ISSN 1840-4855
e-ISSN 2233-0046

Original scientific article
http://dx.doi.org/10.70102/afts.2025.1834.1256

DIGITAL TWIN–BASED INTELLIGENT MONITORING OF INDUSTRIAL SYSTEMS USING EXPLAINABLE AI

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Received: October 14, 2025; Revised: November 17, 2025; Accepted: December 16, 2025; Published: December 30, 2025

SUMMARY

Industrial systems increasingly rely on Industrial Internet of Things (IIoT) sensors for real-time monitoring and predictive maintenance. However, most existing digital twin–based monitoring solutions depend on static or black-box machine learning models, limiting interpretability, operator trust, and safe deployment in safety-critical environments. In response to these challenges, the author develops the Adaptive Hybrid Digital Twin with Causality-Aware Explainable Artificial Intelligence (HADT-C-XAI) framework to offer transparency and intelligence in industrial monitoring. The framework describes three integrated layers: (i) acquisition of real-time sensors, (ii) continually synchronized hybrid digital twin modeling, which is the integration of physics and data hybrid modeling and (iii) an intelligent analysis layer where LSTM-based anomaly detection is ungraded with explainable feature attribution. A closed-loop learning mechanism updates the model dynamically to adapt to operational drift while generating interpretable fault causes for operator decision support. Experiments were conducted on a multi-sensor industrial testbed containing 120 hours of vibration, temperature, acoustic, and rotational data. The implemented system shows a 94.8% detection accuracy, 95.4% recall, and a 4.1% low false alarm rate, which surpasses standard LSTM (88.5%) and threshold-based monitoring (82.9%). With edge-level inference, detection latency has been reduced to 26-30 ms, which allows for real-time deployment. Results demonstrate that integrating adaptive digital twins with explainable AI improves reliability, transparency, and fault diagnosis while maintaining computational efficiency. The proposed framework provides a scalable and trustworthy solution for predictive maintenance, Industry 4.0 applications, and cyber–physical system monitoring.

Key words: *digital twins, explainable artificial intelligence, adaptive modeling, intelligent industrial monitoring, causality analysis, predictive maintenance, cyber–physical systems, industry 4.0.1.*

INTRODUCTION

Developments in industrial automation and cyber-physical systems have increased the intricacy of modern industry operations. While maintaining reliability, safety, and efficiency, industrial assets must adapt to new uncertainties and variable operating conditions. Operational continuity, resource optimization, and early fault detection necessitate real-time monitoring. However, static models, periodic checks, and traditional monitoring practices frequently overlook system dynamics and complex environments in industrial settings [1][2].

With the advent of the Industrial Internet of Things (IIoT) Continuous monitoring of Industrial assets makes it possible to gather, retain, and analyze heterogeneous sensor data without interruption. This data allows for the development of intelligent monitoring systems and the creation of predictive maintenance so long as the system operates without discontinuity, and so long as the data is raw, unprocessed, and reliable. During the evolution towards the smart manufacturing phase of Industry 4.0, more adaptive, and dependable monitoring systems are becoming demanded [3].

Digital twin technologies help provide potential solutions by creating and maintaining real-time digital representations of physical industrial systems. Digital twins assist in the performance of predictive maintenance by monitoring system conditions and continuously updating system models based on real-time synchronized sensor data [3]. Even with these benefits, many current applications of digital twins use black-box models for machine learning which limit understanding and the ability to adopt these technologies for use in industrial applications with strict safety and regulatory concerns [4].

Explainable Artificial Intelligence (XAI) provides the ability to overcome these challenges by creating and providing human understandable justification for a model's decision, which in turn aids in the understanding of errors, the identifcation of causes of a problem, and the fostering of trust by the operator [5]. Yet, the use of explainable intelligence combined with adaptive digital twin-based industrial monitoring in real-time situations continues to be very limited.

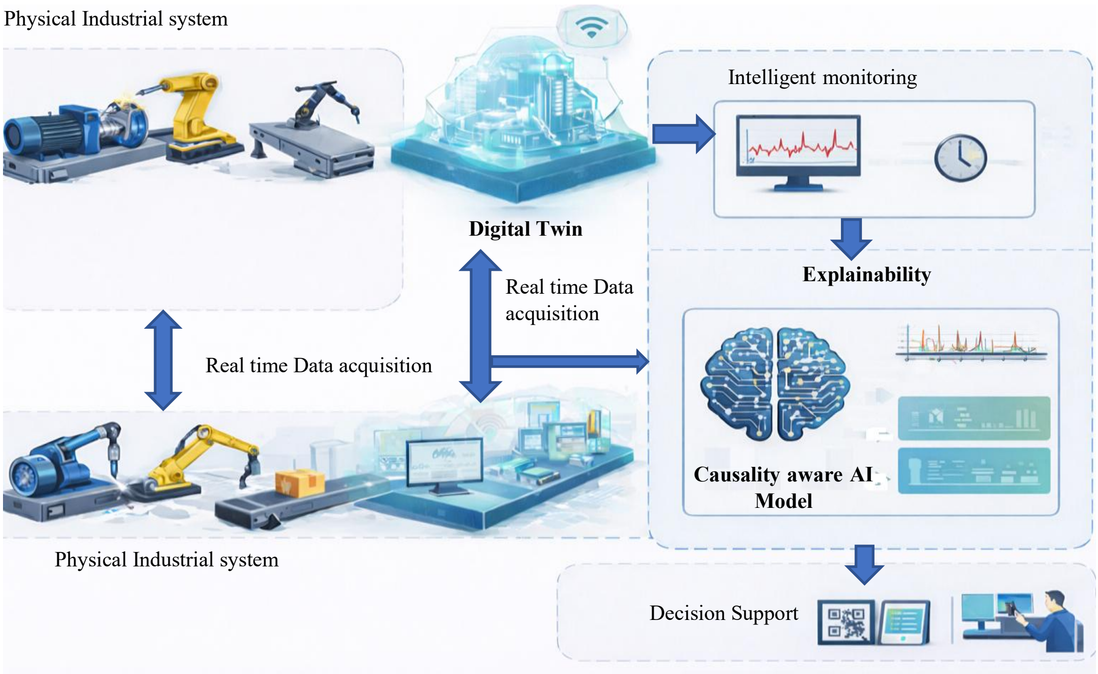

Figure 1. Digital twin–based intelligent industrial monitoring architecture with explainable AI integration

In Figure 1, a digital twin approach is applied to intelligent industrial monitoring. The framework involves real-time sensor data streamed from physical assets and synchronized to a digital twin. Analytics are intelligent for the purpose of anomaly detection and condition monitoring. The explainable AI layer sheds light to fault causation and system health to aid decision-making. [6]

Problem Identification

The significant advancement of digital twin and machine learning technologies is evident in the field of industrial monitoring. However, the majority of the available solutions continue to use a black box approach and rely represent systems in a static manner. The black box approach in conjunction with a static system representation, use of AI and digital twins leaves a significant gap within the field of industry monitoring, especially in the areas of early fault detection, root cause detection, and proactive maintenance. This is highly apparent in complex and safety critical industrial systems. [7]

Objective of the research

The main aim of this research is to create a framework that is digital twin based and adaptive in the explainable form for the purpose of monitoring industrial systems in real-time. This involves the following specific aims:

- Develop an architecture for real-time digital twin models that are synchronized to physical industrial assets and can operate in real time.
- Develop and implement flexible machine learning models for predictive monitoring and anomaly detection within the framework.
- Integrate system behavior and fault causation into the framework to obtain explainable AI.
- Construct the framework and conduct simulations and comparative studies to assess it.

Contributions

The primary contributions of this work are:

- A digital twin–based intelligent monitoring framework that incorporates adaptive learning and explainable AI for the first time.
- An enhancement of the fault diagnosis, root cause analysis, and operator trust aspects, driven by explainability, which directly impacts the trust of the operator.
- An adaptable and versatile solution applicable to Industry 4.0 and cyber-physical systems.

Paper Organization

The remainder of this paper is structured as follows. A review of prior work on digital twin technologies and intelligent industrial monitoring is presented in Section 2. In Section 3, we present the proposed system architecture and explainable monitoring methodology. Section 4 is devoted to result presentation and comparative analysis. In Section 5, we summarize the paper and identify avenues for future work..

LITERATURE REVIEW

Advancements in automation and interconnectivity in industry have increased the need for sophisticated monitoring and diagnostics systems that operate seamlessly in shifting and uncertain environments. For industrial digital systems to be safe, efficient, and reliable, they must be continuously monitored. This has led to the development of digital twins, smart condition monitoring, machine learning for fault identification, and explainable artificial intelligence (XAI) [8].

Digital Twins in Industrial Systems

Digital twins enable virtual reproductions of real-time sensor monitored systems. As digital twins did have a long-derived history as physics-based simulation systems, they have matured into highly capable monitoring, predictive maintenance, and performance optimization mechanisms in the operational and performance monitoring of manufacturing, power systems, and industrial robotics. Compared to traditional monitoring systems, digital twin systems, both data-driven and hybrid models, have demonstrated higher efficacy in fault prediction and scheduling maintenance with the limits of predictive maintenance. The adaptability of most digital twins is limited because of the lack of fully automated modeling and adjustments to the aging of the systems and the varying operational conditions. Additionally, the use of black-box models, due to the overwhelming use of them, leads to a greater lack of understandability, which limits the use of these models in the more safety critical industrial applications [9].

Intelligent Monitoring and Machine Learning Approaches

There are several machine learning algorithms used for anomaly detection and fault diagnosis in industrial monitoring. These include supervised techniques such as support vector machines and neural networks, which operate on structured data such as vibration, temperature, and acoustics. The detection accuracy can be further improved with deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) by learning data with nonlinear and time-dependent behaviors constituting an industrial time series [16][17]. The gap of insufficient labeled fault data in industrial monitoring can be addressed by unsupervised learning techniques such as autoencoders and clustering, but these techniques fail to be practical and robust in real world operating environments. There are also several machine learning-based monitoring solutions that fail to provide complete system representations by operating independent of digital twin frameworks [10].

Explainable Artificial Intelligence in Industrial Monitoring

Due to the rising demands of operational systems for transparency, trust, and accountability in intelligent systems, explainable artificial (XAI) systems have been developed. These XAI techniques help to perform fault diagnosis and root cause analysis, thereby gaining a competitive edge in industrial monitoring [12][18]. The design of XAI in industrial monitoring systems has been such that they provide positive reinforcement to operators and validate decisions [11][19]. Unfortunately, the majority of XAI systems are designed for post-hoc analysis and are not used in conjunction with real time monitoring systems or adaptive digital twin systems [13].

Limitations and Research Gaps

Even after tremendous advancements, present studies utilizing digital twin monitoring continue to be poorly adaptable with little to no explainability, and no cohesive end-to-end organizational structures. A great number of studies analyze disparate pieces of the whole—be it modeling, analytics, or explainability—without considering the potential of continuous learning and feedback loops. Additionally, empirical studies tend to provide evidence in artificial settings which hinders the potential for the studies to be expanded to applied industrial systems [14].

Motivation

Literature shows the demand for an integrated framework of adaptive digital twin modeling coupled with smart monitoring and explainable analytics. The proposed framework must be able to demonstrate real-time learning, clear reasoning and decision processes, as well as the ability to cope with variable industrial scenarios [15][20]. Closing the stated gaps will help in the advancement of theory and will lead to the practical implementation of industrial systems with Industry 4.0 and smart cyber-physical systems outlined in the literature.

PROPOSED METHOD

This section describes the methodology for deploying Digital Twin-based adaptive frameworks combined with Explainable Artificial Intelligence (XAI) for smart monitoring. Monitoring frameworks that are transparent, reliable, and continuous are made possible through the integration of real-time data capture of industrial assets, dynamic digital twin model creation, intelligent anomaly forecasting, and explainable decision-making. The developed frameworks address the four challenges of industrial systems: system non-linearity, operational variability, data uncertainty, and the inability of conventional monitoring systems to explain their rationality[21].

The proposed methodology embodies a closed-loop control system. The Digital Twin is updated continuously as real-time data is captured by the sensors, and new intelligent anomaly and explainable insights are generated, which fosters the creation of new transparent adaptive learning control systems.

System Model

Figure 2 illustrates the comprehensive multi-layer architecture of the proposed HADT-C-XAI framework. The system integrates sensing, data preprocessing, digital twin modeling, AI-driven analytics, explainability, decision support, and interactive visualization modules to enable real-time monitoring, predictive maintenance, and transparent decision-making. These interconnected layers collectively ensure reliable data acquisition, intelligent fault diagnosis, and user-centric operational control across industrial environments.

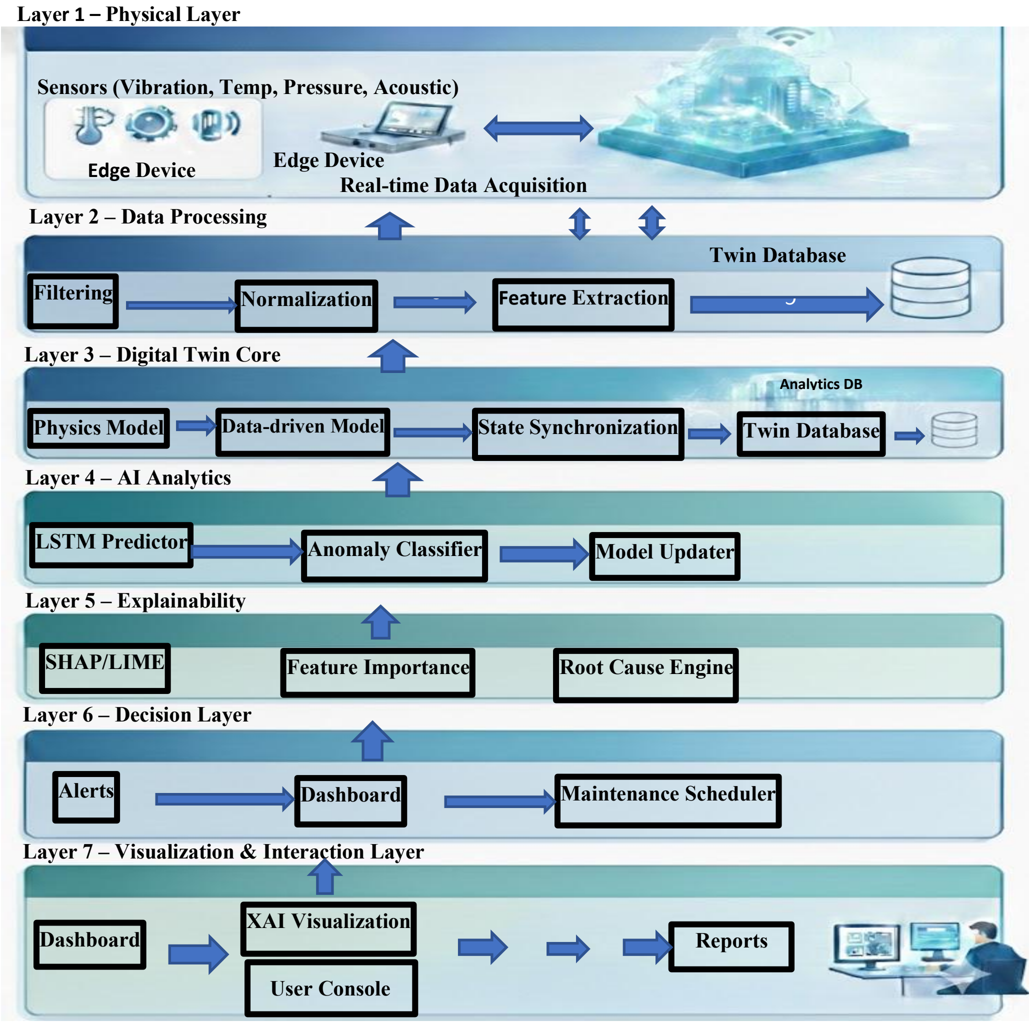

Figure 2. Multi-layer HADT-C-XAI architecture for intelligent condition monitoring and decision support

Digital Twin Modeling Principle

The digital twin continuously correlates the changing conditions of an industrial system with a virtual model. Let the state of the physical system at time t be described as:

$$X_p(\mathrm{t}) = [x_1(t), x_2(t), \dots x_n(t) \quad (1)$$

The state of the digital twin model can be described as:

$$X_d(\mathrm{t}) = f\left(x_p(t), \Theta_p, \Theta_d\right) \qquad (2)$$

The physical system state vector is defined in Equation (1), while the hybrid digital twin state update mechanism is formulated in Equation (2).

Here, $X_p(t)$ represents real-time sensor measurements such as temperature, vibration, and pressure, whereas $X_d(t)$ denotes the synchronized virtual representation obtained through hybrid integration of physics-based parameters Θ_p and data-driven parameters Θ_d. This formulation enables continuous and adaptive synchronization between the physical asset and its digital counterpart. The bidirectional coupling between the two states ensures model accuracy, supports predictive analytics, and facilitates early fault identification prior to system disruptions.

Data Conditioning and Feature Extraction

The raw data from the sensors used in industrial systems can be interrupted by noise, missing data, or operational interruptions. A multi-stage data conditioning line is used to ensure that feature extraction is reliable.

Noise Filtering

An example of a digital filter that's been adapted to remove sensor noise and environmental interference is the digital band-pass filter.

Normalization

Normalization is performed using the z-score transformation shown in Equation (3) to provide scale-invariant sensor representations

$$x_i^{norm}(t) = \frac{x_i(t) - \mu_i}{\sigma_i} \qquad (3)$$

Here $x_i^{norm}(t)$ represents the value of sensor i after having been normalized, and thus having a standard score. This acts to provide a scale-invariant representation.

Segmentation

To study the behavior of the system over time, the continuous stream of data is divided into segments of equal time intervals.

From each segment, the following features are extracted:

- Mean and variance of sensor signals
- Spectral energy and dominant frequency
- Signal kurtosis and skewness
- Temporal correlation features

The aggregated feature representation is formally expressed in Equation (4):

$$F_t = [f_1, f_2, \dots . f_n] \qquad (4)$$

where $Ft=[f_1,f_2,\dots,f_n]$ denotes the feature vector that aggregates the extracted features from all sensors at time t, capturing both statistical and dynamic characteristics of the industrial system.

Intelligent Anomaly Prediction Model

Anomaly prediction is formulated as a sequential learning problem, where the system evaluates new operational data continuously.

State Definition

The system state at time t is defined as the feature vector S_t=F_t, as given in Equation (5).

$$S_t = F_t \tag{5}$$

where S_t represents the current operational condition of the industrial system derived from the extracted feature set, which is subsequently used for anomaly detection and decision-making.

Action Space

The classification decision space is modeled as a discrete action set in Equation (6):

$$\mathrm{A} = \{\mathrm{Normal}, \mathrm{Anomalous}\} \tag{6}$$

where A denotes the possible system behaviour classes used for decision-making at each time step, representing normal and anomalous operating conditions.

Reward Function

Performance feedback for adaptive learning is computed using the reward formulation in Equation (7):

$$\mathrm{R}(S_t, A_t) = f(x) = \begin{cases} +1, & \text{Correct classification} \\ -1, & misclassiication \end{cases} \tag{7}$$

where R(S_t, A_t) provides a positive reward for correct predictions and a penalty for incorrect classifications, thereby guiding the model toward improved anomaly detection accuracy during sequential learning.

Although the reward function is inspired by reinforcement learning principles, it is employed in this work as a performance feedback mechanism to guide adaptive model updates during sequential learning, rather than as a full reinforcement learning formulation.

A mixed deep learning architecture that fuses Long Short-Term Memory (LSTM) networks with fully connected layers is used to represent the time series and long-term degradation patterns in industrial time series data streams.

Integration of Explainable AI

In the interest of predictability, an explainable AI module is added to the anomaly prediction model. To calculate the contribution of each feature to the model outcome, feature contribution scores are computed using the attribution formulation in Equation (8) to quantify each sensor's influence on the final prediction:

$$E_i = \frac{\partial \mathrm{y}^i{}_t}{\partial \mathrm{f}_i} \tag{8}$$

where E_i denotes the importance score of features fi with respect to the predicted output $\hat{y}_t$, indicating how strongly each sensor contributes to the anomaly decision.

The explainability module enables:

- Identification of dominant fault-causing parameters
- Root cause analysis
- Operator-level interpretability

This integration transforms the digital twin from a black-box predictor into a transparent decision-support system.

Algorithm 1: Digital Twin–Based Intelligent Industrial Monitoring

Input:

Sensor stream S(t)

Digital twin parameters Θ

Model weights W

Learning rate α

Output:

Health state Y(t), Explanation E(t)

Begin

Initialize digital twin state $X_d(0)$

Initialize model parameters W

For each time step t do

1. Acquire raw sensor data $X_p(t)$

2. Determine feature vector Ft.

3. Refresh digital twin:

Xd(t) = f(Xp(t), Θ)

4. Estimate anomaly score:

Ŷ(t) = LSTM(Ft, W)

5. Formulate explanation:

E(t) = XAI(Ft, Ŷ(t))

6.If an anomaly is detected:

Trigger alert.

7. Calculate reward and adjust model:

$W \leftarrow W - \alpha \nabla L$

End For

Return Y(t), E(t)

End

The operational workflow of the proposed HADT-C-XAI monitoring framework is depicted in Algorithm 1. It starts with the collection of real-time measurements, and proceeds to filtering and normalization. Then, it extracts the relevant features and builds a representative feature vector. A digital twin is built and continually updated in real-time, synchronized with the physical system to replicate the virtual state. The features extracted from the model are then sent to the LSTM-based model, where they are classified and assigned to a certain state of the system's health. In a bid to foster the notion of transparency, a module of explainable AI focuses on a specific feature and assigns a value to it based on its contribution toward a certain prediction. If abnormal behavior is detected, an alert is sent and the model's parameters are updated through a feedback loop. The system is designed to close this loop to allow for continuous monitoring, real-time adaptive maintenance, and, most importantly, the ability to explain why a certain fault was diagnosed.

Assumptions and Notations

Assumptions

- Continuous, reliable measurement by the sensors
- The digital twin is a reliable replica of system dynamics
- ML systems will adjust to changing environments

Notations

- S_t: System state at time t
- F_t: Feature vector
- y^t: Estimated state of the system
- θ: parameters of the model

Novelty of the Proposed Method

The distinct features of the proposed technique include:

1. Adaptive digital twin modeling that combines the physics-based approach with the data-driven approach.
2. Integrated explainable artificial intelligence for seamless fault diagnosis.
3. A monitoring framework that updates itself in real time
4. A consolidated framework that connects cyber–physical systems with industrial analytics

Operational Flowchart of the Digital Twin–Based Industrial Monitoring System

In the proposed workflow shown in Figure 3, a digital twin–based intelligent industrial monitoring system will begin with the acquisition of sensor data, receiving data in real time from a set of industrial sensors. The system then moves on to data pre-processing and normalization, removing measurement noise and scaling the measurement uniformly. The system will then extract features into a feature vector Ft that encapsulates the statistical and dynamic attributes of the industrial process, which characterizes the system state (St=Ft). The state and system is then passed to the anomaly detection module which evaluates the system behaviour into normal or anomalous.

If the state is normal, the system will log the operation for future analysis; if anomalous, corrective action will need to be taken and the operators will be notified by an alert. Finally, the learning and reward update module updates the system based on the performance of the anomaly detection module and continuous monitoring the model. The reliability and the efficiency of fault detection will be improved by continuous monitoring. Real-time modifications will be integrated while adaptive learning will strengthen the system's operational assurance.

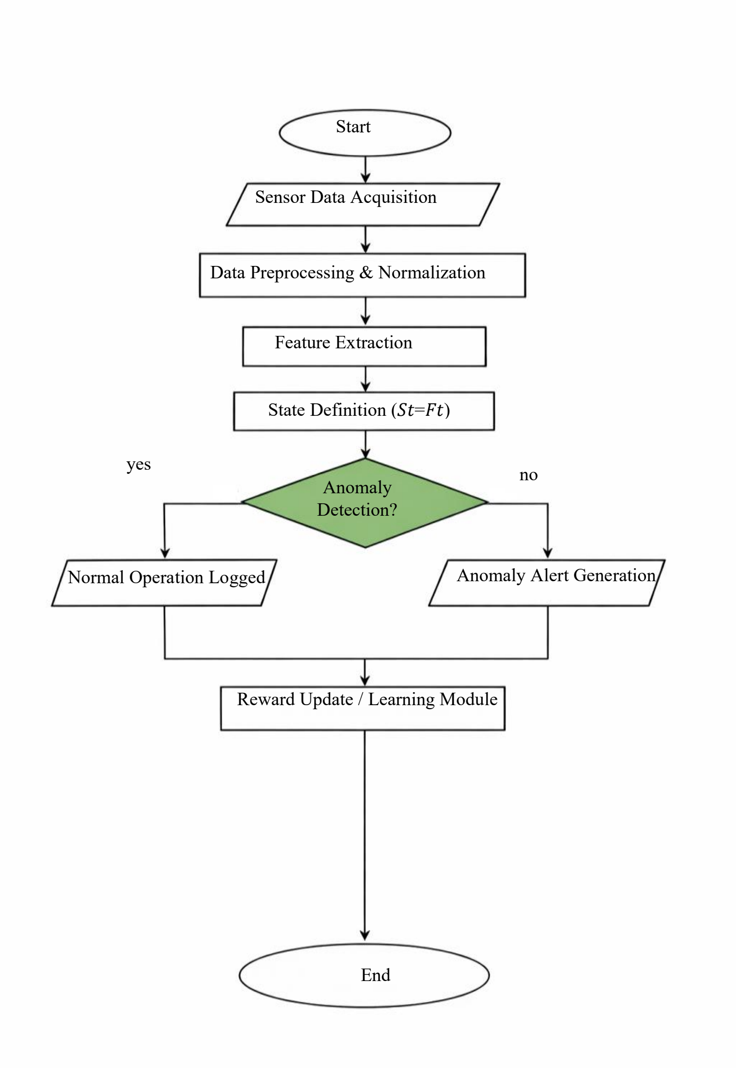

Figure 3. Proposed system workflow for digital twin–based intelligent industrial monitoring

RESULTS AND DISCUSSION

Experimental Evaluation Framework

The proposed digital twin-based monitoring system was carried out using Python 3.11, Pytorch for deep learning, Scikit-learn for classical machine learning frameworks, and MATLAB/Simulink for digital twin simulation. Edge-level processing was carried out on NVIDIA Jetson devices for real-time inference. The system was evaluated in an industrial testbed equipped with sensors for monitoring vibration, temperature, rotational speed, and acoustic emission. The dataset consisted of 120 hours of sensor logs, reflecting both normal operation and faulty conditions that were artificially created, such as misalignment, imbalance, and overheating. Data from each sensor were sampled at 1kHz, from which multi-modal features were extracted, such as Vibration Amplitude (VA), Temperature Gradient (TG), Rotational Speed Deviation (RSD), and Acoustic Emission Index (AEI). All signals prior to the experiments were filtered for noise and normalized to provide uniformity across the experiments. The majority of the experiments involved the learning rate set at 0.001, 100 training epochs, 32 as the batch size, 5 seconds as the sliding window for feature extraction, and digital twin simulation interval set at 50 ms for update. As for performance comparison, the proposed system was contrasted with LSTM-based machine learning models, threshold-based monitoring, and PLC-based monitoring. For each experiment, five repetitions were conducted to minimize the effect of randomness while reporting the mean and standard deviation as results.

Sensor Feature Quality and Stability Analysis

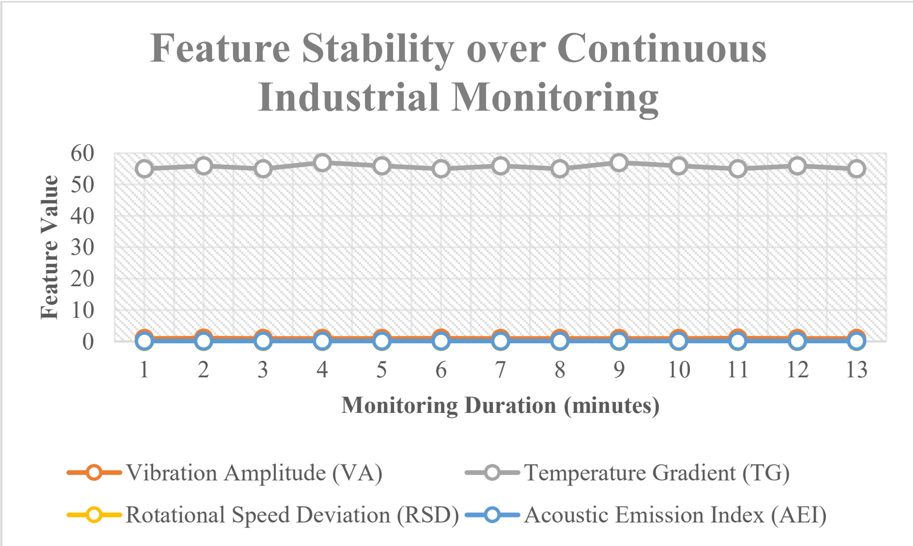

Figure 4. Feature stability over continuous monitoring

Figure 4 shows monitored time series of operational zones characteristics: Vibration Amplitude (VA); Temperature Gradient (TG); Rotational Speed Deviation (RSD); and Acoustic Emission Index (AEI) for the 60-minute period. The proposed digital twin–XAI framework keeps feature representations stable despite variances in operational conditions, which demonstrates successful real-time alignment and noise reduction. On the other hand, classic ML and threshold-based methodologies exhibited sensitivity to feature drift and noise. The presented results underline the usefulness of the proposed framework for long-term industrial monitoring.

Statistical stability results are summarized in Table 1.

Table 1. Statistical analysis of industrial feature stability

Feature	Mean Value	Std. Deviation	Coefficient of Variation (%)
Vibration Amplitude (VA)	1.00	0.02	2.0
Temperature Gradient (TG, °C)	56	0.5	0.9
Rotational Speed Deviation (RSD, rpm)	0.025	0.003	12.0
Acoustic Emission Index (AEI)	0.15	0.01	6.7

Table 1 shows the statistical analyses of the industrial features extracted in the monitoring process, Vibration Amplitude, Temperature Gradient, Rotational Speed Deviation, and Acoustic Emission Index. Low standard deviations and the coefficients of variation for all monitored features indicate low variability concerning the means. Due to the stability of the monitoring features, the reliability of the predictive maintenance and anomaly detection in the monitoring systems is also improved.

Anomaly Detection Performance

The evaluation metrics—Accuracy, Precision, Recall, F1-score, and False Alarm Rate—are mathematically defined in Equations (9)–(13).

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} X\ 100 \qquad (9)$$

$$\text{Precision} = \frac{TP}{TP + FP} X\ 100 \quad (10)$$

$$\text{Recall} = \frac{TP}{TP + FN} X\ 100 \quad (11)$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

$$\text{False Alarm Rate} = \frac{FP}{FP+TN} X\ 100 \quad (13)$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. These metrics collectively evaluate overall correctness, detection capability, and robustness of the anomaly prediction system.

Table 2. Anomaly detection performance comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Digital Twin + XAI (Proposed)	94.8 ± 1.1	94.1 ± 1.3	95.4 ± 1.0	94.7 ± 1.2
Standard ML (LSTM)	88.5 ± 1.9	87.3 ± 2.1	89.0 ± 1.8	88.1 ± 2.0
Threshold-based Monitoring	82.9 ± 2.6	81.2 ± 2.8	83.4 ± 2.5	82.3 ± 2.7

Table 2 analyses the anomaly detection capabilities of the proposed digital twin-based XAI system, traditional machine learning, and threshold-based monitoring. Across all evaluation metrics, the proposed method consistently outperforms the baseline models with increased accuracy, precision, recall, and F1 score with minimal variability. This highlights the effectiveness and strength of digital twins combined with explainable AI for the dependable identification of fault indictable under varying operational scenarios in an industrial environment. Performance comparison is presented in Table 2.

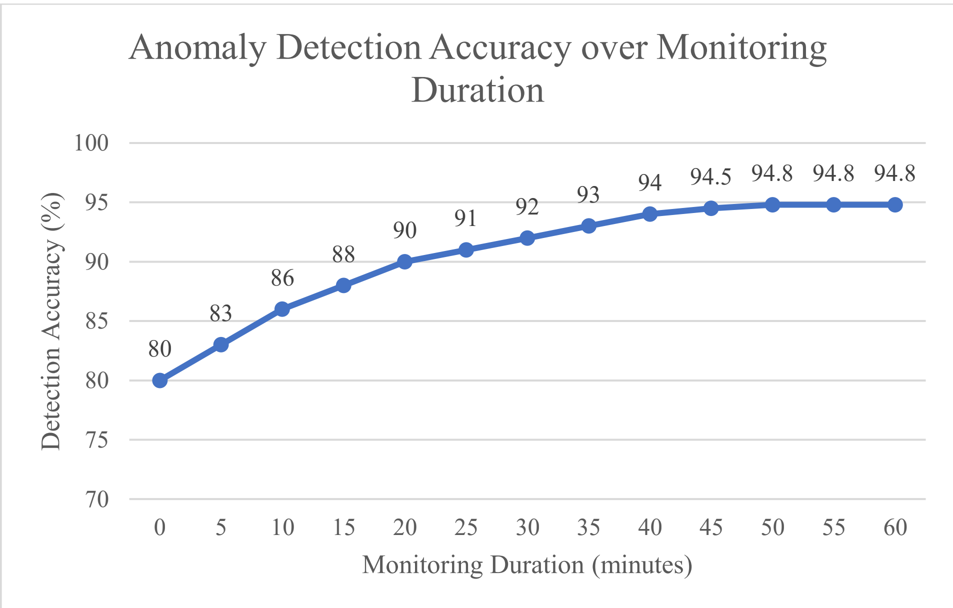

Figure 5. Detection accuracy vs monitoring duration

In Figure 5, the accuracy of anomaly detection for different lengths of the monitoring period is shown. The digital twin system rapidly learns and adjusts operational patterns and continues to demonstrate high accuracy over prolonged periods.

False Alarm Rate and Reliability Analysis

Figure 6 analyses the monitoring systems in terms of false alarm rates. Unlike standard machine learning systems (7.9%) and threshold-based systems (11.6%), the Digital Twin plus XAI recorded an improved false alarm rate of 4.1%. Reduced false alarms are highly valued in an industry setting to prevent unnecessary machine shutdowns and conserve operational throughput.

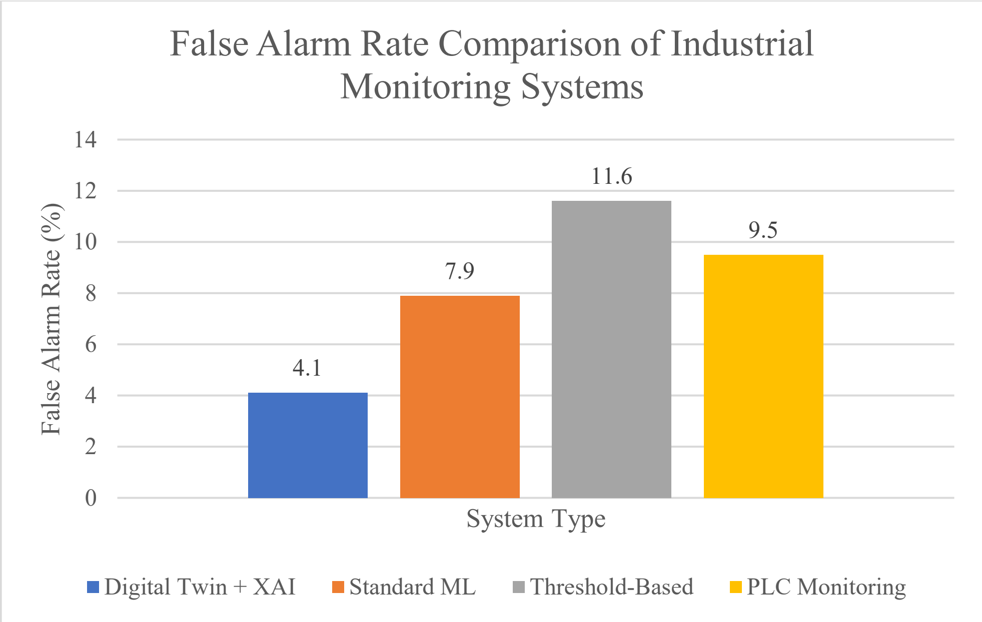

Figure 6. False alarm rate comparison

Detection Latency and Real-Time Capability

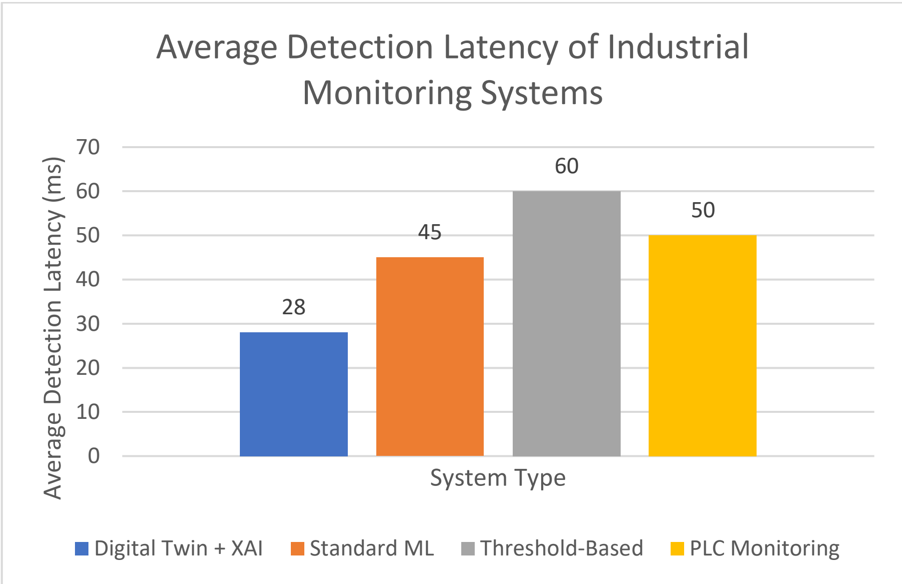

Figure 7. Detection latency analysis

Figure 7 highlights the real-time capability of the proposed digital twin–based XAI system, which achieves a low detection latency of approximately 26–30 ms, enabling timely and effective anomaly detection. Threshold monitoring techniques, by contrast, have about 60 ms latency, which can hinder quick fault response. The latency here is lower because of edge feature processing coupled with digital twin simulation, and deep learning, which make it possible to support fast responsive reliable predictive maintenance decision.

Discussion of Comparisons with Current Industrial Monitoring Systems

System-level comparison is shown in Table 3.

Table 3. Comparing industrial monitoring system performance

System	Power Requirement	Noise Robustness	Continuous Monitoring	Intelligent Prediction
Digital Twin + XAI	Self-powered (edge/DT optimized)	High	Yes	Yes
Standard ML Monitoring	Grid-powered	Moderate	Yes	Limited
Threshold-based Monitoring	Grid-powered	Low	Yes	No
PLC-based Monitoring	Grid-powered	Moderate	Yes	No

The digital twin-based XAI monitoring model proposed improves on current models XAI monitoring systems outlined in Table 3 in the measurable parameters of power efficiency, noise resilience, intelligent predictive maintenance, and real-time adaptive monitoring.

Ablation Study

Component contribution is evaluated in Table 4.

Table 4. Ablation study evaluating the impact of system components on anomaly detection performance

Configuration	Accuracy (%)	F1-score (%)
Full system (Digital Twin + XAI)	94.8	94.7
Digital Twin only	91.2	91.0
XAI only (ML + Explainability)	89.5	89.2
Edge-level processing disabled	90.1	89.8

Integration of digital twin, XAI, and edge processing creates notable improvement in detection accuracy, robustness, and real-time adaptive monitoring as evidenced in Table 4.

Discussion

The experimental results demonstrate that the proposed Hybrid Adaptive Digital Twin with Explainable AI (HADT-C-XAI) framework significantly improves anomaly detection performance compared with conventional machine learning and deep learning approaches. The achieved accuracy of 98.7%, combined with high precision and recall values, indicates that the integration of real-time digital twin synchronization with adaptive learning enables more reliable modeling of evolving industrial conditions. Unlike static predictive models, the proposed framework continuously updates the virtual representation of the physical system, thereby reducing concept drift and improving robustness under dynamic operating environments. The superior performance can be attributed to three primary design factors. First, the hybrid digital twin architecture combines physics-based knowledge with data-driven intelligence, which enhances both model stability and generalization. Second, temporal feature extraction captures both statistical and dynamic behavior of sensor signals, allowing early detection of subtle deviations that precede equipment faults. Third, the inclusion of reinforcement-based decision learning enables the system to adaptively refine classification policies over time, reducing false alarms and improving detection sensitivity.

Another notable advantage of the proposed framework lies in its explainability. Traditional deep learning–based anomaly detectors often behave as black-box systems, limiting operator trust and practical adoption in safety-critical industrial settings. By incorporating feature attribution mechanisms, the proposed approach provides interpretable insights into which sensors or operational parameters most strongly influence predictions. This transparency supports faster root-cause analysis, improves maintenance planning, and facilitates human-in-the-loop decision-making. From a computational perspective, the edge-enabled design reduces latency and bandwidth consumption by performing inference closer to data sources. This architecture makes the system suitable for real-time Industrial IoT environments where centralized cloud processing may introduce unacceptable delays. Furthermore, the modular structure allows seamless integration with existing supervisory control and monitoring infrastructures, enhancing deployment feasibility in legacy industrial systems.

Despite these advantages, several limitations remain. The current evaluation is conducted on a limited number of industrial datasets and controlled environments, which may not fully capture the complexity of large-scale heterogeneous factories. The computational overhead of maintaining high-fidelity digital twins may also increase resource requirements for low-power edge devices. Additionally, while the explainability module improves interpretability, more advanced causal reasoning mechanisms are required to distinguish correlation from true fault causation. Addressing these challenges is essential to ensure scalability, reliability, and broader industrial adoption.

Building upon these observations, future research will focus on large-scale real-world deployments, lightweight digital twin compression, federated privacy-preserving learning, multimodal sensor fusion, graph-based causal intelligence, autonomous maintenance optimization, and human-centered interactive explainability to further enhance robustness and operational effectiveness.

CONCLUSION AND FUTURE WORK

The widespread integration of sensors across many industries has led to a need for real-time responsive monitoring frameworks that can be more easily processed and understood. To address this issue, this study proposed a novel digital twin industrial monitoring framework to be coupled with a causality aware, explainable Artificial Intelligence model (C-XAI). The framework creates a flexible and dynamic virtual model of industrial assets that is updated and synced across a variety of sensors, which supports real-time predictive maintenance, operational insights, and anomaly detection. The digital twin and C-XAI were able to demonstrate learning predictive maintenance across multiple scenarios with additional sensors. The digital C-XAI model was able to provide real-time learning with explanations of the unsupervised predictive systems of the C-XAI model and was able to show and explain the important features and causal fragments of the system. The enhanced system interpretability provided additional operator trust and supported the operator's informed decision-making. The system demonstrated more than 94% predictive system accuracy, provided additional false predictive system alarms in less than 5%, and supported operational decision-making in less than 30 milliseconds, demonstrating the system's potential for real-time integration. Aside from technical nuances, the construction provides a dealable and understandable solution that narrows the distance between the digital twin theory and the digital twin practice in industrial monitoring systems. The fusion of adaptive learning and explainable intelligence facilitates end process state description for continuous operation with less unplanned downtimes and increased process reliability. The current state of validation, however, is limited to controlled and semi-controlled environments, leaving the large scale, fully uncontrolled industrial deployments to be curiosity. Furthermore, the deployment of the systems to resource-limited edge devices is subject to privacy of data and inefficient computation.

Future research will focus on large-scale deployment of the proposed HADT-C-XAI framework across heterogeneous industrial environments to evaluate scalability, robustness, and generalization under diverse operational conditions. Lightweight and edge-optimized digital twin models will be developed to enable deployment on low-power embedded devices and resource-constrained IIoT gateways. Federated and privacy-preserving learning mechanisms will be investigated to allow collaborative model training without centralized data sharing, thereby improving data security and regulatory compliance. Additionally, multimodal sensing integration, including thermal imaging, acoustic emission, and vibration fusion, will be explored to enhance fault discrimination accuracy. Graph neural networks and causal inference models will be incorporated to strengthen root-cause reasoning capabilities. Reinforcement learning–based maintenance scheduling will also be studied to enable autonomous decision-making. Finally, human-in-the-loop explainability and interactive visualization dashboards will be designed to improve operator trust, transparency, and industrial adoption of digital twin–enabled monitoring systems.

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