

Editorial

Fault Diagnosis in IoT Applications: Advances, Challenges, and Future Directions

Giovanni Cicceri ^{1,*}  and Fabrizio De Vita ² ¹ Department of Biomedicine, Neuroscience and Advanced Diagnostics (BiND), University of Palermo, 90127 Palermo, Italy² Department of Engineering, University of Messina, 98166 Messina, Italy; fdevita@unime.it

* Correspondence: giovanni.cicceri@unipa.it

1. Introduction

The rise of the Internet of Things (IoT) has revolutionized the way industrial, structural, and environmental systems are monitored and maintained [1,2]. With billions of interconnected sensors, actuators, and smart embedded devices continuously monitoring the physical world, the IoT ecosystem enables real-time data acquisition, intelligent decision-making, and automation across domains such as smart manufacturing, energy systems, healthcare, transportation, and environmental monitoring [3,4]. In this context, fault diagnosis, comprising fault detection, isolation, and prediction, has become a cornerstone of resilient IoT system design [5,6]. The massive interconnectivity introduces, in fact, critical challenges in ensuring reliability, availability, and safety. Failures, degradations, or anomalies in IoT devices and networks can have cascading effects, leading to performance degradation, production downtime, safety risks, or even systemic failures [7]. The goal is to identify abnormal behavior in sensors, actuators, or communication links and to ensure timely mitigation before failures propagate.

Traditional rule-based or threshold-based monitoring techniques are no longer sufficient for modern IoT ecosystems characterized by data heterogeneity, scarcity data quality, dynamic environments, and large-scale distributed architectures [8]. Consequently, there has been a paradigm shift toward data-driven and model-based fault diagnosis frameworks, leveraging artificial intelligence (AI), machine learning (ML), deep learning (DL), and hybrid physics-informed methods to enhance detection accuracy, adaptivity, and scalability. Recent advances in edge and fog computing have further enabled real-time diagnostics at the network edge, reducing latency and bandwidth requirements [9,10]. At the same time, digital twin technologies have opened new frontiers by creating virtual replicas of physical systems that can simulate degradation dynamics and predict future failures under varying operational conditions [11,12]. In parallel, the incorporation of federated/incremental/continuous learning and privacy-preserving models is addressing data confidentiality challenges, allowing multiple IoT devices to collaboratively learn diagnostic models without sharing raw data [13,14].

Despite these advances, fault diagnosis in IoT applications remains a multifaceted and evolving research domain, with open challenges at several levels. For instance, on the data level, IoT devices often produce noisy, incomplete, and asynchronous data streams, requiring robust preprocessing, feature selection, and fusion techniques. On the algorithmic level, deep neural networks and ML models have shown high performance but often lack interpretability, leading to concerns about their explainability and trustworthiness in critical domains and applications.



Received: 10 October 2025

Accepted: 14 October 2025

Published: 27 October 2025

Citation: Cicceri, G.; De Vita, F. Fault Diagnosis in IoT Applications: Advances, Challenges, and Future Directions. *J. Sens. Actuator Netw.* **2025**, *14*, 104. <https://doi.org/10.3390/jsan14060104>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

From a systems perspective, IoT architectures must support decentralized and scalable diagnostic mechanisms capable of adapting to dynamically changing topologies, limited computational resources, and intermittent connectivity. In addition, cross-domain generalization remains an unsolved issue: models trained on specific datasets or environments frequently fail to generalize to other contexts due to sensor diversity, differing operational conditions, or domain shifts. This problem has motivated growing interest in transfer learning, domain adaptation, and meta-learning approaches, which aim to enable knowledge reuse across heterogeneous IoT systems. Another emerging direction involves the integration of physics-based modeling with data-driven learning, producing hybrid frameworks that combine the interpretability of first-principles models with the adaptability of AI-driven approaches. Moreover, the adoption of Explainable Artificial Intelligence (XAI) techniques in fault diagnosis is increasingly recognized as essential for building user trust and compliance with industrial safety standards. These “white-box” models that can highlight the most influential features or causal relationships behind a detected fault are critical in domains such as aerospace, autonomous systems, and healthcare. Complementary to this, uncertainty quantification and probabilistic fault reasoning provide valuable confidence estimates that guide decision-making in safety-critical operations.

This editorial aims to summarize the latest advances in IoT fault diagnosis, outline persistent challenges, and highlight promising research directions that will shape the next generation of intelligent and self-reliable IoT systems. By bringing together contributions from diverse scientific and industrial domains, this Special Issue provides a comprehensive perspective on how AI-driven, physics-informed, and distributed intelligence paradigms can converge to ensure trustworthy, explainable, and energy-efficient fault diagnosis across the IoT landscape.

2. An Overview of Published Articles

The papers published in this Special Issue present a comprehensive exploration of AI-based fault diagnosis and predictive maintenance frameworks across a variety of IoT-driven domains. The works cover a wide range of methods, including DL, reinforcement learning, signal processing, data fusion, and ontology-based modeling, illustrating the interdisciplinary nature and practical relevance of the field.

Kim et al. (List of Contributions, 5) introduced an advanced data augmentation framework for vibration-based fault detection in industrial centrifugal pumps. Their approach integrates GANs, variational autoencoders, and LSTM networks to enrich limited fault data and improve classification accuracy. The proposed method achieved up to 30% performance improvement over baseline models, demonstrating how synthetic data generation can significantly enhance robustness in predictive maintenance systems. Lee et al. (List of Contributions, 6) proposed a spectral-based diagnostic framework for shot blast machines, combining Fast Fourier Transform (FFT) spectral features with XGBoost classification and feature importance ranking. The study achieved 98% detection accuracy, proving that interpretable, lightweight ML models can deliver industrial-grade diagnostic performance with reduced computational cost. Zero et al. (List of Contributions, 4) presented a clustering-based predictive maintenance methodology for IoT-monitored bus systems. Their approach employs unsupervised reliability analysis and temporal pattern recognition to anticipate system failures and optimize maintenance schedules. Results showed enhanced reliability, reduced false alarms, and significant operational cost savings, underlining the utility of data-driven fleet management frameworks.

Jammalamadaka et al. (List of Contributions, 7) developed a fault-tolerant IoT networking architecture that integrates power fault prediction, isolation, and composite networking topologies at the device layer. The proposed method improves network longevity by 61%,

increases success rate by 21%, and reduces false alarm rate by 77%, demonstrating the benefits of hybrid topologies and AI-assisted fault isolation for resilient IoT systems. Hendriks et al. (List of Contributions, 1) proposed a structured data ontology for industrial asset monitoring, designed to integrate heterogeneous sensor, maintenance, and condition-monitoring data. The ontology enables consistent interoperability and semantic reasoning within AI-based diagnostic workflows, advancing the standardization of data representation for prognostics and health management systems. Kaliyannan et al. (List of Contributions, 2) investigated deep and reinforcement learning approaches for tool condition monitoring in milling processes. By comparing DNN, CNN, and SARSA reinforcement learning models, they found that the RL-based approach achieved the highest accuracy (98.66%) and adaptivity under variable cutting conditions, demonstrating the potential of reinforcement learning in adaptive manufacturing diagnostics.

Ma et al. (List of Contributions, 9) designed a sensor fusion-based anomaly detection framework for flood forecasting IoT systems. The method fuses multi-stream sensor data through pairwise differential time-series modeling, followed by ML-based anomaly detection. Tested on synthetic datasets built from one year of real data, the system improved the F1-score by 10.8%, confirming that sensor fusion can effectively reduce false positives in environmental IoT monitoring. Janeliukstis et al. (List of Contributions, 8) analyzed the influence of environmental factors on resonance frequencies in structural health monitoring (SHM) systems. They introduced a support vector regression (SVR) model to remove temperature and humidity effects from vibration data, significantly improving damage detection sensitivity and reliability in long-term SHM deployments. Del Priore and Lampani (List of Contributions, 10) presented a Graph Neural Network (GNN)-based framework for real-time damage detection and localization in composite aerospace structures. Using strain mode shapes from finite element simulations as graph input, the GNN achieved an AUC of 0.97 and an average localization error of 3%, outperforming CNN and fully connected networks, and highlighting the potential of topology-aware deep learning in aerospace SHM. Patanè et al. (List of Contributions, 3) explored predictive modeling for vehicle-to-grid (V2G) energy systems, comparing Dynamic Mode Decomposition (DMD) and LSTM neural networks for forecasting available energy capacity. The study demonstrated that hybrid temporal models can accurately capture the nonlinear dynamics of distributed energy resources, promoting fault-resilient and sustainable smart grid management.

3. Conclusions

The papers collected in this Special Issue collectively demonstrate how AI, ML, and IoT technologies are converging to redefine the principles of fault diagnosis, predictive maintenance, and system resilience. The ten published contributions span multiple domains, from industrial equipment monitoring and manufacturing processes to smart cities, energy systems, and aerospace structures, reflecting the interdisciplinary essence and practical relevance of this research area. Across these works, several trends clearly emerge. First, the increasing adoption of DL architectures (e.g., CNNs, LSTMs, and GNNs) is enabling the automatic extraction of complex fault signatures from multi-sensor data, significantly improving diagnostic accuracy. Second, RL and adaptive control mechanisms are enhancing the ability of IoT systems to self-optimize under changing operational conditions. Third, the rise of ontology-based modeling and digital twin technologies highlights a movement toward knowledge-driven and interpretable fault diagnosis, bridging the gap between data analytics and domain expertise.

Despite the remarkable advances presented in this Special Issue, several open challenges persist. The robustness and generalization of diagnostic models across heterogeneous IoT environments remain open issues, especially when dealing with limited labeled

data and dynamically evolving system behaviors. The explainability and transparency of AI-based diagnostics are essential to ensure trust and regulatory compliance in safety-critical applications. Moreover, resource constraints at the edge of IoT networks continue to limit the deployment of computationally demanding AI models, calling for further research in lightweight and energy-efficient inference strategies. Looking ahead, the future of fault diagnosis in IoT applications will likely revolve around synergistic frameworks that integrate edge computing, explainable AI, FL, and digital twin modeling. Such frameworks will not only detect faults but also predict their evolution, recommend corrective actions, and autonomously reconfigure system operations, ushering in the era of self-healing, trustworthy, and sustainable IoT ecosystems.

Author Contributions: Writing—original draft preparation, G.C. and F.D.V.; writing—review and editing, G.C. and F.D.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The Guest Editors would like to express their sincere gratitude to all the authors for their valuable contributions and to the reviewers for their constructive feedback and dedication. Special thanks are extended to the JSAN editorial team for their continuous support and professionalism throughout the publication process.

Conflicts of Interest: The authors declare no conflicts of interest.

List of Contributions

1. Hendriks, J.; Azarm, M.; Dumond, P. Structured Data Ontology for AI in Industrial Asset Condition Monitoring. *J. Sens. Actuator Netw.* **2024**, *13*, 23. <https://doi.org/10.3390/jsan13020023>.
2. Kaliyannan, D.; Thangamuthu, M.; Pradeep, P.; Gnansekaran, S.; Rakkiyannan, J.; Pramanik, A. Tool Condition Monitoring in the Milling Process Using Deep Learning and Reinforcement Learning. *J. Sens. Actuator Netw.* **2024**, *13*, 42. <https://doi.org/10.3390/jsan13040042>.
3. Patanè, L.; Sapuppo, F.; Napoli, G.; Xibilia, M. Predictive Models for Aggregate Available Capacity Prediction in Vehicle-to-Grid Applications. *J. Sens. Actuator Netw.* **2024**, *13*, 49. <https://doi.org/10.3390/jsan13050049>.
4. Zero, E.; Sallak, M.; Sacile, R. Predictive Maintenance in IoT-Monitored Systems for Fault Prevention. *J. Sens. Actuator Netw.* **2024**, *13*, 57. <https://doi.org/10.3390/jsan13050057>.
5. Kim, D.; Kareem, A.; Domingo, D.; Shin, B.; Hur, J. Advanced Data Augmentation Techniques for Enhanced Fault Diagnosis in Industrial Centrifugal Pumps. *J. Sens. Actuator Netw.* **2024**, *13*, 60. <https://doi.org/10.3390/jsan13050060>.
6. Lee, J.; Okwuosa, C.; Shin, B.; Hur, J. A Spectral-Based Blade Fault Detection in Shot Blast Machines with XGBoost and Feature Importance. *J. Sens. Actuator Netw.* **2024**, *13*, 64. <https://doi.org/10.3390/jsan13050064>.
7. Jammalamadaka, K.; Chokara, B.; Jammalamadaka, S.; Duvvuri, B. Making IoT Networks Highly Fault-Tolerant Through Power Fault Prediction, Isolation and Composite Networking in the Device Layer. *J. Sens. Actuator Netw.* **2025**, *14*, 24. <https://doi.org/10.3390/jsan14020024>.
8. Janeliukstis, R.; Ratnika, L.; Gaile, L.; Rucevskis, S. Environmental Factors in Structural Health Monitoring—Analysis and Removal of Effects from Resonance Frequencies. *J. Sens. Actuator Netw.* **2025**, *14*, 33. <https://doi.org/10.3390/jsan14020033>.
9. Ma, A.; Karande, A.; Dahlquist, N.; Ferrero, F.; Nguyen, N. Sensor Fusion Enhances Anomaly Detection in a Flood Forecasting System. *J. Sens. Actuator Netw.* **2025**, *14*, 34. <https://doi.org/10.3390/jsan14020034>.
10. Del Priore, E.; Lampani, L. Real-Time Damage Detection and Localization on Aerospace Structures Using Graph Neural Networks. *J. Sens. Actuator Netw.* **2025**, *14*, 89. <https://doi.org/10.3390/jsan14050089>.

References

1. Kumar, S.; Tiwari, P.; Zymbler, M. Internet of Things is a revolutionary approach for future technology enhancement: A review. *J. Big Data* **2019**, *6*, 1–21. [\[CrossRef\]](#)
2. Salih, K.O.M.; Rashid, T.A.; Radovanovic, D.; Bacanin, N. A comprehensive survey on the Internet of Things with the industrial marketplace. *Sensors* **2022**, *22*, 730. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Coito, T.; Firme, B.; Martins, M.S.; Vieira, S.M.; Figueiredo, J.; Sousa, J.M. Intelligent sensors for real-Time decision-making. *Automation* **2021**, *2*, 62–82. [\[CrossRef\]](#)
4. Abdulhussain, S.H.; Mahmmoud, B.M.; Alwhelat, A.; Shehada, D.; Shihab, Z.I.; Mohammed, H.J.; Abdulameer, T.H.; Alsabah, M.; Fadel, M.H.; Ali, S.K.; et al. A Comprehensive Review of Sensor Technologies in IoT: Technical Aspects, Challenges, and Future Directions. *Computers* **2025**, *14*, 342. [\[CrossRef\]](#)
5. De Vita, F.; Bruneo, D.; Das, S.K. On the use of a full stack hardware/software infrastructure for sensor data fusion and fault prediction in industry 4.0. *Pattern Recognit. Lett.* **2020**, *138*, 30–37. [\[CrossRef\]](#)
6. Atassi, R.; Alhosban, F. Predictive Maintenance in IoT: Early Fault Detection and Failure Prediction in Industrial Equipment. *J. Intell. Syst. Internet Things* **2023**, *9*, 231–238. [\[CrossRef\]](#)
7. Zheng, D.; Fu, X.; Liu, X.; Xing, L.; Peng, R. Modeling and Analysis of Cascading Failures in Industrial Internet of Things Considering Sensing-Control Flow and Service Community. *IEEE Trans. Reliab.* **2024**, *74*, 2723–2737. [\[CrossRef\]](#)
8. Kumar, S.S.; Agarwal, S. Rule based complex event processing for IoT applications: Review, classification and challenges. *Expert Syst.* **2024**, *41*, e13597. [\[CrossRef\]](#)
9. Bablu, T.A.; Rashid, M.T. Edge computing and its impact on real-time data processing for IoT-driven applications. *J. Adv. Comput. Syst.* **2025**, *5*, 26–43.
10. Islam, U.; Alatawi, M.N.; Alqazzaz, A.; Alamro, S.; Shah, B.; Moreira, F. A hybrid fog-edge computing architecture for real-time health monitoring in IoMT systems with optimized latency and threat resilience. *Sci. Rep.* **2025**, *15*, 25655. [\[CrossRef\]](#)
11. Qian, C.; Liu, X.; Ripley, C.; Qian, M.; Liang, F.; Yu, W. Digital twin—Cyber replica of physical things: Architecture, applications and future research directions. *Future Internet* **2022**, *14*, 64. [\[CrossRef\]](#)
12. Al Zami, M.B.; Shaon, S.; Quy, V.K.; Nguyen, D.C. Digital twin in industries: A comprehensive survey. *IEEE Access* **2025**, *13*, 47291–47336. [\[CrossRef\]](#)
13. Cicceri, G.; Tricomi, G.; Benomar, Z.; Longo, F.; Puliafito, A.; Merlino, G. Dilocc: An approach for distributed incremental learning across the computing continuum. In Proceedings of the 2021 IEEE International Conference on Smart Computing (SMARTCOMP), Irvine, CA, USA, 23–27 August 2021; pp. 113–120.
14. Zhang, L.; Lei, X.; Shi, Y.; Huang, H.; Chen, C. Federated learning for iot devices with domain generalization. *IEEE Internet Things J.* **2023**, *10*, 9622–9633. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.