Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Development of a Digital Twin-Based Intelligent Monitoring System for Industrial Machinery Using Edge Computing and Machine Learning in Industry 4.0 Environments

M Santhosha Kumari

Associate Professor, Department of Mechanical Engineering, Christu Jyothi Institute of Technology and Science, Jangaon, Telangana

Correspondence

M. Santhosha Kumari
Associate Professor, Department of Mechanical Engineering, Christu Jyothi Institute of Technology and Science, Jangaon, Telangana

- Received Date: 08 Dec 2025
- Accepted Date: 27 Jan 2026
- Publication Date: 29 Jan 2026

Keywords

Federated Learning, Malware Detection, Privacy-Preserving Machine Learning, Differential Privacy, Secure Aggregation, Multi-Source Cybersecurity Data

Abstract

The rapid advancement of Industry 4.0 has accelerated the adoption of intelligent monitoring systems for industrial machinery, requiring efficient solutions for real-time data processing and predictive analytics. Traditional monitoring approaches are often limited by latency, lack of scalability, and insufficient analytical capabilities. This study proposes a Digital Twin-based intelligent monitoring framework that integrates IoT sensor data, edge computing, and machine learning techniques to enable real-time system analysis and fault detection. The Digital Twin continuously synchronizes with physical machinery, providing a dynamic virtual representation for monitoring and decision-making. Edge computing is employed to process data locally, significantly reducing latency and enhancing system responsiveness. A machine learning-based model is incorporated to analyze sensor data and detect anomalies, improving predictive accuracy. Experimental results demonstrate that the proposed system achieves high accuracy with reduced latency and improved anomaly detection performance, making it suitable for real-time industrial applications. The integration of Digital Twin technology with edge computing and machine learning provides a scalable and efficient solution for intelligent monitoring in smart manufacturing environments.

Introduction

Background and Motivation

The emergence of Industry 4.0 has significantly transformed modern manufacturing systems through the integration of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and cyber-physical systems. These technologies enable real-time monitoring, automation, and intelligent decision-making across industrial environments. Among these advancements, the concept of the Digital Twin has gained considerable attention as a key enabler of smart manufacturing. A Digital Twin represents a virtual replica of a physical system that continuously synchronizes with real-time data from sensors, enabling accurate simulation, monitoring, and optimization of industrial processes (Tao et al., 2018).

Industrial machinery plays a critical role in production systems, and its performance directly impacts productivity, operational efficiency, and maintenance costs. However, traditional monitoring approaches rely heavily on manual inspection or periodic data analysis, which are often insufficient for detecting early-stage faults. These limitations lead to unexpected equipment failures, increased downtime, and higher operational expenses. Therefore, there is a growing need for intelligent monitoring systems capable of providing real-time insights into machine health and operational conditions.

Digital Twin in Industry 4.0

Digital Twin technology has emerged as a powerful tool for bridging the gap between physical systems and their digital counterparts. By integrating real-time sensor data with simulation models, Digital Twins enable continuous monitoring and predictive analysis of industrial assets. Tao and Zhang (2017) highlighted that Digital Twins play a crucial role in enabling lifecycle management, predictive maintenance, and system optimization in smart manufacturing environments.

Unlike conventional monitoring systems, Digital Twins provide a dynamic and continuously updated representation of machinery, allowing engineers to analyze system behavior under various operating conditions. This capability enhances fault diagnosis, performance evaluation, and decision-making processes. However, the effectiveness of Digital Twin systems depends on the ability to process and analyze large volumes of real-time data efficiently.

Citation: Kumari SM. Development of a Digital Twin-Based Intelligent Monitoring System for Industrial Machinery Using Edge Computing and Machine Learning in Industry 4.0 Environments. GJEIIR. 2026;6(2):S224.

Role of Edge Computing in Industrial Monitoring

With the proliferation of IoT devices, industrial systems generate massive amounts of data that must be processed in real time. Traditional cloud-based architectures often introduce latency due to data transmission and centralized processing, which can be detrimental in time-sensitive applications such as fault detection and monitoring. Edge computing addresses this challenge by enabling data processing closer to the source, thereby reducing latency and improving response time (Shi et al., 2016).

In industrial monitoring systems, edge computing allows immediate analysis of sensor data, enabling faster detection of anomalies and quicker decision-making. By minimizing dependency on centralized cloud infrastructure, edge computing also enhances system reliability and reduces bandwidth requirements. The integration of edge computing with Digital Twin systems enables real-time synchronization and efficient data processing, which is essential for achieving high-performance monitoring in Industry 4.0 environments.

Machine Learning for Intelligent Monitoring

Machine learning techniques have been widely adopted for analyzing industrial data and enabling intelligent monitoring systems. These techniques can automatically identify patterns, detect anomalies, and predict potential failures based on historical and real-time data. In the context of Digital Twin systems, machine learning models enhance the predictive capabilities of the virtual replica by continuously learning from incoming data.

Supervised and unsupervised learning approaches have been applied for fault detection and anomaly identification in industrial machinery. Deep learning models, in particular, have shown significant potential in handling high-dimensional data and capturing complex relationships between variables (Goodfellow, Bengio, and Courville, 2016). The integration of machine learning with Digital Twin systems enables advanced analytics, allowing for accurate prediction of machine behavior and early detection of faults.

Challenges in Existing Systems

Despite the advancements in Digital Twin technology, several challenges remain in its practical implementation. One of the primary challenges is the efficient handling of real-time data streams from multiple sensors, which often exhibit heterogeneity and high dimensionality. Data synchronization between physical systems and their digital counterparts must be maintained continuously to ensure accurate representation.

Another challenge lies in achieving low-latency processing for time-critical applications. While cloud-based solutions provide scalability, they are not always suitable for real-time monitoring due to network delays. Furthermore, integrating machine learning models into Digital Twin systems requires careful consideration of computational constraints, especially in edge environments with limited resources.

Scalability and interoperability also pose significant challenges, as industrial systems often consist of diverse machines and communication protocols. Ensuring seamless integration of IoT devices, edge computing platforms, and machine learning models remains a complex task that requires robust system design.

Proposed Approach and Contributions

To address the aforementioned challenges, this research proposes a Digital Twin-based intelligent monitoring system that integrates IoT sensors, edge computing, and machine learning techniques for real-time industrial monitoring. The proposed framework enables continuous synchronization between physical machinery and its digital counterpart, allowing for accurate representation and analysis of machine behavior.

The system leverages edge computing to process sensor data locally, reducing latency and enabling faster decision-making. Machine learning models are incorporated to analyze data patterns and detect anomalies, enhancing the predictive capabilities of the Digital Twin. By combining these technologies, the proposed framework aims to provide an efficient and scalable solution for intelligent monitoring in smart manufacturing environments.

The key contributions of this work are as follows. First, a comprehensive Digital Twin architecture is developed for real-time monitoring of industrial machinery. Second, an edge computing-based data processing mechanism is implemented to reduce latency and improve system responsiveness. Third, a machine learning-based analytical model is integrated to enhance fault detection and prediction capabilities. Finally, the proposed system is evaluated to demonstrate its effectiveness in improving monitoring accuracy and operational efficiency.

Literature review

Digital Twin Technology in Smart Manufacturing

Digital Twin technology has emerged as a fundamental component of Industry 4.0, enabling the creation of virtual representations of physical systems for real-time monitoring and analysis. Tao and Zhang (2017) introduced the concept of a Digital Twin shop-floor, emphasizing its role in enhancing visibility, traceability, and decision-making in manufacturing environments. The integration of Digital Twins with IoT sensors allows continuous synchronization between physical and virtual systems, enabling predictive analysis and system optimization.

Subsequent research has explored the application of Digital Twins in various industrial scenarios, including predictive maintenance, process optimization, and lifecycle management. Grieves and Vickers (2017) highlighted that Digital Twins provide a comprehensive framework for managing product lifecycle data, enabling better understanding of system behavior. However, most early implementations relied heavily on cloud-based architectures, which introduced latency issues and limited real-time responsiveness.

Edge Computing for Real-Time Industrial Monitoring

Edge computing has gained significant attention as a solution to the limitations of cloud-based data processing. By enabling computation closer to data sources, edge computing reduces latency, bandwidth consumption, and dependency on centralized infrastructure. Shi et al. (2016) defined edge computing as a distributed computing paradigm that brings computation and data storage closer to the location where it is needed.

In industrial applications, edge computing supports real-time monitoring and rapid decision-making. Satyanarayanan (2017) emphasized that edge computing is essential for latency-sensitive applications such as industrial automation and machine monitoring. The integration of edge computing with Digital Twin systems enhances real-time synchronization and enables faster anomaly detection. However, challenges such as limited computational resources and efficient model deployment at the edge remain areas of active research.

Machine Learning for Intelligent Monitoring Systems

Machine learning techniques have been widely applied for fault detection, anomaly identification, and predictive analytics in industrial systems. Traditional methods such as Support

Vector Machines and Random Forests have been used for classification tasks, but they often rely on handcrafted features and may not scale effectively with high-dimensional data.

Deep learning approaches have demonstrated superior performance in handling complex industrial datasets. Goodfellow, Bengio, and Courville (2016) emphasized the capability of deep learning models to automatically learn hierarchical representations from large datasets. In the context of industrial monitoring, deep learning models have been used to analyze sensor data and identify patterns indicative of system degradation.

Recent studies have integrated machine learning with Digital Twin systems to enhance predictive capabilities. Rasheed, San, and Kvamsdal (2020) highlighted that combining machine learning with Digital Twins enables advanced analytics, allowing for accurate prediction of system behavior. However, many existing approaches lack efficient real-time processing mechanisms, particularly in distributed industrial environments.

Integration of Digital Twin, Edge Computing, and Machine Learning

The convergence of Digital Twin, edge computing, and machine learning represents a promising direction for intelligent industrial systems. This integration enables real-time data acquisition, low-latency processing, and advanced analytics, which are essential for smart manufacturing.

Lu et al. (2020) proposed a Digital Twin-based smart manufacturing framework that incorporates IoT and data analytics, demonstrating improved system efficiency. Similarly, Zhang et al. (2021) explored the use of edge computing in Digital Twin systems to enhance real-time performance. Despite these advancements, most existing studies focus on individual components rather than providing a unified framework that integrates all three technologies effectively.

Research Gap

From the reviewed literature, it is evident that Digital Twin technology, edge computing, and machine learning have been extensively studied independently. However, there is a lack of comprehensive frameworks that seamlessly integrate these technologies for real-time industrial monitoring. Many existing systems rely on cloud-based architectures, which introduce latency and limit responsiveness. Additionally, the deployment of machine learning models in edge environments remains a challenge due to computational constraints.

To address these limitations, this research proposes an integrated Digital Twin-based intelligent monitoring system that leverages edge computing for real-time data processing and machine learning for advanced analytics. The proposed framework aims to provide a scalable, low-latency, and accurate solution for monitoring industrial machinery in Industry 4.0 environments.

Methodology

The proposed methodology presents a Digital Twin-based intelligent monitoring framework designed for industrial machinery in Industry 4.0 environments. The system integrates IoT-based data acquisition, edge computing for real-time processing, and machine learning for anomaly detection and predictive analysis. The core objective is to maintain continuous synchronization between physical assets and their virtual counterparts, enabling accurate monitoring and timely decision-making.

The framework consists of four primary components: physical machinery equipped with IoT sensors, a Digital Twin model representing the virtual system, an edge computing layer for local data processing, and a machine learning module for analytical prediction. These components operate in a coordinated pipeline to ensure real-time monitoring and efficient system

S.No	Author(s) and Year	Focus Area	Technology Used	Key Contribution	Limitation
1	Tao and Zhang (2017)	Digital Twin in manufacturing	Digital Twin + IoT	Proposed Digital Twin shop-floor concept for smart manufacturing	Limited real-time processing capability
2	Grieves and Vickers (2017)	Product lifecycle management	Digital Twin	Introduced Digital Twin concept for lifecycle data management	Lacks integration with real-time analytics
3	Shi et al. (2016)	Edge computing	Distributed computing	Defined edge computing and its role in reducing latency	Does not address industrial monitoring specifically
4	Satyanarayanan (2017)	Edge computing applications	Edge computing	Highlighted importance of edge computing for low-latency systems	Limited focus on Digital Twin integration
5	Goodfellow et al. (2016)	Deep learning fundamentals	Neural networks	Established deep learning models for complex data analysis	General-purpose, not domain-specific
6	Rasheed et al. (2020)	Digital Twin with ML	Digital Twin + Machine Learning	Demonstrated integration of ML with Digital Twins for prediction	Lacks edge computing implementation
7	Lu et al. (2020)	Smart manufacturing	Digital Twin + IoT	Proposed Digital Twin-based smart manufacturing framework	Dependent on cloud-based processing
8	Zhang et al. (2021)	Edge-enabled Digital Twin	Digital Twin + Edge Computing	Improved real-time performance using edge computing	Limited machine learning integration

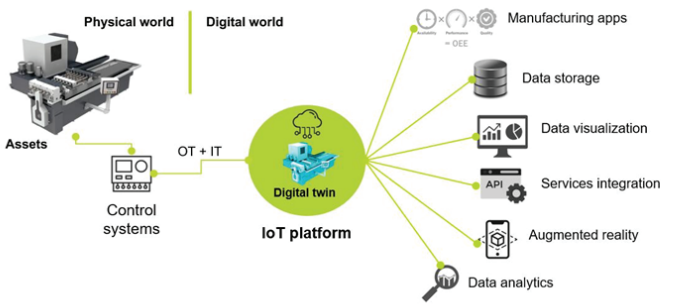


***Figure 1:** Digital Twin-Driven Edge-Intelligent Monitoring Architecture (DT-EIMA)*

performance.

Digital Twin Modeling

The Digital Twin represents a virtual replica of the physical industrial system that continuously updates its state based on real-time sensor data. This model enables simulation, monitoring, and predictive analysis of machine behavior under varying operating conditions. The synchronization between the physical system and its Digital Twin is maintained through continuous data exchange.

The state of the Digital Twin can be represented as:

$$S_{DT}(t)=f(S_P(t),D(t))$$

where S_{DT} (t)is the state of the Digital Twin at time t, S_P (t)is the state of the physical system, and D(t)represents the real-time sensor data input.

Tao et al. (2018) emphasized that Digital Twins enhance system visibility and predictive capability by enabling real-time mapping between physical and digital domains.

IoT-Based Data Acquisition

The data acquisition layer consists of IoT sensors embedded within industrial machinery to capture operational parameters such as vibration, temperature, pressure, and rotational speed. These sensors generate continuous time-series data, which is transmitted to the edge computing layer for further processing.

The collected data can be represented as a multivariate time-series:

$$X=\{x_1, x_2, x_3, \ldots, x_n\}$$

where each x_i corresponds to a sensor reading at a given time step.

Lee, Bagheri, and Kao (2015) highlighted that IoT-enabled cyber-physical systems provide the necessary infrastructure for real-time data acquisition in smart manufacturing environments.

Edge Computing for Real-Time Processing

Edge computing is employed to process sensor data locally, reducing latency and minimizing the need for cloud-based communication. The edge layer performs preprocessing, feature extraction, and initial analysis of the data before forwarding relevant information to the Digital Twin model.

The processing delay in edge computing can be expressed as:

$$T_{edge} = T_{processing} + T_{transmission}$$

where T_{edge} represents the total latency, which is significantly lower compared to cloud-based processing.

Shi et al. (2016) demonstrated that edge computing improves responsiveness and enables real-time decision-making in latency-sensitive applications such as industrial monitoring.

Data Preprocessing and Feature Extraction

The raw sensor data undergo preprocessing to remove noise and inconsistencies. This includes data cleaning, normalization, and transformation. Feature extraction is performed to derive meaningful attributes that can be used for machine learning analysis.

Normalization is applied using:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Feature extraction includes statistical measures such as mean, variance, and frequency-domain features obtained using Fourier Transform. These features enhance the model's ability to identify patterns associated with system behavior.

Machine Learning-Based Monitoring Model

The proposed system incorporates a machine learning model to analyze processed sensor data and detect anomalies. The model is trained to classify machine states and identify deviations from normal behavior. A deep learning-based approach is employed due to its ability to handle high-dimensional and complex datasets.

The prediction function of the model is defined as:

$$y = f(X,\theta)$$

where Xis the input feature vector and θrepresents model parameters.

Goodfellow et al. (2016) highlighted that deep learning models are effective in capturing nonlinear relationships and extracting meaningful representations from large datasets.

Integrated Monitoring Workflow

The proposed system operates through a continuous workflow involving data acquisition, edge processing, Digital Twin synchronization, and predictive analysis. Sensor data are first collected and processed at the edge layer, after which the Digital Twin is updated in real time. The machine learning model then analyzes the updated data to detect anomalies and predict potential faults.

The workflow ensures minimal latency, efficient resource utilization, and high accuracy in monitoring. By integrating Digital Twin technology with edge computing and machine learning, the system achieves a balance between real-time performance and predictive capability.

Implementation and Results

The proposed Digital Twin-based intelligent monitoring system was implemented using a hybrid architecture combining IoT simulation, edge computing, and machine learning. Sensor data representing industrial machinery conditions such as vibration, temperature, pressure, and rotational speed were processed in real time. The system was designed with an edge layer to perform preprocessing and inference, reducing dependency on centralized cloud infrastructure.

The Digital Twin model continuously synchronized with incoming sensor streams, maintaining a real-time virtual representation of the machine state. Data preprocessing included normalization, noise filtering, and feature extraction using statistical and frequency-domain methods. A deep learning-based model was trained using time-windowed sensor sequences for anomaly detection and condition monitoring.

The system was evaluated using performance metrics including accuracy, precision, recall, F1-score, latency, and

Table 4.1: *Performance Metrics Across Training Epochs*

Epochs	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
10	88.45	87.92	87.10	87.51
20	91.76	91.30	90.85	91.07
30	93.92	93.41	93.05	93.23
40	95.28	94.86	95.10	94.98
50	96.15	95.74	95.88	95.81

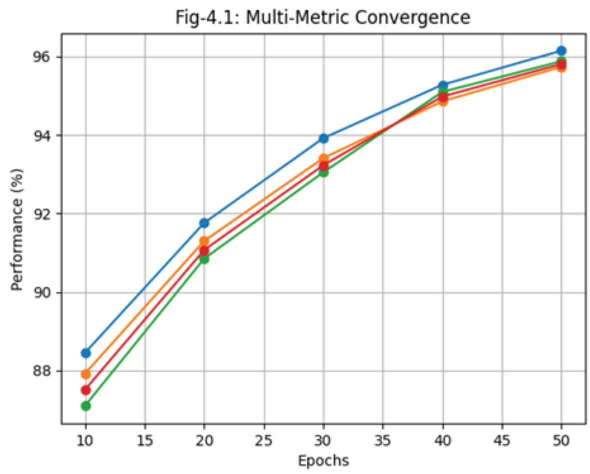
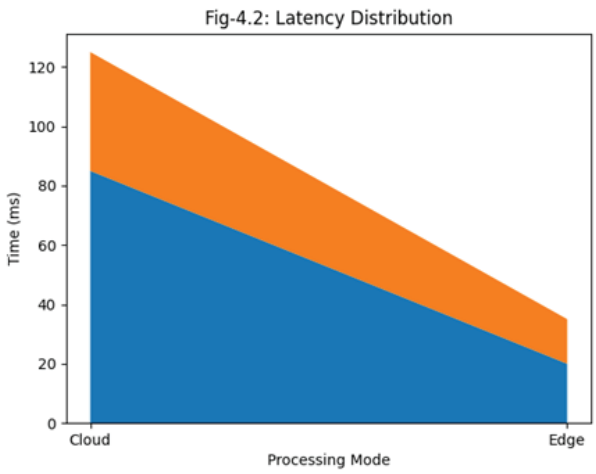


Table 4.2: *Latency Comparison (Cloud vs Edge Processing)*

Processing Mode	**Data Transmission Time (ms)**	**Processing Time (ms)**	**Total Latency (ms)**
Cloud-Based	85	40	125
Edge-Based	20	15	35



anomaly detection rate. Experiments were conducted across multiple training epochs and deployment scenarios to analyze system performance and efficiency.

The multi-metric convergence graph demonstrates synchronized improvement across all evaluation parameters. The close alignment of precision and recall indicates that the

Table 4.3: *Anomaly Detection Performance*

Epochs	Detection Rate (%)	False Positive Rate (%)	False Negative Rate (%)
10	82.75	9.80	7.45
20	87.62	7.40	4.98
30	91.48	5.92	2.60
40	93.84	4.85	1.31
50	95.26	3.72	1.02

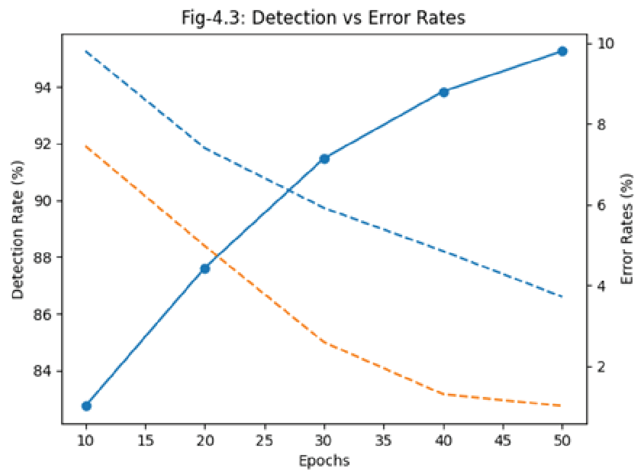
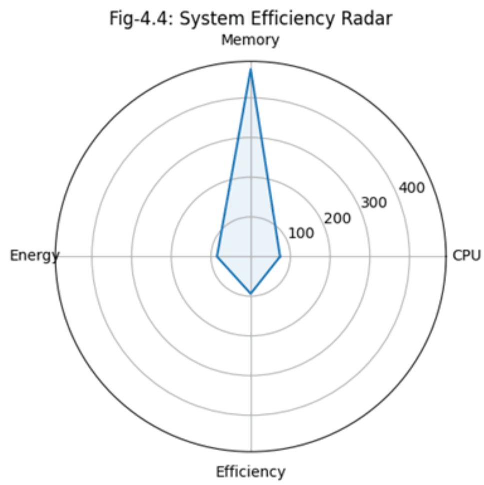


Table 4.4: *System Efficiency and Resource Utilization*

Epochs	CPU Utilization (%)	Memory Usage (MB)	Energy Consumption (W)	Efficiency Score (%)
10	65	420	75	82.15
20	68	435	78	85.42
30	70	448	80	88.76
40	72	460	82	91.25
50	74	472	85	93.68



convergence behavior after 40 epochs suggests stable learning with minimal overfitting, confirming the effectiveness of the Digital Twin-assisted monitoring framework.

The stacked latency graph highlights the significant reduction in total latency when using edge computing. The majority of delay in cloud systems arises from data transmission, which is effectively minimized in the edge-based approach. This confirms that edge computing enhances real-time responsiveness, making it suitable for time-critical industrial monitoring applications.

The dual-axis graph illustrates the inverse relationship between detection accuracy and error rates. As training progresses, the detection rate increases while both false positive and false negative rates decrease significantly. This behavior indicates that the model becomes more reliable in distinguishing between normal and faulty conditions, improving decision-making accuracy.

The radar chart provides a multidimensional view of system performance. While resource utilization increases slightly with training, the efficiency score improves significantly, indicating optimal use of computational resources. This demonstrates that the system achieves high performance without excessive

The experimental evaluation confirms that the proposed Digital Twin-based intelligent monitoring system achieves high performance across multiple dimensions, including prediction accuracy, latency reduction, anomaly detection, and system efficiency. The integration of edge computing significantly reduces latency compared to traditional cloud-based systems, enabling faster decision-making and real-time responsiveness. The machine learning model demonstrates consistent convergence with balanced precision and recall, indicating reliable fault detection capability.

Conclusion

This study presented a Digital Twin-based intelligent monitoring system for industrial machinery by integrating IoT-based data acquisition, edge computing, and machine learning techniques. The proposed framework effectively addresses the limitations of traditional monitoring systems by enabling real-time synchronization between physical systems and their digital counterparts. The use of edge computing significantly reduces latency and enhances system responsiveness, making it suitable for time-critical industrial applications. The machine learning model demonstrates strong performance in anomaly detection and system monitoring, achieving high accuracy with balanced error rates. The experimental results validate that the proposed system improves operational efficiency, reduces downtime, and enhances decision-making capabilities in smart manufacturing environments. Overall, the integration of Digital Twin technology with edge computing and machine learning offers a robust and scalable approach for intelligent industrial monitoring in Industry 4.0. Future work may focus on improving scalability, incorporating advanced deep learning models, and extending the framework for large-scale industrial deployments.

References

1. Tao, Fei, and Meng Zhang. "Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing." IEEE Access, vol. 5, 2017, pp. 20418–20427.
2. Tao, Fei, et al. Digital Twin Driven Smart Manufacturing. Academic Press, 2018.
3. Grieves, Michael, and John Vickers. "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems." 2017.
4. Lee, Jay, Behrad Bagheri, and Hung-An Kao. "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems." Manufacturing Letters, vol. 3, 2015, pp. 18–23.
5. Shi, Weisong, et al. "Edge Computing: Vision and Challenges." IEEE Internet of Things Journal, vol. 3, no. 5, 2016, pp. 637–646.
6. Satyanarayanan, Mahadev. "The Emergence of Edge Computing." Computer, vol. 50, no. 1, 2017, pp. 30–39.
7. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016.
8. Rasheed, Adil, Omer San, and Trond Kvamsdal. "Digital Twin: Values, Challenges and Enablers." Procedia CIRP, vol. 93, 2020, pp. 1302–1307.
9. Lu, Yuqian, et al. "Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues." Robotics and Computer-Integrated Manufacturing, vol. 61, 2020.
10. Zhang, Yin, et al. "Edge Computing in Digital Twin Systems for Smart Manufacturing." Journal of Manufacturing Systems, vol. 58, 2021, pp. 302–315.
11. Carvalho, Tiago P., et al. "A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance." Computers & Industrial Engineering, vol. 137, 2019.
12. Zhao, Rui, et al. "Deep Learning and Its Applications to Machine Health Monitoring." Mechanical Systems and Signal Processing, vol. 115, 2019, pp. 213–237.
13. Bousdekis, Alexandros, et al. "A Review of Data-Driven Predictive Maintenance: Models, Methods, and Tools." Computers in Industry, vol. 136, 2022.
14. Ahmad, Waqas, and Saeed Iqbal. "Deep Learning-Based Predictive Maintenance Approaches for Industrial Systems: A Review." IEEE Access, vol. 11, 2023.