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DAM SAFETY: AN INTELLIGENT MODEL FOR ANOMALY DETECTION IN INSTRUMENTATION DATA

SEGURANÇA DE BARRAGENS: UM MODELO INTELIGENTE PARA A DETECÇÃO DE ANOMALIAS EM DADOS DE INSTRUMENTAÇÃO

SEGURIDAD DE PRESAS: UN MODELO INTELIGENTE PARA LA DETECCIÓN DE ANOMALÍAS EN LOS DATOS DE INSTRUMENTACIÓN

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ABSTRACT
Dam safety is an area of high criticality in engineering, where early detection of anomalies is critical to prevent disasters. Traditional monitoring methods often analyze instrumentation data in isolation, failing to identify complex, contextual deviations that may foreshadow structural failures. This work proposes and validates an advanced methodology for the detection of anomalies in dam monitoring data, based on the synergy between a robust attribute engineering and the Local Outlier Factor (LOF) unsupervised machine learning algorithm. Using a synthetic dataset that emulates the behavior of multiple instruments (piezometers, water level indicators, Pars-hall flume and rain gauges.) over three years, the model was trained to identify normality patterns in a multidimensional space. The results demonstrate the conclusive superiority of the proposed approach, which achieved an F1-Score of 0.868 and, crucially, an accuracy of 100%, eliminating the occurrence of false positives. In contrast, traditional methods such as Boxplot and Linear Regression performed significantly less. The qualitative analysis confirmed the model's ability to detect contimental anomalies, such as flow peaks in periods of drought, which would be ignored by univariate analyses. It is concluded that the methodology not only increases the reliability of detection, but also provides a basis for diagnosing the nature of anomalies, representing a significant advance for the intelligent automation of dam structural health monitoring.

Keywords: Technology. Prevention. Data. Analysis. Instruments. Control.

RESUMO
A segurança de barragens é uma área de alta criticidade na engenharia, onde a detecção precoce de anomalias é fundamental para prevenir desastres. Métodos tradicionais de monitoramento frequentemente analisam dados de instrumenta- ção de forma isolada,

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falhando em identificar desvios complexos e contextuais que podem prenunciar falhas estruturais. Este trabalho propõe e valida uma me- todologia avançada para a detecção de anomalias em dados de monitoramento de barragens, baseada na sinergia entre uma robusta engenharia de atributos e o algoritmo de aprendizado de máquina não supervisionado Local Outlier Factor (LOF). Utilizando um conjunto de dados sintético que emula o comportamento de múltiplos instrumentos (piezômetros, indicadores de nível d'água, Calha Pars- hall e pluviômetros.) ao longo de três anos, o modelo foi treinado para identificar padrões de normalidade em um espaço multidimensional. Os resultados de- monstram a superioridade conclusiva da abordagem proposta, que alcançou um F1-Score de 0,868 e, crucialmente, uma precisão de 100%, eliminando a ocor- rência de falsos positivos. Em contraste, métodos tradicionais como Boxplot e Regressão Linear apresentaram desempenho significativamente inferior. A aná- lise qualitativa confirmou a capacidade do modelo de detectar anomalias contex- tuais, como picos de vazão em períodos de estiagem, que seriam ignorados por análises univariadas. Conclui-se que a metodologia não apenas eleva a confia- bilidade da detecção, mas também fornece uma base para o diagnóstico da na- tureza das anomalias, representando um avanço significativo para a automação inteligente do monitoramento da saúde estrutural de barragens.

Palavras-chave: Tecnologia. Prevenção. Dados. Análise. Instrumentos. Controle.

RESUMEN
La seguridad de presas es un área crítica en ingeniería, donde la detección temprana de anomalías es crucial para prevenir desastres. Los métodos tradicionales de monitoreo suelen analizar los datos de instrumentación de forma aislada, sin identificar desviaciones complejas y contextuales que pueden anticipar fallas estructurales. Este trabajo propone y valida una metodología avanzada para la detección de anomalías en datos de monitoreo de presas, basada en la sinergia entre la ingeniería robusta de características y el algoritmo de aprendizaje automático no supervisado Local Outlier Factor (LOF). Utilizando un conjunto de datos sintéticos que emula el comportamiento de múltiples instrumentos (piezómetros, medidores de nivel de agua, canales Parshall y pluviómetros) durante tres años, el modelo se entrenó para identificar patrones normales en un espacio multidimensional. Los resultados demuestran la superioridad concluyente del enfoque propuesto, que alcanzó una puntuación F1 de 0,868 y, crucialmente, una precisión del 100 %, eliminando los falsos positivos. Por el contrario, los métodos tradicionales como el diagrama de caja y la regresión lineal obtuvieron un rendimiento significativamente peor. El análisis cualitativo confirmó la capacidad del modelo para detectar anomalías contextuales, como los caudales máximos durante los períodos secos, que de otro modo pasarían desapercibidas mediante análisis univariados. Se concluye que la metodología no solo aumenta la fiabilidad de la detección, sino que también proporciona una base para diagnosticar la naturaleza de las anomalías, lo que representa un avance significativo para la automatización inteligente del monitoreo de la salud estructural de las presas.

Palabras clave: Tecnología. Prevención. Datos. Análisis. Instrumentos. Control.

1 INTRODUCTION

Dams are vital engineering structures for socioeconomic development, serving purposes such as water supply, power generation, and tailings containment. However, the history of dam engineering is marked by catastrophic failures, including the recent disasters in Mariana (2015) and Brumadinho (2019) in Brazil, which highlighted the urgent need to improve safety practices. The response to these events has been tightening regulations and a push for the adoption of more advanced monitoring technologies.

Monitoring the structural health of a dam is carried out through a network of instruments, such as piezometers (PZ), water level indicators (INA), flow meters (Parshall Channel) and rain gauges. Traditionally, the analysis of the data generated by these instruments is done in isolation or through simple correlations. This approach is insufficient to capture the complex interplay between the various physical variables that govern the behavior of the structure. The main gap in current practices is the difficulty in detecting contextual anomalies, deviations that are not extreme in magnitude, but that are anomalous given the operational context as an increase in pore pressure without the corresponding increase in the reservoir level.

This work addresses this gap, with the aim of developing and validating a machine learning-based methodology for the detection of anomalies in dam monitoring data. The study focuses on the integrated analysis of data from multiple instruments, using the Local Outlier Factor (LOF) algorithm powered by domain-informed attribute engineering. The central hypothesis is that this approach can identify subtle and contextual deviations with greater accuracy and reliability than traditional statistical methods, providing a more effective tool for analysis of safety.

2 THEORETICAL FRAMEWORK

The monitoring of a dam is based on the continuous measurement of key parameters. Piezometers are geotechnical instruments that measure the pore pressure (neutral pressure) inside the massifs and in their foundations, a critical parameter for stability analysis. Piezometric monitoring is crucial to verify the position of the water table and detect irregular percolations, since an unexpected increase in pore pressure can reduce soil strength and decrease the safety factor of the structure. Water Level Indicators monitor hydrostatic load, while Parshall Troughs have their most critical application in the continuous measurement of percolation flow collected by drain systems. The Parshall Channel is considered an early warning instrument of very high relevance, as a sudden increase in the flow can indicate the beginning of an internal erosion process.

Isolated analysis of the data is insufficient; The real potential lies in integrated analysis to understand cause-and-effect relationships, establishing a signature of normality for the structure. The correlation between the reservoir level and the percolation flow rate is vital, as a disproportionate increase in the flow rate in relation to the level can be a strong indication of internal erosive processes. According to Dunnicliff (1993), the fundamental purpose of monitoring is not only to record data, but to identify, as early as possible, any deviations from the expected and safe performance. An anomaly, defined as data that does not fit the standard of normality, can indicate both a structural pathology and a failure in the measurement system, a duality that requires careful investigation.

The interpretation of these data has evolved from subjective graphical analyses to quantitative methods, whose intrinsic objective is to build a reliable model of the "normal behavior" of the structure. Graphical analysis, although simple and capable of revealing obvious trends for an experienced engineer, is limited by subjectivity. To overcome this, statistical models such as least squares regression have been applied, but their effectiveness is compromised by the rise sensitivity to outliers, which can distort the model and mask the very anomaly that is to be detected. As an evolution, robust regression models emerged, designed to be less influenced by outliers. The work of Han et al. (2023) is exemplary, proposing an online outlier recognition method based on improved M-robust regression, which increases the reliability of the alert system.

The frontier of research lies in artificial intelligence algorithms that learn complex patterns directly from data. According to Salazar et al. (2017), machine learning algorithms can be trained with historical data to learn normal behavior and issue automatic alerts. Among them, the Local Outlier Factor (LOF), proposed by Breunig et al. (2000), stands out for being a density-based algorithm that evaluates the degree of isolation of a point in relation to its local neighborhood. Its main advantage is the ability to detect contextual anomalies and its multidimensional nature, crucial for the early detection of complex failure mechanisms that manifest themselves through small but simultaneous changes in multiple instruments. The approach can be extended to a multipoint analysis, which allows the identification of shape anomalies, such as the atypical response of an instrument to an external event. The implementation of such models in real-time systems, as explored by Li et al. (2020), is a growing trend to create automated and efficient early warning systems.

3 METHODOLOGY

To develop and validate the model rigorously, a quantitative and experimental methodology was adopted in four main steps.

3.1 SYNTHETIC DATA GENERATION

A synthetic dataset was generated in Python, simulating daily readings from 12 instruments (1 rain gauge, 3 INAs, 6 PZs and 2 CPs) over three years. This approach allowed for the creation of a controlled environment with known and labeled anomalies (4% of the data), outperforming the main limitation of real data (which are not labeled) and enabling an objective evaluation of the model's performance with metrics such as accuracy and recall. The synthesis incorporated seasonality, physical correlations between the instruments, and Gaussian noise to emulate the actual behavior.

3.2 ATTRIBUTE ENGINEERING

The transformation of raw data into informative attributes was the most critical step. The objective was to provide the algorithm with the necessary temporal and physical context for an intelligent analysis. Four types of attributes were created. Multi-scale temporal attributes using Z-Scores calculated in mobile windows of 3, 7 and 30 days to capture deviations in different time scales. This method is exemplified in equation 1.

$$Z-Score_w(x_t) = \frac{x_t - \mu_w(t)}{\sigma_w(t) + \epsilon} \quad (1)$$

Where:

xt = value of reading at time t

μw(t) = moving average of the reading with window w

σw(t) = movable standard deviation of reading with window w

ε = small constant to avoid division by zero

Trend attributes that demonstrate deviation from the exponentially weighted moving average (EWMA) to identify breaks in the current trend. EWMA is defined by equation 2.

$$EWMA_t = \alpha \cdot x_t + (1 - \alpha) \cdot EWMA_{t-1} \qquad (2)$$

Where:

xt = value of reading at time t

α = is the smoothing factor

Attributes of sudden variation showing the daily difference in readings to detect abrupt peaks or falls, calculated following equation 3.

$$\text{Variation1d}(t) = \text{xt} - \text{x}_{t-1} \qquad (3)$$

Where:

xt = value of reading at time t

Attributes of physical context, being the ratios between instruments to explicitly model the expected physical interrelationships. They are demonstrated in equation 4 and equation 5.

$$\text{PZ/INA Reason} = \frac{\text{AveragePZ} + 1}{\text{AverageINA} + 1} \qquad (4)$$

$$\text{Flow Rate} = \frac{\text{CP+0.1 Rain}}{\text{+0.1 Flow}} \qquad (5)$$

3.3 LOCAL OUTLIER FACTOR

Local outlier factor (LOF) is an unsupervised method that quantifies the degree of anomaly of a data point based on its local density relative to its nearest neighbors. The fundamental principle is that other beings have a significantly lower density compared to neighboring points.

The mathematical formalization of lof starts from some key definitions. The reachability distance of a point P with respect to a point O is defined as the maximum between the actual distance between them and the K-distance of O (the distance to its nearest Kth neighbor). This definition is demonstrated in equation 6.

$$\mathrm{reachdistk}(p, o) = \max\{d(p, \mathrm{the}), k - \mathrm{distance}(o)\} \quad (6)$$

Where:

$d(p, o)$ = Euclidean distance between points p and o;

$k - \mathrm{distance}(o)$ = distance between the and its nearest kth neighbor.

From it, the local reachability density of a point p is calculated, which is the inverse of the average of the reachability distances of p to its neighboring k. The calculation is done using equation 7.

$$\mathrm{lrdk}(p) = \frac{|\mathrm{Nk}(p)|}{\sum_{0 \in \mathrm{Nk}(p)} \mathrm{reachdistk}(p,o)} \quad (7)$$

Where:

$\mathrm{Nk}(p)$ = set of k closest neighbors of p;

Finally, the Local Outlier Factor of p is the average ratio of the local reachability density of its neighbors to its own local reachability density. Equation 8 was used to calculate the LOF value.

$$LOF_k(p) = \frac{1}{|N_k(p)|} \sum_{0 \epsilon N_k(p)} \frac{lrd_k(o)}{lrd_k(p)} \quad (8)$$

Where:

$\mathrm{Nk}(p)$ = set of k nearest neighbors of p

$\mathrm{LRDK}(p)$ = local reachability density of p

An LOF value close to 1 suggests that the point p has a density similar to that of its neighbors (inlier). A value significantly greater than 1 indicates which is in a much less dense region than its neighbors, and is therefore an outlier. The implementation was carried out in Python, using the scikit-learn library, treating each instant of time as a vector of high dimensionality composed of all the readings and attributes generated.

3.4 VALIDATION AND PERFORMANCE METRICS

The performance of the LOF model was compared with three standard statistical methods, namely standard deviation, boxplot and linear regression. The evaluation was made using the classification metrics, made possible by the use of labeled synthetic data. Accuracy that measures the proportion of correct detections among all alerts generated by the model. It's demonstrating in equation 9.

$$\text{Accuracv} = \frac{\text{True Positives True}}{\text{Positives+Fal} \qquad \text{Positive}} \tag{9}$$

The Recall (Sensitivity) demonstrates the proportion of real anomalies that the model was able to find. It is exemplified in equation 10.

$$\text{Recall} = \frac{\text{True Positives True Positives+Fals}}{\text{Negative}} \tag{10}$$

The F1-Score is the harmonic mean between Accuracy and Recall, used as the main metric for optimization. It is presented in equation 11.

$$\text{F1} - \text{Score} = 2 \cdot \frac{\text{Accuracy} \cdot \text{Recall}}{\text{Accuracy+Recal l}} \tag{11}$$

4 RESULTS AND DISCUSSIONS

The optimization of hyperparameters resulted in a final configuration of the LOF model with n_neighbors=25 and an anomaly percentile of 97%, achieving a maximum F1-Score of 0.868. The comparative analysis of performance, consolidated in Table 1, reveals the superiority of the proposed approach

Table 1

Comparative table of performance of detection models

Method	Precision	Recall (Sensitivity)	F1-Score
LOF	1,000	0,767	0,868
Standard Deviation (3-Sigma)	0,634	0,605	0,619
Linear Regression	1,000	0,302	0,464
Boxplot	0,115	0,512	0,187

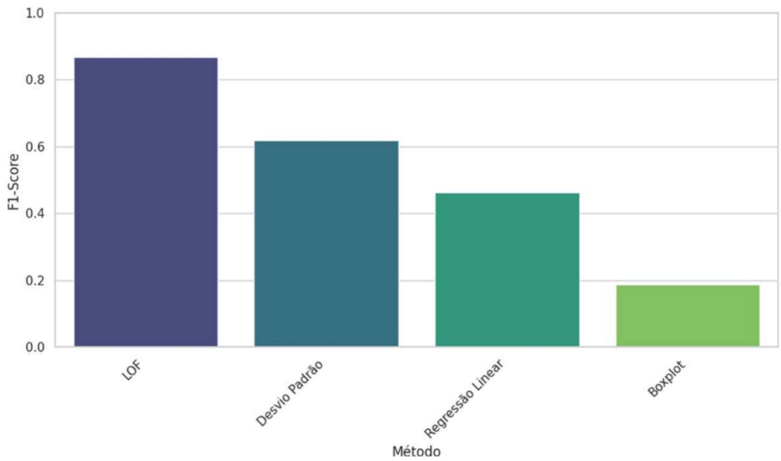
Source: Prepared by the authors, 2025.

The most striking result is the LOF model's accuracy of 1,000, indicating the total absence of false positives. Operationally, this is crucial as it eliminates "alarm fatigue" and ensures that every alert generated by the system is credible and worthy of investigation. The Recall of 0.767 demonstrates that the model was able to identify more than 76% of the actual anomalies, a high sensitivity for a safety-critical application. The F1-Score of 0.868 confirms the outstanding balance between the two metrics.

In contrast, traditional methods have failed because of their inability to interpret context. The Boxplot, being univariate, classified normal seasonal variations as anomalies, resulting in a very low accuracy (0.115). Linear Regression, although accurate, was unable to model the complexity of the system, leading to a very low recall (0.302). Figure 1 shows the comparison between the methods by the F1-Score metric.

Figure 1

Graph comparing F1-Score result between methods

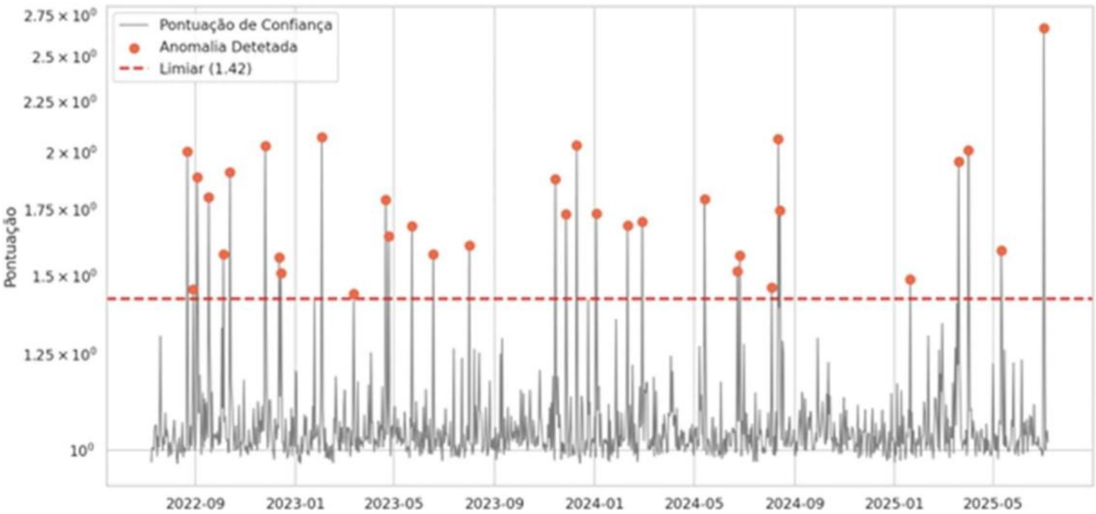


Source: Prepared by the authors, 2025.

Figure 2 presents the time series of the confidence score generated by the LOF for each data point, where the points classified as anomalies are highlighted, exceeding the detection threshold. Red dots indicate detected anomalies that exceed the classification threshold (dashed line), calculated from the optimal percentile of 97.0%. The Y-axis is in logarithmic scale for better visualization.

Figure 2

Historical Confidence Score Chart



Source: Prepared by the authors, 2025.

A specific analysis was carried out to evaluate the model's performance in the most recent period, corresponding to the last six months of the data set. Table 2 presents the metrics for this interval.

Table 2

Model Performance Metrics in the Last 6 Months Metric

Precision	1,000
Recall (Sensitivity)	0,833
F1-Score	0,909

Source: Prepared by the authors, 2025.

Based on the performance analysis, a significant improvement is observed in the evaluation metrics, notably in the F1-Score, when considering the last six months of the three-year period compared to the full assessment. The main reason for this evolution lies in the progressive maturation of temporal attributes, which form the basis of the predictive capacity of the model. At the beginning of the analysis period, the 30-day Z-Score, or the deviation from the exponential moving average, is calculated with a limited data history, resulting in a less reliable definition of normal behavior. However, after accumulating a history of approximately two and a half years, these same attributes reach a state of robustness, as they have already incorporated multiple seasonal cycles, rain events, and several days of regular operation. Consequently, the baseline that defines normality becomes very well established, allowing the model to discern with high precision subtle deviations from common operational variations.

This maturation of the attributes directly impacts the effectiveness of the density model, which operates by learning the typical distribution of normal data points. The overall performance, calculated over the three years, is inevitably attenuated by the inclusion of the initial learning period, in which the model's definition of normality was still being consolidated. In contrast, the assessment focused on the last six months reflects the model's performance in its mature state, where a solid understanding of normal data maximizes its ability to identify anomalies.

Table 3 details examples of anomalies detected in the last 6 months, accompanied by the automatic diagnosis generated by the system. The diagnosis is inferred from the attributes that most contributed to the high LOF score of the point, offering an initial insight to the security team.

Table 3

Sample of Anomalies Detected and Diagnosis Generated (Last 6 Months)

DATE	Affected Instrument(s)	Pont. LOF	Possible Diagnosis
15/03/2025	CP_1	3.54	Unexpected high flow (no rain)
02/05/2025	PZ_3, PZ_4	5.21	Persistent deviation from the monthly average
18/06/2025	INA_1	4.77	Sharp/sudden daily variation

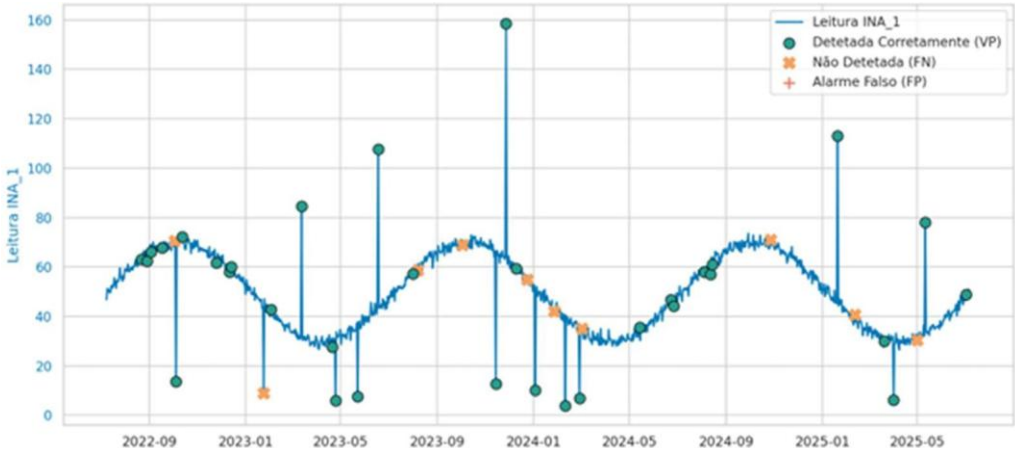
Source: Prepared by the authors, 2025.

In short, the performance improvement shows that the system operates at its maximum capacity when its temporal attributes are fully mature, demonstrating a fundamental characteristic of intelligent monitoring systems: the ability to become more reliable and accurate as they accumulate more experience.

Qualitative analysis reinforces these findings. The model was able to correctly identify a peak flow in a Parshall Channel as anomalous, not because of its magnitude, but because it occurred during a period without rainfall. This detection of a break in the expected physical correlation is something that univariate or simple regression methods would not be able to do. Reading histories are presented below, with Figure 3 being the readings of INA 1, Figure 4 of PZ4 and Figure 5 of CP1. Points classified as True Positive (PV), False Negative (FN) and False Positive (FP) are highlighted, allowing visual evaluation of the model's performance for this specific instrument

Figure 3

Instrument Reading Water Level Indicator 1



Source: Prepared by the authors, 2025.

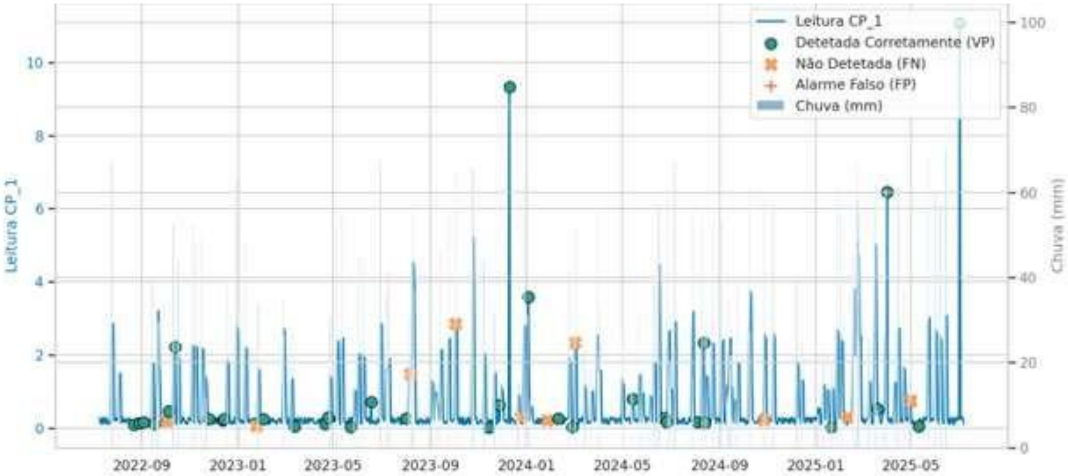
Figure 4

Reading the Piezometer 4 instrument

Source: Prepared by the authors, 2025.

Figure 5

Reading the Parshall Rail 1 Instrument



Source: Prepared by the authors, 2025.

5 CONCLUSION

This work demonstrated that the combination of domain-informed attrition engineering with the Local Outlier Factor algorithm constitutes a robust and meaningful methodology for the detection of anomalies in dam monitoring data. The main contribution does not lie in the isolated application of an algorithm, but in the synergy created, which allows the model to interpret the physical and temporal context of the data.

The quantitative results, especially the 100% accuracy and high recall, validate the approach as a reliable tool, capable of transforming the monitoring of a reactive process into a proactive and intelligent. The proposed system not only warns of deviations, but also provides insights for a preliminary diagnosis, optimizing the time and resources of the engineering team.

In short, the validated methodology represents a qualitative advance in dam safety, offering an intelligent sentinel that amplifies the surveillance capacity of engineers, allowing human attention to be focused where it is most critical and strengthening the safety culture in the management of these vital structures

6 RECOMMENDATIONS FOR FUTURE WORK

The limitations recognized in this study pave a clear path for future investigations, aiming to further bring the academic prototype closer to a high-impact engineering solution. The next more critical step is the application and validation of the entire structure in a set of historical monitoring data of a real dam, which will require partnerships with regulatory agencies or operators to obtain data and the domain knowledge of their engineers to validate the anomalies and explanations generated, testing the robustness of the methodology against challenges such as missing values and noise.

To rigorously position the approach, it is essential to conduct a comprehensive comparative study of the LOF model against other prominent anomaly detection algorithms in the literature, evaluating not only performance metrics but also inference time and demand for computational resources. It is imperative that future implementations consider the evolution of normal dam behavior over time. A real system should include mechanisms for continuous monitoring of model performance and for periodic retraining. Finally, there is a significant architectural gap between the analytical prototype and a robust real-time alerting system. Developing a complete machine learning operations (MLOps) architecture capable of operating 24/7 is a necessary step in translating academic success into real engineering impact strengthening the safety culture and mitigating the risks inherent in these vital structures.

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