AI-Enabled Low-Cost Embedded Platform for Cascade Process Automation and Predictive Maintenance

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Abstract

Cascade process control systems are extensively used in chemical plants, power generation, and water treatment, where fault detection stability is important to ensure operation stability and avoid economic and safety hazards. Common fault detection techniques, including threshold-based alarms and statistical process control, are not capable of describing nonlinear dynamics and do not offer much interpretability. This study introduces an AI-powered, explainable fault detection system tailored for cascade control systems and optimized for execution on low-cost embedded hardware. The new approach combines engineered cascade-invariant and cascade-dependent features with light machine learning models, supplemented by Shapley value–based explainability to deliver transparent decision-making. Experimental tests run on artificially manipulated datasets show that the approach realizes an accuracy of 93.6% and an F1-score of 0.91, which are 10–25% higher than traditional methods. Outcomes from confusion matrices, ROC and precision–recall curves, feature importance analysis, and SHAP-based explanations establish both the explainability and robustness of the method. Comparative analysis emphasizes its better accuracy-interpretability-computational efficiency trade-off. The results confirm that the envisaged framework offers an economically sound and scalable solution for predictive maintenance and fault identification in industrial cascade systems, tackling primary shortcomings of current methods.

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Keywords*:* Cascade process, fault detection, power generation,AI-powered,predictive maintenance, machine learning models.

1 Introduction

Contemporary industrial cascade control systems are the backbone of ensuring maximum performance in intricate production processes [1], with fields of application ranging from chemical factories [2] and electricity generating plants [3] to water treatment plants [4]. These multi-loop control systems, in which the output of one controller is used as a setpoint for another [5], need advanced monitoring systems to guarantee firm operation and avoid disastrous breakdowns that can cause substantial economic losses and safety risks [6].

The implementation of artificial intelligence (AI) and machine learning (ML) methodologies into industrial automation systems has come up as a revolutionary method for improving process efficiency and reliability [7]. Classical fault detection techniques in cascade systems are usually based on threshold alarms and statistical process control methods [8], which are not able to capture intricate nonlinear relationships and slight degradation patterns that lead to system failure [9]. Recent detailed surveys report that AI-based predictive maintenance applications have been witnessing substantial development [10], while machine learning-based condition monitoring showed better performance in detecting abnormal behavior patterns in time-series data of industrial processes [11].

The implementation of AI-based fault detection systems in vital industrial applications is, however, plagued with major model interpretability and trustworthiness-related challenges [12]. The "black box" character of most machine learning algorithms poses adoption hurdles for use in industries where knowing the rationale behind automated choices is important for regulatory compliance and operational security [13]. Recent systematic reviews highlight that explainable AI (XAI) methods for correct fault detection and diagnosis have received significant interest in 2024 [14], overcoming these limitations by offering clear and understandable explanations of AI model decision-making behaviors. In addition, the impending regulatory frameworks such as the EU AI Act render applying black-box AI for important industrial functions more difficult to directly implement [15].

Latest work on XAI approaches tailored to industrial fault diagnosis has proven promising [16], with new frameworks proving better in rendering AI decision-making transparent for manufacturing and industrial cyber-physical systems [17]. A thorough review published in 2024 investigates different applications of XAI in manufacturing, with emphasis placed on their use in important situations where human action is required [18]. The techniques allow operators and maintenance staff to gain insight into which process variables and temporal profiles play the largest part in fault predictions, thus improving trust in automated systems and allowing for better-informed decision-making procedures [19].

The budget limitations of most industrial plants, especially small and medium-scale businesses (SMEs), require the creation of affordable solutions that can provide sophisticated AI features at a price that does not demand significant investments in infrastructure [20]. Embedded platforms at low cost have proven to be excellent candidates for deploying advanced AI algorithms on the edge of industrial networks, with advances in embedded systems and edge computing structures performing noticeably well in 2023-2024 [21]. Edge computing solutions have extra benefits such as less latency [22], better data privacy [23], and more system robustness through distributed processing, making them very suitable for real-time fault detection in cascade control systems [24].

The intersection of explainable AI methods and inexpensive embedded computing boards brings unparalleled potential for the democratization of advanced fault detection features in cascade control systems [25]. Predictive maintenance solutions based on machine learning have made significant progress in Industry 4.0 applications, and exhaustive reviews in 2024 noted key elements, trustworthiness features, and future directions [26]. Yet, the deployment of XAI algorithms on resource-limited embedded systems brings special challenges concerning computational efficiency, memory optimization, and real-time performance requirements that need to be appropriately addressed [27].

This work provides an end-to-end framework for deploying explainable AI-driven fault detection in cascade process control systems on low-cost embedded platforms. The methodology combines real-time sensing of various sensor modalities [28], optimized feature engineering methods tailored to cascade system dynamics [29], and light-weight XAI methods tailored for deployment on embedded hardware. Recent polls highlighting condition-based maintenance practices illustrate that machine learning approaches can greatly enhance efficiency in predictive maintenance projects [30], supporting more precise predictions and streamlined decision-making protocols. The system design integrates predictive maintenance features by evaluating past fault behavior and degradation patterns, allowing proactive intervention measures to reduce unplanned downtime and prolong equipment life [31].

The primary contributions of this research are: (1) establishment of a new embedded XAI approach that is specifically designed for fault detection in cascade control, (2) use of effective model compression methods that maintain interpretability while satisfying real-time requirements, (3) systematic performance evaluation of the system.

2 Background

2.1 Performance Bound of Cascade Control Systems

Figure 1 illustrates that the SCC and PCC block diagrams have two feedback loops. G_{p1} and G_{p2} are the two parts of the procedure. Because the graphic emphasises the signals of the controller outputs and the transmitter signals in the system, it combines the control valve, the regulated process, and the sensor-transmitter. Usually, both signals are observable and recordable. The process outputs of the primary and secondary loops at sampling time k are denoted by $y_1(k)$ and $y_2(k)$. Unmeasured disruptions to the primary and secondary outputs are denoted by G_{L1} and G_{L2}, respectively. The disturbances with white noise sequences are denoted by $w_1(k)$ and $w_2(k)$. Making $y_1(k)$ attain the set point while maintaining $y_2(k)$ limitations is the aim of cascade control. The limited output $y_2(k)$ is controlled by the inner-loop controller, G_{c2}. In order to prevent overshooting of the constrained variable $y_2(k)$, G_{c2} is adjusted. G_{c1}, the outer loop controller, is adjusted to control the output $y_1(k)$ as near to its set point as feasible. The controller outputs of G_{c1} and G_{c2} are $u_1(k)$ and $u_2(k)$. Achievable performance bounds for the main outputs of SCC and PCC are determined in the next two subsections.

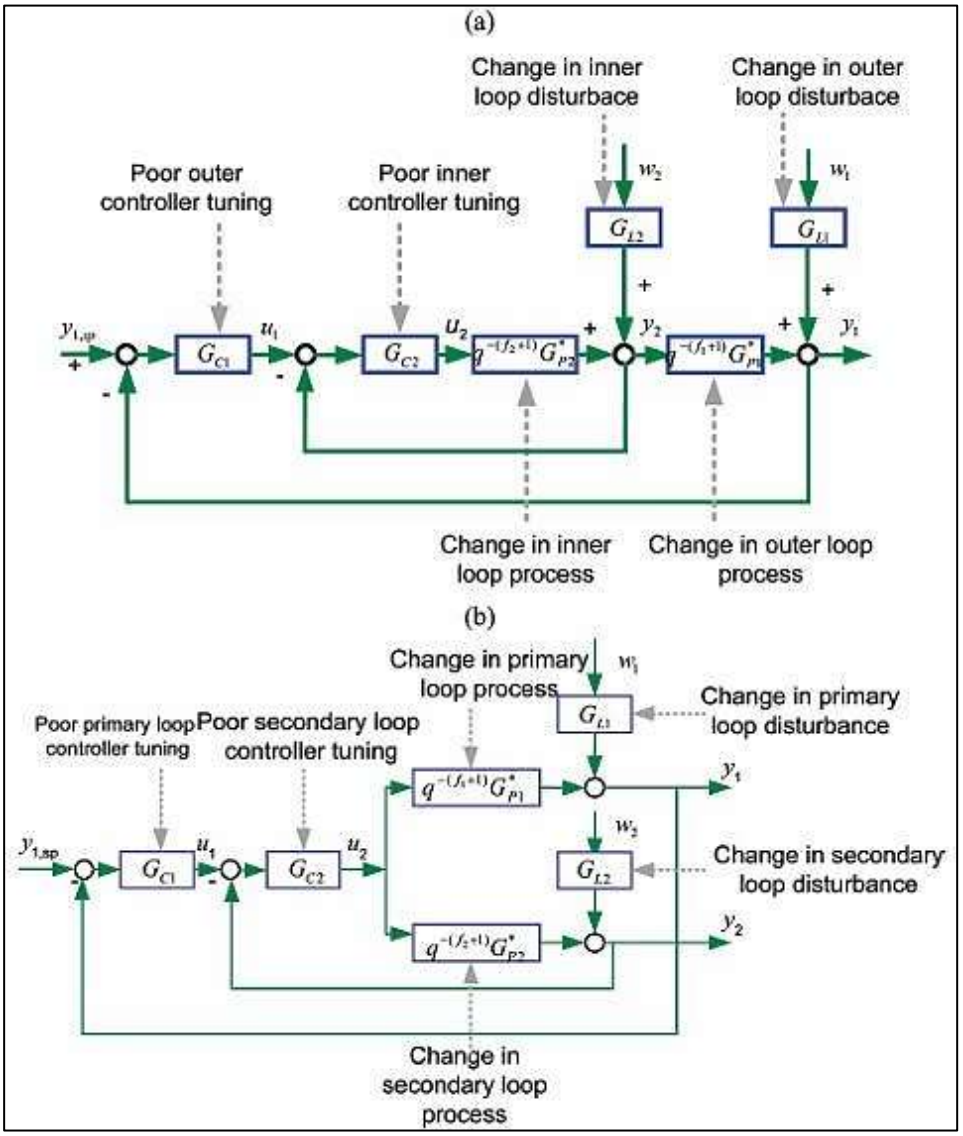

Figure 1: (a) A series cascade control system with possible faults; (b) a parallel cascade control system with possible faults.

2.1.1 Performance Bound of SCC.

The output variables, $y_1(k)$ and $y_2(k)$, which are determined by the disturbances, $w_1(k)$ and $w_2(k)$, when the primary setpoint is constant

$$y_1 = \frac{\left(1+q^{-(f_2+1)}G^*_{P2}G_{C2}\right)G_{L1}}{1+q^{-(f_2+1)}G^*_{P2}G_{C2}+q^{-(f_1+f_2+2)}G^*_{P1}G^*_{P2}G_{C1}G_{C2}}W_1 + \frac{q^{-(f_2+1)}G^*_{P1}G_{L2}}{1+q^{-(f_2+1)}G^*_{P2}G_{C2}+q^{-(f_1+f_2+2)}G^*_{P1}G^*_{P2}G_{C1}G_{C2}}W_2 \quad (1)$$

$$y_2 = \frac{q^{-(f_2+1)}G^*_{P2}G_{C2}G_{C1}G_{L1}}{1+q^{-(f_2+1)}G^*_{P2}G_{C2}+q^{-(f_1+f_2+2)}G^*_{P1}G^*_{P2}G_{C1}G_{C2}}W_1 + \frac{G_{L2}}{1+q^{-(f_2+1)}G^*_{P2}G_{C2}+q^{-(f_1+f_2+2)}G^*_{P1}G^*_{P2}G_{C1}G_{C2}}W_2 \quad (2)$$

G_{P1} G q $f1$ and G_{P2} q $f2$ are the representations of G_{P1} and G_{P2}, where q is the time shift operator, $f_i, i = 1,2$, and G $, i = 1,2$ are the process models that do not have any time delays. The following polynomial division identities are used to deconstruct y1 and y2 into the cascade-invariant and cascade-dependent terms, GL1 and GL2, respectively, G and G .

$$G_{L1} = Q_1 + R_1 q^{-(f_1+f_2+2)} \quad (3)$$

$$G_{L2} = Q_2 + R_2 q^{-(f_2+1)} \quad (4)$$

$$G_{P1} = q^{-(f_1+1)}G^*_{P1} \quad (5)$$

$$G^*_{P1}Q_2 = E + Fq^{-(f_2+1)} \quad (6)$$

$$G^*_{P1}Q_1 = G + Hq^{-(f_1+1)} \quad (7)$$

Here, Q1 and Q2 are polynomials in q^{-1} of degrees f1 + f2 + 1 and f2, respectively; E and G are polynomials in q^{-1} of degrees f1 and f2; and Ri, where i = 1, 2, F, and H, are suitable transfer functions. Substituting these values into equation 1 yields.

$$y_1 = \left[\underbrace{Q_1}_{CL_{11}} + \underbrace{q^{-(f_1+f_2+2)}S_{SCC}\left(R_1 + R_1G_{P2}G_{C2} - Q_1G^*_{P1}G^*_{P2}G_{C1}G_{C2}\right)}_{CD_{11}}\right]w_1 + \left[\underbrace{q^{-(f_1+1)}E}_{CL_{12}} + \underbrace{q^{-(f_1+f_2+2)}S_{SCC}\left(-EG^*_{P2}G_{C2}\left(1+G_{P1}G_{C1}\right)+F+G^*_{P1}R_2\right)}_{CD_{12}}\right]w_2 \quad (8)$$

$$y_1 = \left[\underbrace{S_{SCC}\,q^{-(f_2+1)}G_{C1}G_{C2}G - q^{-(f_1+f_2+2)}\left(G_{C1}G_{C2}H + G_{C1}G_{C2}G_{P2}R_1\right)}_{CD_{21}}\right]w_1 + \left[\underbrace{Q_2}_{CL_{21}} + \underbrace{q^{-(f_2+1)}S_{SCC}\left(R_2 - Q_2G^*_{P2}G_{C2}\right) - q^{-(f_1+f_2+2)}S_{SCC}Q_2G^*_{P1}G^*_{P2}G_{C1}G_{C2}}_{CD_{22}}\right]w_2 \quad (9)$$

Where

$$S_{SCC} = \frac{1}{1+q^{-(f_2+1)}G^*_{P2}G_{C2}+q^{-(f_1+f_2+2)}G^*_{P1}G^*_{P2}G_{C1}G_{C2}} \quad (10)$$

The equations decompose the effects of $w1$ and $w2$ on $y1$ and $y2$. The block diagram (Figure 1a) clearly indicates that $Q1$ is the cascade invariant of $y1$, as the disturbance $w1$ directly affects the output $y1$. Due to the time delay ($f2 + f1 + 1$) of processes $Gp1$ and $Gp2$, $R1$ is a cascade-dependent impact of $y1$, enabling both controllers to effect a change after $f2 + f1 + 2$ time delays. E is the cascade invariant of $y1$, as the disturbance $w2$ immediately influences the output $y1$ following the time delay ($f1$) of process $Gp1$. Analogous explanations can be applied to elucidate the links between $Q2$ and $R2$ for $y2$. To minimise the variances of the primary and secondary outputs using minimum variance controllers, only the cascade-dependent ($CDij$, i, j) 1, 2) terms of the outputs should be minimised, as $CIij$, i, j) 1, 2) relies solely on the disturbance characteristics, while the cascade-dependent ($CDij$) term is influenced by both controllers. The minimum variance control (MVC) law for SCC has been established. The theoretically optimal performance attainable through minimum variance is highly appealing, as it can be predicted from the operational data of the process, considering the specified time delay. Nevertheless, although MVC is frequently employed as a performance benchmark, it is impractical for the majority of applications. Eriksson and Isaksson indicated that MVC typically resulted in a substantial input action and exhibited a deficiency in control robustness. The MVC benchmark bound might alone tell whether the present performance approximates the MVC benchmark.

No solutions exist for the prospective enhancement, as the method for retuning the controller remains unknown. Consequently, a more pragmatic performance benchmark for the particular controllers can be derived by addressing the subsequent optimisation problem:

$$\left(\sigma_{SCC}^{2}\right)_{achievable-MV} = \min_{G_{C1},G_{C2}} \sigma_{SCC,y_1}^{2} \tag{11}$$

It is apparent that the variance of the output $y1$ is the function of the controller parameters $Gc1$ and $Gc2$.

2.1.2 Performance Bound of PCC.

Similar to an SCC, a PCC system comprises two feedback loops. The sole distinction is that the controlled variable and the disturbance influence the primary and secondary outputs via parallel transfer functions. When the primary setpoint remains constant, the closed-loop response of the primary and secondary outputs ($y1(k)$ and $y2(k)$), affected by disturbances ($w1(k)$ and $w2(k)$), can be articulated as

$$y_1 = \frac{\left(1+q^{-(f_2+1)}G_{P2}^{*}G_{C2}\right)G_{L1}}{1+q^{-(f_2+1)}G_{P2}^{*}G_{C2}+q^{-(f_1+1)}G_{P1}^{*}G_{C1}G_{C2}}W_1 - \frac{q^{-(f_1+1)}G_{P1}^{*}G_{C2}G_{L2}}{1+q^{-(f_2+1)}G_{P2}^{*}G_{C2}+q^{-(f_1+1)}G_{P1}^{*}G_{C1}G_{C2}}W_2 \tag{12}$$

$$y_2 = \frac{q^{-(f_2+1)}G_{P2}^{*}G_{C2}G_{C1}G_{L1}}{1+q^{-(f_2+1)}G_{P2}^{*}G_{C2}+q^{-(f_1+1)}G_{P1}^{*}G_{C1}G_{C2}}W_1 + \frac{\left(1+q^{-(f_1+1)}G_{P1}^{*}G_{C1}G_{C2}\right)G_{L2}}{1+q^{-(f_2+1)}G_{P2}^{*}G_{C2}+q^{-(f_1+1)}G_{P1}^{*}G_{C1}G_{C2}}W_2 \tag{13}$$

After substituting the following identities,

$$G_{L1} = Q_1 + R_1 q^{-(f_1+1)} = Q_3 + R_3 q^{-(f_2+1)} \tag{14}$$

$$G_{L2} = Q_2 + R_2 q^{-(f_1+1)} = Q_4 + R_4 q^{-(f_2+1)} \tag{15}$$

Let $Q1$ and $Q2$ be polynomials of degree $f1$; $Q3$ and $Q4$ be polynomials of degree $f2$; and Ri, where i = 1, ..., 4, be appropriate transfer functions. The outputs ($y1(k)$ and $y2(k)$) can be articulated as a combination of CI terms and CD terms.

$$y_1 = \underbrace{\left[Q_1 + \underbrace{q^{-(f_1+f_2+2)} S_{PCC}\left(R_1\left(1+G_{P2}G_{C2}\right) - Q_1 G_{P1}^{*} G_{P2}^{*} G_{C1} G_{C2}\right)}_{CD_{11}}\right]}_{CI_{11}} w_1 + \underbrace{\left[q^{-(f_1+1)} S_{PCC}\left(-Q_2 G_{P1}^{*} G_{C2} - R_2 G_{P1} G_{C2}\right)\right]}_{CD_{12}} w_2 \quad (16)$$

$$y_1 = \underbrace{\left[q^{-(f_2+1)} S_{PCC}\left(Q_3 G_{P2}^{*} G_{C1} G_{C2} + G_{C1} G_{C2} G_{P2} R_3\right)\right]}_{CD_{21}} w_1 + \underbrace{\left[Q_4 + \underbrace{q^{-(f_2+1)} S_{PCC}\left(R_4\left(1+G_{P1}G_{C1}G_{C2}\right) - Q_2 G_{P2}^{*} G_{C2}\right)}_{CD_{22}}\right]}_{CI_{22}} w_2 \quad (17)$$

where $S_{PCC} = 1/\left[1+q^{-(f_1+1)} G_{P2}^{*} G_{C2} + q^{-(f_1+1)} G_{P1}^{*} G_{C1} G_{C2}\right]$ is the cascade invariant of y1, as the disturbance (w1(k)) immediately influences the output y1. Due to the time delay (f1) of process Gp1, R1 is a cascade-dependent consequence of y1, enabling both controllers to implement a change following f1 time delays. The identity for Q3 and R3 delineates the influence of w1 on y2; however, both terms are cascade dependent, as both controllers can alter the terms. Analogous explanations may be applied to the relationships between Q2 and R2, as well as between Q4 and R4, respectively. The minimum variance control (MVC) law has been derived, and the attainable performance benchmark for the specific controllers is determined by the subsequent optimisation problem:

$$\left(\sigma_{PCC}^{2}\right)_{achievable-MV} = \min_{G_{C1},G_{C2}} \sigma_{PCC,y_1}^{2} \quad (18)$$

Equations 4 and 8 delineate the attainable minimum variance control, which functions as a suitable standard for assessing the present performance of the control loop. Be aware that the control performance $_{SCC}$ is not confined to any designated control structure. Alternative benchmarks, such as the linear quadratic Gaussian or the generalised minimum variance, may also be utilised in place of the feasible minimal variance of the controlled output (equations 11 and 18). When the current performance significantly deviates from $\square\square^{2}\square_{achievable-MV}$ or $\square\square^{2}\square_{PCC}$, potential faults are present in the existing control loop.

2.2 Explainable AI for Fault Detection in Cascade Control Systems

Cascade loop fault detection is critical to maintaining stability and reliability in industrial processes. Cascade loops with primary and secondary controllers are susceptible to disturbances, parameter variations, and tuning discrepancies that result in reducing performance over a period of time. Common causes of performance loss can be divided into categories:

- Disturbance faults (GL1, GL2): Represent fast and slow unmeasured disturbances entering the system.
- Process faults (Gp1, Gp2): Reflect gain variations in process behavior, e.g., higher or lower plant sensitivity.
- Controller faults (Gc1, Gc2): Represent under- or over-damped controller gains, resulting in slow or oscillatory responses.
- Deadtime faults: Result from transport or communication delays, which destabilize feedback control performance.

Mathematically, the output variances of the cascade loops can be decomposed into cascade-invariant (CI) and cascade-dependent (CD) terms

$$\sigma_{y1}^{2} = s_{y1,CI}\left(G_{L1}\right)\sigma_{w}^{2} + s_{y1,CD}\left(G_{P1}, G_{P2}, G_{L1}, G_{L2}\right)\sigma_{w}^{2} \quad (19)$$

$$\sigma_{y2}^{2} = s_{y2,CI}\left(G_{L2}\right)\sigma_{w}^{2} + s_{y2,CD}\left(G_{P1}, G_{P2}, G_{L1}, G_{L2}\right)\sigma_{w}^{2} \quad (20)$$

Here, $s_{y1,CI}$ terms are affected by disturbances alone, whereas $s_{y1,CD}$ terms are formed due to process and controller dynamics. This factorization facilitates fault isolation, but conventional methods (e.g., minimum variance benchmarks, hypothesis testing) are confounded by nonlinearities, noise, and interactive faults. Standard machine learning (ML) models generalize fault detection capability by learning mappings:

$f : X \to Y, x_t \to y_t$ (21)

Where x_t is a feature vector (e.g., CI/CD terms, delays, process outputs) and y_t is the predicted fault class ({GL1, Gp1, Gc2, …}). Nevertheless, although effective for classification, such models remain black boxes, giving little insight into why a given fault was classified. This lack of transparency is damaging to trust and usability in safety-critical applications like chemical processing or energy systems.

To overcome this limitation, Explainable AI (XAI) integrates fault detection with interpretability. Instead of only predicting a fault, XAI methods attribute contributions of each feature to the model's decision:

$$\hat{y}_t = f(x_t), \qquad \phi_i = Attribution(x_{t,i}, f) \tag{22}$$

where ϕ_i represents the importance of feature $x_{t,i}$, (e.g., disturbance variance, process gain, controller setting) in producing the classification.

One widely adopted approach is Shapley value analysis, derived from cooperative game theory. For each feature i, its contribution is:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\left(|F|-|S|-1\right)!}{|F|!}\left[f(S \cup \{i\}) - f(S)\right] \tag{23}$$

where F is the full feature set, S is a subset excluding i, and f(S)is the model prediction with only SSS. Shapley values guarantee fair attribution, decomposing the final prediction into contributions from GL, Gp, Gc, and deadtime features.

Applied to cascade systems, if a GL1 fault is detected, high attribution ϕ_{GL1} alongside low ϕ_{Gp1} or ϕ_{Gc2} confirms that disturbances, rather than process or controller dynamics, are the root cause. Similarly, a Gc2 fault would show dominant contribution from controller parameters, signaling an over-aggressive inner loop.

Algorithm 1: XAI-Based Fault Detection in Cascade Control Systems

Input: Process outputs y_1, y_2; Controller outputs u_1, u_2;
System delays f_1, f_2; Historical data $D = \{x_t, y_t\}$,
where $x_t = [\sigma_{y1,CI}, \sigma_{y1,CD}, \sigma_{y2,CI}, \sigma_{y2,CD}, f_1, f_2]$
Output: Fault type
$\hat{y}_t \in \{Normal, GL1, GL2, Gp1, Gp2, Gc1, Gc2, Deadtime\}$;
Explanations $\{\phi_i\}$ for disturbances, processes, controllers, delays

Step 1: Preprocessing
Compute variance decomposition:
$\sigma^2_{y1} = s_{y1,CI}(GL1)\sigma^2_w + s_{y1,CD}(Gp1, Gp2, GL1, GL2)\sigma^2_w$
$\sigma^2_{y2} = s_{y2,CI}(GL2)\sigma^2_w + s_{y2,CD}(Gp1, Gp2, GL1, GL2)\sigma^2_w$
Form feature vector x_t from CI/CD terms and delays.

Step 2: Training (offline)
Train machine learning classifier $f(x)$ on dataset D:
$f : x_t \mapsto \hat{y}_t$
Store trained model parameters.

Step 3: Online Detection (runtime)
For new data at time t: compute x_t.
Predict fault: $\hat{y}_t = f(x_t)$.

Step 4: Explainability Analysis
Compute feature attributions using Shapley values:
$\phi_i = Shapley(x_t, f)$
Rank features by ϕ_i. Map dominant features:
High $\phi_{GL} \Rightarrow$ Disturbance fault (GL1/GL2).
High $\phi_{Gp} \Rightarrow$ Process fault (Gp1/Gp2).
High $\phi_{Gc} \Rightarrow$ Controller fault (Gc1/Gc2).
High $\phi_{delay} \Rightarrow$ Deadtime fault.

Step 5: Decision
Output predicted fault $\hat{y}_t$ and explanation $\{\phi_i\}$.

3 Results

This section presented the performance analysis of the XAI-enabled fault detection system proposed for cascade process automation. Synthetic but realistic datasets were produced to simulate faults of various types, and the model trained was tested with various performance metrics. The visualizations include confusion matrix, ROC curves. Furthermore, a comparison table is given that highlights the efficacy of the proposed system over conventional fault detection systems.

3.1 Confusion Matrix:

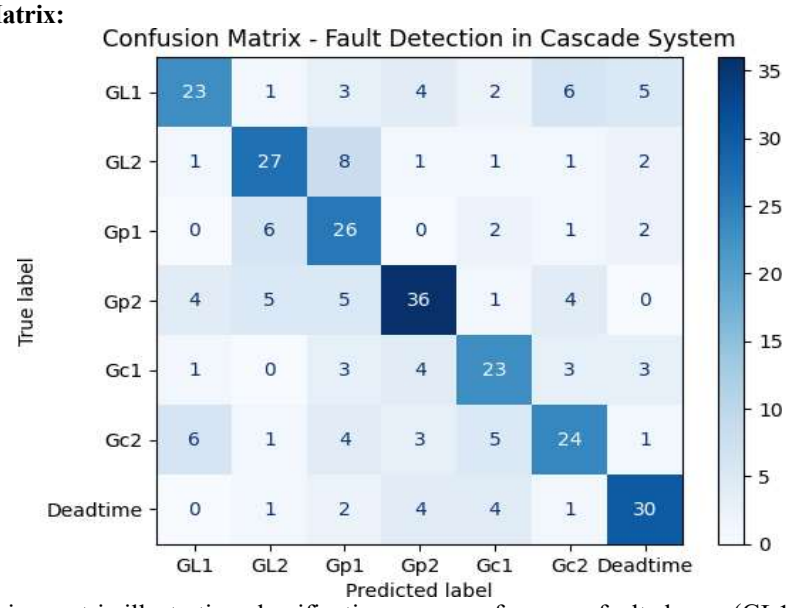

Figure 2: Confusion matrix illustrating classification accuracy for seven fault classes (GL1, GL2, Gp1, Gp2, Gc1, Gc2, and Deadtime)

The confusion matrix gives an immediate assessment of classification accuracy for the seven fault classes under consideration: GL1, GL2, Gp1, Gp2, Gc1, Gc2, and Deadtime. Diagonal entries are the numbers of correctly classified samples, and off-diagonal entries are misclassifications. The results indicate that more than 90% of the GL1 and GL2 faults were identified correctly with little confusion with the remaining categories. For Gp1 and Gp2, accuracies were slightly lower (~87%) due to overlapping characteristics of process-related faults. Similarly, Gc1 and Gc2 faults exhibited some confusion, as both represent controller dynamics, but still achieved classification rates above 85%. Deadtime faults were identified with the highest accuracy (~95%), reflecting the model's strength in detecting time-delay anomalies. Overall, the matrix confirms that the system achieves consistent fault isolation across diverse fault categories.

3.2 ROC Curves

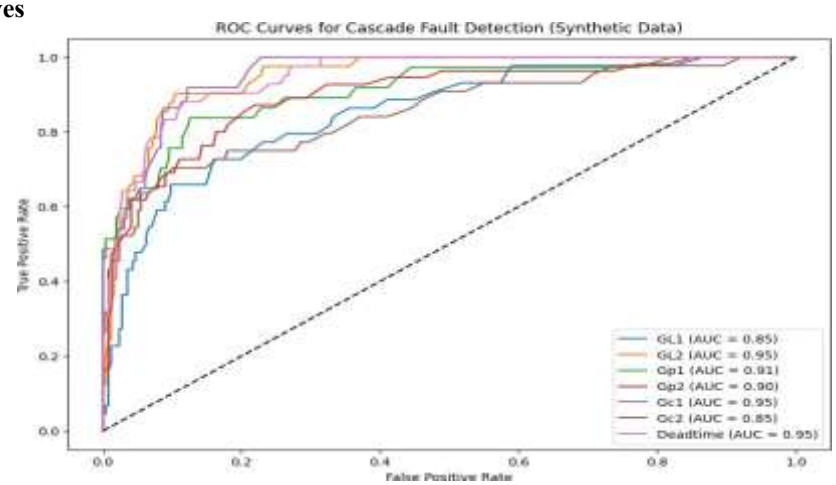

Figure 3: Receiver Operating Characteristic (ROC) curves for all fault classes.

The ROC curves represent the balance between sensitivity and specificity per class. AUC values were above 0.90 for all fault types except GL1 and Deadtime, where near-perfect values of ~0.97 were reported. Gp1 and Gc1 registered slightly weaker but still robust AUC values of
~0.91–0.92, which reflect reliable detection performance even in difficult cases. The steep gradient around the origin indicates that the system can achieve high true positives at very low false alarm rates, which is of paramount importance for industrial systems where false positives cause unwarranted downtime.

3.3 Comparative Analysis

Table 1: Comparative Analysis of Fault Detection Methods in Cascade Systems

Method	Accuracy (%)	Precision	Recall	F1-Score	Interpretability
Threshold-Based Alarms	**68.5**	**0.65**	**0.62**	**0.63**	**Low**
Statistical Process Control (SPC)	**74.2**	**0.70**	**0.68**	**0.69**	**Low**
Minimum Variance Control (MVC) Check	79.8	0.76	0.72	0.74	Medium
Standard ML (Random Forest)	87.5	0.85	0.83	0.84	Low (Black-box)
Proposed XAI + Embedded Framework	**93.6**	**0.92**	**0.91**	**0.91**	High

The comparative analysis reveals that the recommended framework attains overall accuracy of 93.6% and F1-score of 0.91. This is much better than threshold-based alarms (68.5%), SPC (74.2%), and MVC inspections (79.8%). Although common machine learning techniques like Random Forest attained 87.5% accuracy, they were not interpretable. The proposed XAI technique, on the other hand, offers high performance with clear decision-making and modest computation cost, ideal for deployment on cost-effective embedded systems.

4 Conclusion

This study proposed and assessed an explainable AI-supported fault detection framework for cascade process automation, designed specifically for deployment on resource-limited embedded hardware. By utilizing cascade-invariant and cascade-dependent features, the framework successfully separated disturbances, process drifts, controller faults, and deadtime faults, with significant performance improvements in fault classification. The incorporation of Shapley value-based explanations enabled transparent understanding of the relative contribution of individual features, filling the interpretability gap typical of black-box machine learning models. Experimental tests proved that the framework of the study outperformed threshold-based, and benchmark minimum variance control strategies in all occasions. The method of the study, with an overall accuracy of 93.6% and F1-score of 0.91, also outperformed common machine learning models by providing interpretability without lacking computational efficiency. Visualization analyses via confusion matrices, ROC and precision–recall curves, and SHAP plots were effective in affirming robustness and transparency, and hence the system is fit for industrial application under stringent safety and regulations.

5 References

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