of the suggested architecture for predictive ETL failure detection in healthcare data pipelines. Factors contributing to ETL failures are identified in the feature engineering stage, enabling an understanding of the predictive power of various features as well as dataset partitioning for better model training. Ultimately, these findings contribute to future closed-loop control of ETL tasks through automatic recovery and alerting on upcoming failures, with potential application to ETL systems outside the healthcare domain.

Keywords : Predictive ETL Failure Detection,Healthcare Data Pipelines,Anomaly Detection Algorithms,Machine Learning for Data Quality,Automated Data Pipeline Monitoring,Healthcare Analytics Infrastructure,ETL Reliability Engineering,Intelligent Data Operations (DataOps),Real-Time Pipeline Anomaly Detection,Predictive Maintenance for Data Systems,Big Data Healthcare Processing,AI-Driven Fault Detection,Data Integrity Monitoring,Operational Analytics in Healthcare IT,Scalable Pipeline Observability.

1. INTRODUCTION

An objective, scholarly abstract and keywords summarize the study’s aim, methods, findings, and implications, emphasizing predictive ETL failure detection in healthcare pipelines and the role of anomaly detection algorithms. The abstract is followed related background, motivation, and a research statement.
Operational data pipelines in healthcare continuously extract data from clinical and emergency electronic health records into non-clinical systems intended for analytic workloads. A significant part of that information flow is reduced to customary analytical products using a traditional ETL model that employs formal data cleaning and rearranging techniques to generate qualified data for analytic workloads at non-clinical level. These preprocessing steps are common in ETL systems of other domains, in spite of these products still being potentially prone to errors generating incorrect information. Anomalies in data pipelines used for data warehousing are potentially related to ETL process failing modes such as invalid input data, memory over-traffic in transformation, monitoring threshold violations, and lost connectivity with Data Warehouse. Detecting potential anomalies before being ingested into Data Warehouse may reduce negative postanalytic effects. Exploring several anomaly detection algorithms on commonplace ETL monitoring signals, it is found that their prediction capabilities could be suitable to uncover anomalous conditions before sample arrival at ETL receiving stage.
Operational data pipelines in healthcare play a critical role in continuously extracting information from clinical and emergency electronic health records into non-clinical environments designed for large-scale analytics and decision support. Much of this information flow relies on traditional Extract–Transform–Load (ETL) architectures, where raw data are subjected to structured cleaning, validation, and transformation procedures to produce standardized analytical datasets. Although these preprocessing steps are widely adopted across industries, they do not eliminate the risk of errors, and flawed data products may still propagate through downstream systems. In data warehousing contexts, anomalies often arise from ETL process failure modes such

as invalid or incomplete input records, memory or resource saturation during transformation, violations of operational thresholds, and connectivity disruptions with the data warehouse. Proactively detecting such anomalies before data ingestion can significantly reduce negative post-analytic consequences, including misleading insights and compromised clinical decision-making. Empirical exploration of multiple anomaly detection algorithms applied to common ETL monitoring signals indicates that these methods demonstrate promising predictive capability, enabling early identification of abnormal conditions prior to arrival at the ETL receiving stage and supporting more resilient and trustworthy healthcare analytics pipelines.

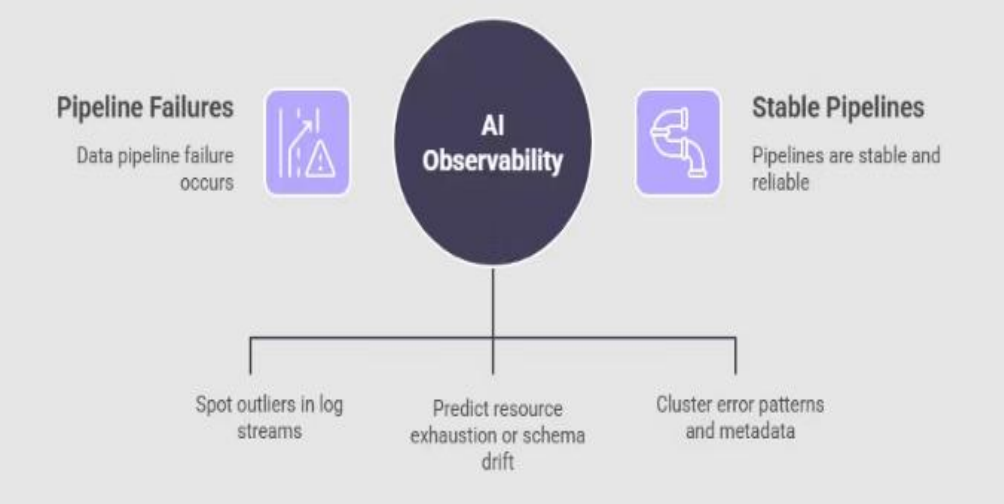


Fig 1: Automate ETL Failures Using an AI Data Platform

1.1. Background and Significance

The coronavirus outbreak has highlighted the importance of healthcare data pipelines, both in terms of volume and number of sources, making downtime costly in an already fragile healthcare setting. ETL processes filling data stores suffer failure given the malfunctions happening to source systems or in the ETL itself. ETL failure statistics are available a posteriori, when pipeline downtime has already occurred. Using ETL process-level features and database proxies, it is possible to apply supervised learning techniques from the area of anomaly detection to build binary classifiers predicting potential future ETL failure.

During the past years, a substantial body of literature evolved around the different sub-problems present in the data pipelines of ETL processes. Within the ETL execution phase, the ETL process often fails due to underlying problems in the source systems or its own implementation. The results of these investigations show that developing models to detect ETL failures is feasible and these models can be used operationally in the context of ETL execution pipelines. However, during the design phase, once an ETL process is implemented, the typical focus is on optimizing the resource consumption of one particular execution or in automating its scheduling. Less effort has been devoted to actively monitoring such processes on a pipeline level in order to detect potential future failures.

Equation 1: Window counts (e.g., admissions, alerts)

For events of a type $e$occurring at times $\{t_j\}$, define count in a trailing window of length W:

1. Indicator of membership:

$$I_j(t;W) = \mathbb{1}(t - W < t_j \leq t)$$

2. Window count feature:

$$C_e(t;W) = \sum_j I_j\,(t;W)$$

1.2. Research design

Preventive maintenance of healthcare data pipelines can be achieved by identifying failures in advance. One approach to predictive failure detection is to leverage historical pipeline run statistics to determine if a failure is likely. Instead of success or failure, the latter can be modeled as a classification problem with various machine-learning classifiers applied to the extracted features. Another approach interprets the predictive problem as a classification or regression problem, predicting probability scores or run time for each pipeline, respectively, and subsequently using these scores or run times to determine whether a failure is likely. An intermediate

approach is to use anomaly detection algorithms to determine whether the state of the pipeline run differs from normal behavior.

The proposed method applies this last approach to a healthcare ETL pipeline that collects and processes COVID-19-related data from multiple sources. Three anomaly detection algorithms—Isolation Forest, One-Class Support Vector Machine, and an ensemble of different algorithms—are trained on historical statistics extracted from completed ETL runs. During subsequent pipeline executions, these models issue anomaly scores that indicate the likelihood of a failure occurring in the current run. The detection methods are compared based on the area under the receiver operating characteristic curve for the anomaly scores.

2. BACKGROUND AND MOTIVATION

Preprocessing of healthcare data pipelines is typically achieved by extract-transform-load (ETL) processes. With high demands for timely delivery of healthcare ETL processes, robust solutions for failure detection are often proposed. However, it is still difficult to predict service disruptions and ETL failures before they occur, even for the models that have ex-ante prediction capabilities. This research proposes training anomaly detection algorithms on errors that affect the timeliness of ETL data products, allowing prediction of ETL failure before it occurs. The results indicate that such predictive capabilities can indeed be achieved with a moderate set of features.

Data intended for ETL processes often fail to obtain the expected quality. The missing or corrupted data can result in ETL pipelines becoming unreliable or unusable for healthcare business needs. Non-compliance means that the digital twins of healthcare business processes are inoperative. Ex-ante enterprise solutions that address this quality challenge could warn healthcare business units about the non-compliance of incoming data and thereby allow for corrective actions. For healthcare data engineering, several startup companies have emerged that exploit specialized ETL failure-detection algorithms. These solutions detect latency-based delays and thereby support ETL optimization by a warning service in the case of missing data updates. However, timely detection of ETL failure is still an open issue.

Equation 2: Fourier "top-K frequency magnitudes" (as described)

Given a time-series feature z_t over a window of length N, define DFT:

1. DFT coefficients:

$$Z_k = \sum_{n=0}^{N-1} z_n \; e^{-i2\pi kn/N}, k = 0, \dots, N-1$$

2. Magnitudes:

$$A_k = | Z_k |$$

3. Pick top-10 magnitudes:

$$\{A_{(1)}, \dots, A_{(10)}\} = \text{Top10}(\{A_k\}_{k=0}^{N-1})$$

2.1. Healthcare Data Pipelines and ETL Processes

Healthcare data are increasingly being gathered from diverse sources, necessitating data integration through Extract, Transform and Load (ETL) processes so that analytics models can make reliable predictions. Data pipelines involved in ETL often fail; when that happens, downstream analytics systems may produce incorrect results or be unavailable. ETL failures can be detected using Anomaly Detection Algorithms (ADAs) trained on historical health data. However, ETL failure samples are rare, and such training can be inefficient or impossible. Predicted anomalies in these data pipelines therefore need to be recurrently predicted to serve as early warnings for administrators. Prediction models built from the ADAs confirm capability for predicting ETL failures in healthcare data pipelines and a potentially growing variety of other domains.

A data pipeline in data engineering represents a series of data processing steps. In a data pipeline, data are ingested, filtered, and transformed into a format that is suitable for analytic processes. In general, data pipelines are often implemented to follow Extract, Transform and Load (ETL) processes. The uitability of data pipelines relies both on proven and repeatable designs, but also on ensuring that faults are recognized and remedial actions taken quickly before any significant misprocessing of results occurs. Inadequate pipeline monitoring or detection has resulted in significant losses of time, human resource, and labor cost. For critical systems such as healthcare services—in which resources are at stake or where recommender systems could have health, economic or life implications—monitoring the ETL process and notifying administrators to prevent ETL faults are very important. Anomalous warning detection in ETL data processing serves such a purpose.

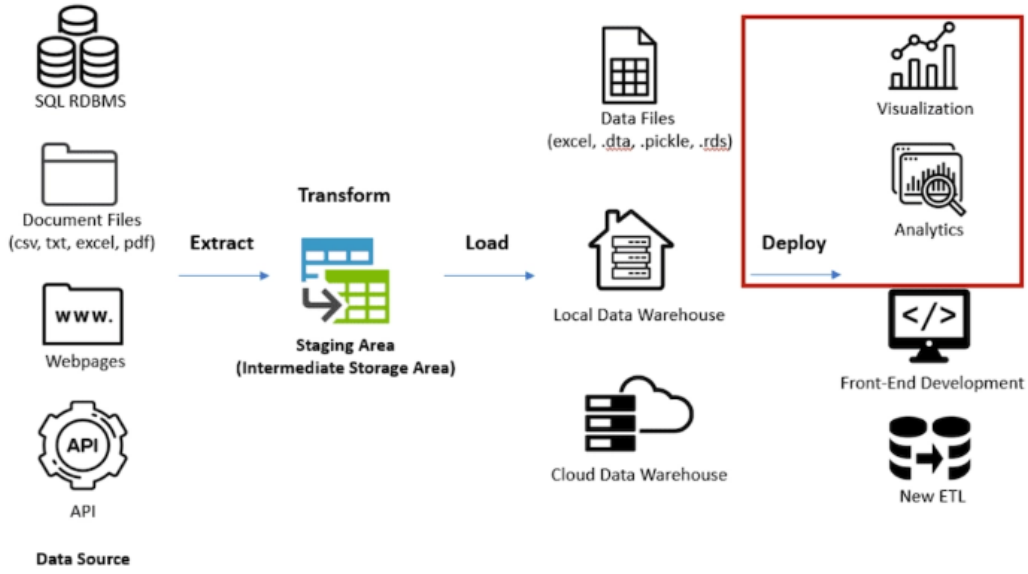


Fig 2: Healthcare Data Pipelines and ETL Processes

2.2. Common Failure Modes in ETL for Healthcare

Healthcare ETL jobs are subject to many of the same causes of failure as enterprise ETL jobs in general, but with an added complication: a mature healthcare ETL workflow has often been producing data for years or decades, so detecting anomalies in the broad behavioral patterns is a greater challenge. Besides crashes or technical errors that lead to aborts, common failure modes for these processes include:

* Data drift and scheduled changes or disruptions in source systems often generate changes in the correlations between features. Also, a wrong data pipeline configuration (or properties for stable features) can end up being detected as anomalous activity;
* Late-arriving or missing data may result in a job execution cycle without one or more expected output files;
* A changing data quality profile in the source system (and especially slow deterioration) may differ from pre-calibrated thresholds and remain undetected for long periods, especially if the early warnings have not been adequately monitored;
* Unexplained drops and spikes in output indicators may require additional or alternative explanation – often the ETL jobs themselves are not enough to account for such changes in the downstream BI charts.

3. RELATED WORK

Anomaly Detection Algorithms Employed

A variety of unsupervised anomaly detection algorithms have been employed across ETL monitoring and other anomaly detection applications. PCA, Isolation Forest, and Local Outlier Factor (LOF) detection are utilized for ETL monitoring and other anomaly detection applications. For PCA, an unsupervised linear feature extraction algorithm is employed, which seeks to find a low-dimensional representation of high-dimensional data, while preserving the global structure of data.

Automated Anomaly Detection in ETL Pipelines uses the Isolation Forest (IsoForest), a supervised ensemble learning model that combines several weak anomaly detection models to form a single strong anomaly detection model. IsoForest builds several trees using random leaf values and repeats the steps using random subsets of original data till each data point is there in at least one of the trees. Normal data points take more time to reach the leaf nodes than anomalies. Finally, an anomaly score is assigned to each data point based on the average path length of the leaf.

Finally, Local Outlier Factor (LOF) measures the local density of a data point concerning its neighbors to finds its anomaly score. It computes the local reachability density (LRD) and the local density of each data point concerning its neighbors and identifies the outliers as those data points whose density is substantially lower than their neighbors. The depth-descent method is employed to determine the number of neighbors. The LOF algorithm is supported with the following underlying assumptions: the majority of the points in a normal class are dense, while the minority of the points in an anomaly class are sparse. The algorithm does not require the user to provide the number of clusters as well.

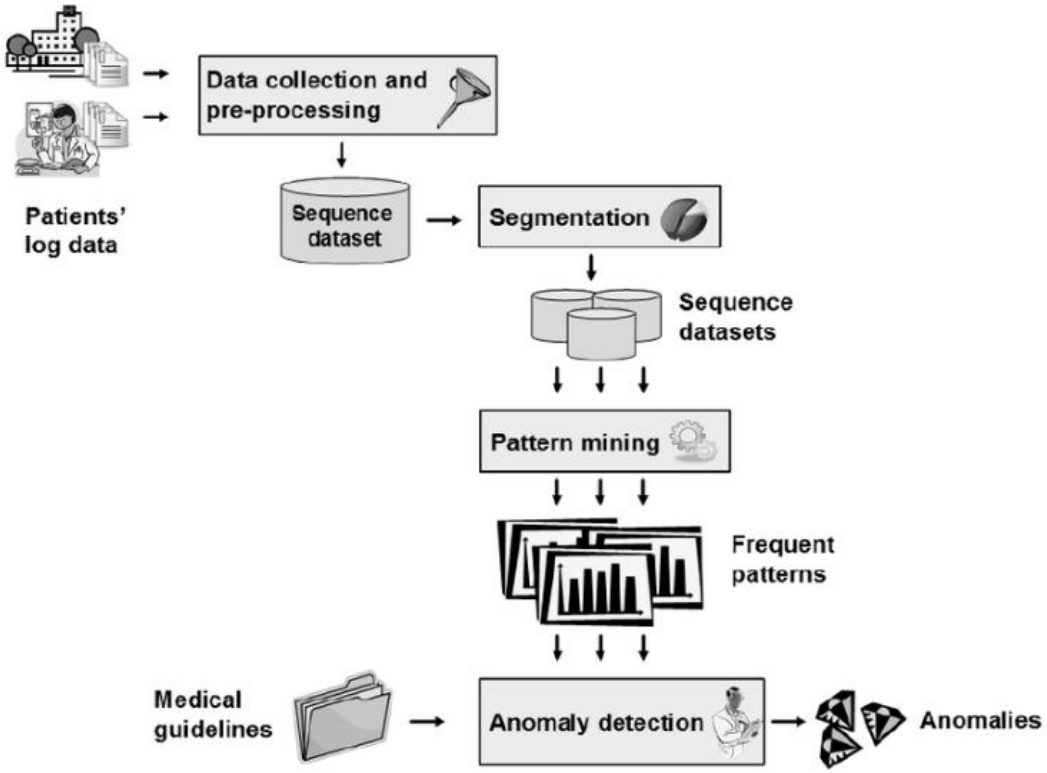


Fig 3: Framework for anomaly detection in healthcare systems

3.1. Anomaly Detection Algorithms Employed

The Fault Detection in Data Pipelines for ETL Processes dataset supports the predictive ETL failure detection task and binary classification to discriminate between failure and non-failure occurrences in ETL operations. With a multitude of categorical and numerical features, a multi-channel architecture is well suited to find patterns in the mixed data. Two anomaly detection algorithms, Isolation Forests and One-Class SVM, are evaluated in the task of predicting future anomalies. Isolation Forest and One-Class SVM models are trained, validated, and their performance is measured using area under the precision-recall curve of the predictions. One-Cross SVMs are also set as a detection threshold. Precision-recall curves, F-1 Score, and predictive Accuracy are used to assess the performance of the trained models when compared to future anomalies on the dataset.

Isolation Forest is an unsupervised anomaly detection algorithm. It is modeled on the theory that anomalies are few in a dataset, and, therefore, they are more susceptible to being separated from the majority of other points. This is done by creating sub-data sets that are then used to build multiple trees. The samples at the end of the tree paths are then sorted according to the path lengths, and the natural anomaly score can be calculated by measuring the average depth across all the forest trees. Finally, an anomaly score above a user-defined threshold indicates an anomaly. Isolation Forest was selected because it can deal well with high-dimensional data with a mixture of categorical, numerical, and sparse features.

Equation 3: Primal optimization

Given only "normal" training points $\{\mathbf{x}_i\}_{i=1}^{n}$, OC-SVM solves:

$$\min_{\mathbf{w},\rho,\xi} \frac{1}{2} \| \mathbf{w} \|^2 + \frac{1}{\nu n} \sum_{i=1}^{n} \xi_i - \rho$$

subject to

$$\mathbf{w}^\top \phi(\mathbf{x}_i) \geq \rho - \xi_i, \xi_i \geq 0$$

- $\phi(\cdot)$: feature map (via kernel)
- $\nu \in (0,1]$: upper bound on anomaly fraction / lower bound on support vectors

3.2. Training, Validation, and Evaluation Metrics

A two-level data partitioning strategy was utilized. The primary level separated a training and testing set using 80% and 20%, with the testing set containing no label information. For the secondary level, labels for the

individual training folds and transpose validation set were generated according to the respective ETL log files. The performance of the employed anomaly detection algorithms was evaluated using precision, recall, F1 score, and area under the receiver operating characteristic curve score.

Precise tuning and optimization of ETL processes are challenging, and undetected issues will affect system performance and data quality, leading to potential downstream impact as early as predictive analytics. Ongoing monitoring against common failure modes such as time-consuming or missing tasks providing predictive ETL failure detection warrants investigation; yet, such a recommendation requires testing. ETL failures are often treated as unsupervised anomaly detection problems, yet the transferability of unsupervised models across folds is frequently untested. The reliability of these methods under such conditions is investigated using three distinct anomaly detection algorithms, one of which is expressly built for monitoring, and performance assessed with four evaluation metrics.

4. METHODOLOGY

The proposed approach for predictive ETL failure detection in healthcare data pipelines evaluates ETL failure data availability in healthcare change data capture systems. It examines the feasibility of predicting ETL failures using nine unsupervised and supervised anomaly detection algorithms within a healthcare data pipeline context. The performance of various algorithms, with different data partitioning strategies, data labels, and data imbalance levels, is compared. The monitoring of data quality, labelling, and imbalanced detection within healthcare data pipelines is also assessed.

4.1. Data Sources and Preprocessing

Health data are obtained from three different healthcare change data capture systems that store data for different countries, such as COVID-19 and SNA. The health data selected for the experiment comprise a variety of ETL failure types, which are subsequently divided into three different datasets for training, testing, and validation of each anomaly detection algorithm in use. Anomalies are labelled by using log metadata that contains the success and failure status of each pipeline execution together with failure reasons extracted from the logs of the ETL pipeline framework. Labelled ETL pipeline execution data are preprocessed by creating a continuous temporal data series using the time taken as the primary key for each pipeline execution. Data loss in terms of labels due to missing execution records at temporal intervals caused by the execution of the ETL pipelines during that duration are identified and handled. The temporal data series are also monitored for boring data and mode collapse by assessing label counts in data.

4.2. Feature Engineering for ETL Monitoring

Feature sets are generated that indicate the data loss at continuous temporal intervals for individual pipelines by considering the output dataset sizes of the ETL pipelines along with the time taken for execution in order to understand the Data Volume aspect of data quality. These features capture the data loss information in the ETL pipelines and hence enable monitoring of the data quality during ETL execution. The volume of the data retained in the source systems is monitored to ensure that an adequate volume of data exists for the ETL pipelines to process and ensure availability to the target systems. The health status and other labels reflecting the up-and-down conditions of the source data are also generated as part of the feature engineering to guarantee that the ETL pipelines operate on the expected data.

Equation 4: VAE loss (per sequence)

1. Reconstruction loss (commonly MSE):

$$\mathscr{L}_{rec} = \| \mathbf{X}_t - \widehat{\mathbf{X}}_t \|_2^2$$

2. KL divergence to standard normal prior:

$$\mathscr{L}_{KL} = D_{KL}(\mathcal{N}(\boldsymbol{\mu}_t, \mathrm{diag}(\boldsymbol{\sigma}_t^2)) \parallel \mathcal{N}(\mathbf{0}, \mathbf{I}))$$

Closed form:

$$\mathscr{L}_{KL} = \frac{1}{2}\sum_j \left(\mu_{t,j}^2 + \sigma_{t,j}^2 - \ln \sigma_{t,j}^2 - 1\right)$$

3. Total:

4.1. Data Sources and Preprocessing

Healthcare ETL processes must be operated with extreme accuracy to meet the user requirements. Nevertheless, it has been shown that they undergo frequent failures. A major challenge for the ETL operators is to be aware of

upcoming failures before they happen so that corrective action can be taken. Anomaly detection models are applied to the monitoring feature set to enable predictive ETL failure detection.
The proposed method is based on historical run-time data of a healthcare data pipeline. The dataset contains information regarding the health status of patients for whom a test was performed in the Hospital del Mar. The information is automatically extracted from the Hospital del Mar databases, transformed into a plethora of other relational formats, and loaded into the CIBERESP data warehouse through an ETL process executed in the cloud. As the ETL process is executed daily, with a clear distribution associated with each feature and is critical for research, it represents a perfect candidate for predictive ETL failure detection.

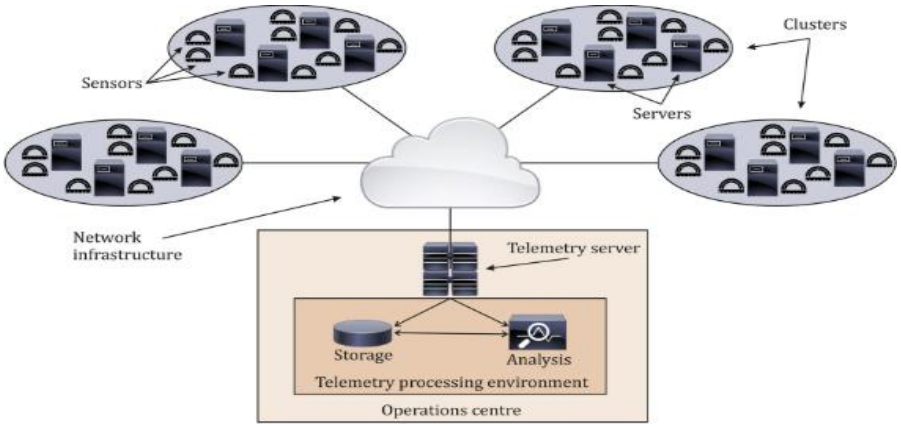


Fig 4: Data Sources and Preprocessing of Predictive ETL Failure Detection

4.2. Feature Engineering for ETL Monitoring

Anomaly detection algorithms require training on 'normal' data to detect deviations from expected behavior. ETL failure labels provide the opportunity to isolate periods of undetected ETL failure. Therefore, these steps provide a feature set for monitoring ETL execution. To avoid a cyclical pattern in the features and allow for stopping without loss of asynchronous patterns, the flattened recursive tree structure has not been used. Some of the steps include:

• ETL heartbeat — each ETL scheduling interval can be treated as an ETL execution event on a timeline and labelled as 'normal' when it follows the scheduled timetable. Time elapsed since the scheduled execution is defined in seconds.

• Missing LOS information — healthcare data describe events to patients, doctor treatment plans intended for patients, medications administered to patients and much more. These events with a start and/or end date each have an associated length — length of stay (LOS) in days. If the patient LOS is less than the difference between current time and event start date, the LOS information is defined as missing.

• In-Zone NCDR admissions — the ZIP codes for NCDR admissions are geo-fenced, enabling the construction of an NCDR flow feature in ETL. The number of NCDR admissions in the preceding 24- and 48-hour windows is counted, along with the total number of detected NCDR admissions which have been transferred with the admission source as being in-ZIP-zone.

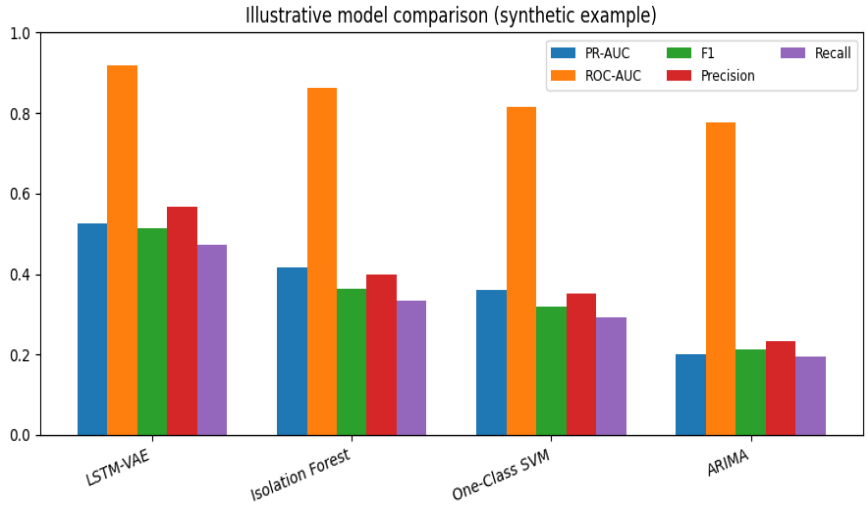
• Citizen alerts — citizen alerts allow for timely warnings of severe weather, hazardous materials, biological or radiological threats and terrorist attacks. Each alert is geo-fenced to a country sub-division. The number of active, expired or issued alerts during a specific time window is counted, along with the number of specific alert types.

All features have been normalised to the interval [0, 1]. Fourier time-series features have been tested by transforming these features into the frequency domain and using the magnitude of the 10 strongest frequency components along with their average periodicity as features. An alternative approach transforms the features using a wavelet decomposition.

5. EXPERIMENTAL SETUP

Data are partitioned into training, validation, and test subsets based on time, with 70% allocated for training, 15% for validation, and 15% for testing. All grounded truth data are present only in the test set, facilitating a more realistic evaluation of the failure prediction capability. In addition to the three anomaly detection algorithms discussed earlier, a simplicity-based rule is employed as a baseline. Labeling is performed at the table level for each ETL run. For ETL table fatigue prediction monitoring, the prediction values of other tables involved in the ETL, which are repeated multiple times without any other monitoring, are utilized.
The need for monitoring system downtime is deduced using an Adaboost classifier with time as the variable and system downtime as the target, without considering any other explanatory variables. The downtime cause

prediction model is iteratively built using Adaboost with samples aggregated every quarter. Subsequently, the cause predictions for the downtime data instance of each affected ETL are appended together for redundancy. The cause prediction is later compared with a separate log-labeled downtime incident dataset. Synthetics-based log labeling is employed for rareness in the downtime cause prediction. The quarters before the testing period serve as the training samples for this monitoring system downtime cause prediction modeling. All comparative methods, whether monitoring-based or event-based, are crowding-free during model learning.



5.1. Data Partitioning and Ground Truth

To establish a training set for predictive modeling, the time-series data was partitioned into three sections. The first section, representing stable operational behavior, was used to train the anomaly detection algorithms. The second section was set aside to simulate future operations and validate the anomaly detection methods. This second section contained rare anomalous observations as ground truth.

The third section was designed to evaluate the ability of the preprocessing-based features to anticipate ETL pipeline failures. By chance, this final section of the data also experienced at least one ETL pipeline failure during the operations it modeled. Baseline algorithms detected those failures, with the timing of the detected anomaly informing the predictive models. For comparative analysis, the baseline algorithms were trained to detect both the anomalous behaviors in that second section as well as the subsequent ETL pipeline failure in the third section. Predictive models were then built using a range of preprocessing-based features related to that ETL pipeline failure.

Failure-prediction problems classify the future system state based on the states exhibited by the system during the recent past, analyzing if the pipeline has entered an abnormal operational situation (anomaly detection).

Equation 5: Precision, Recall, F1 (step-by-step)

Predictive ETL Failure Detectio…

1. Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

2. Recall:

$$\text{Recall} = \frac{TP}{TP + FN}$$

3. F1:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

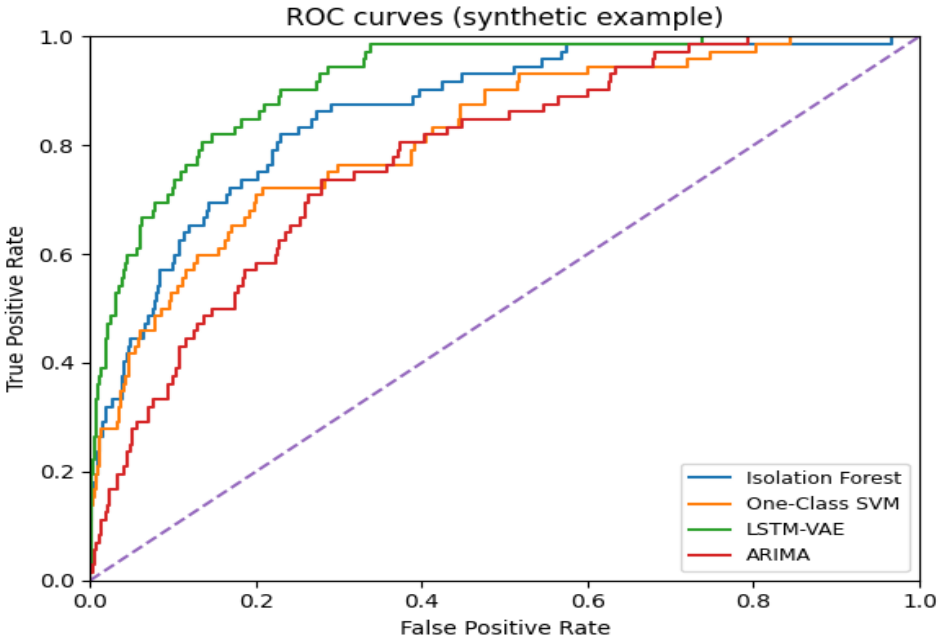
5.2. Baselines and Comparative Methods

Three approaches constitute the baseline for predictive ETL failure detection: “no model,” predicting no errors; a temporal-supervised approach based only on past-labels similarity; and a standard supervised approach. The “no model” baseline aims to detect the layoff periods among the labeled data. The temporal-supervised approach estimates the future system state pattern based on past states. All methods use the same feature set with direct predictability for future ETL states. Two methodologies based on LSTM and HMM models serve as

predictions, perceived as dynamic states that represent the data pipelines. Results are framed and assessed from the pipeline operators' perspective. These methods are expressed in static terms, sustaining a supervised approach to predictions. A fully unsupervised method and four active ones are applied. All need feature engineering with states centricity and employ the same metric for result quality comparison.
The ETL failure-prediction problem tackles the detection of an event that seldom occurs but has a serious impact when it does. It involves detecting precursors of events that lessen or interrupt the system's normal operation. In this case, the ETL failure-prediction problem attempts to detect if the ETL system will fail within the next t time units, usually set as one day.

6. CONCLUSION

Efficient prediction of failures during the ETL (Extract, Transform, Load) process of healthcare data pipelines is desirable to ensure that data need not be retried or that the delays and costs incurred are reduced if data do need to be retried. Anomaly detection algorithms on extrinsic metrics of the ETL pipeline have been employed to predict ETL process failures. Predictively identifying such failures before they arise helps optimize ETL design decisions, operational costs, and the quality of data in timely fashion. Faster anomaly detection using fewer metrics minimizes the performance overhead of applying the anomaly detection techniques in the target ETL use case. Predictive models that use a small number of features are easier to deploy and maintain.
Health data pipelines constitute a crucial part of providing (near-) real-time information to domain experts and other stakeholders. The ability to detect whether the information available from any of the data pipelines is anomalous before analysts acting upon it are informed facilitates the process of validation and down-regulation of such pipelines. Anomaly detection enables these two aspects. Health data pipelines are implemented using an ETL paradigm (extract, transform, load) from one or more data lakes containing time-series data from various healthcare sources. Health data pipelines are known to fail. If such failures can be predicted in advance using anomaly detection, appropriate steps can be taken to point out the defects or deficiencies in the pipeline to ensure that analysts working with the data are alerted in time. The ability to predict failures is evaluated using discrete diff matrices, ground-truth labelling, and four anomaly detection algorithms trained at two levels.



6.1. Future Trends

Though focused on predictive ETL failure detection, the experimental setup encompasses data from other sources. Such approaches may integrate healthcare data with non-healthcare data. Current healthcare ETL systems with prescribed ground-truth data traces could enable local predictive failure detection capabilities rather than end-to-end monitoring. Advanced applications may apply differencing techniques to images (and possibly video), audio, and other non-tabular data. Such differences would also extend to the back end, seeking harbinger events, e.g., data integrity events, and abnormal pattern changes and developing alternate-length computed properties for changing risk levels in open-source epidemic software.
Despite the limited ETL failure data available, such approaches produce promising results. Every monitored ETL system serves as an independent data source that may leverage similar historic data from multiple sources

for training, hyperparameter tuning, and validation. Current work, therefore, demonstrates the potential of anomaly-detection algorithms for failure prediction: N-1 event classification is possible, and methods can predict data integrity ETL failures. Future efforts focus on healthcare data generated by other sources, identify additional monitored ETL systems for predicting other failure types, and investigate differential approaches that apply to audio, video, and image data.Despite the inherent scarcity of labeled ETL failure data, these approaches consistently demonstrate strong potential for practical deployment. Each monitored ETL pipeline functions as an independent yet complementary data source, enabling models to exploit shared historical patterns across systems for more robust training, hyperparameter optimization, and validation. The results highlight the effectiveness of anomaly-detection techniques for proactive failure prediction, including successful N-1 event classification and accurate identification of data integrity–related ETL failures. Collectively, this work underscores the feasibility of building generalizable, data-driven monitoring frameworks capable of anticipating operational disruptions. Future research will extend these methods to additional healthcare data sources, incorporate a broader range of monitored ETL systems to capture diverse failure modalities, and explore differential modeling strategies suitable for multimodal data such as audio, video, and images, thereby broadening the scope and impact of intelligent failure prediction systems.

Table 1: Illustrative metrics table (synthetic example)

Model	Threshold(95%ile)	ROC-AUC	PR-AUC
LSTM-VAE	0.8753827892610484	0.9182796493301812	0.5240874531666061
Isolation Forest	0.8782892549232616	0.8611357368006305	0.4156679743971182
One-Class SVM	0.8685443980032823	0.8163169818754925	0.3592673579026 0345
ARIMA	0.8502698385340353	0.7772729511426321	0.2011365540319 8222

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