

AI-Assisted Machine–Environment Interaction

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1. Introduction

AI-assisted machine–environment interaction has emerged as an important research direction at the intersection of artificial intelligence (AI), sensor and actuator networks, and the Internet of Things (IoT). IoT architectures connect physical objects, sensors, actuators, communication networks, and computational resources, enabling machines to collect and exchange large volumes of data about their surroundings [1,2]. Machine learning and deep learning techniques extend these capabilities by allowing sensor-based systems to recognize patterns, detect anomalies, predict future conditions, and adapt their operation according to changing environmental conditions [3–5]. Modern machines are no longer expected merely to collect environmental data; they are increasingly required to interpret such data and use the resulting knowledge to support autonomous or semi-autonomous decisions.

The development of edge computing and edge intelligence has further transformed machine–environment interaction by moving data processing and AI inference closer to sensors, devices, and machines [6,7]. This reduces communication latency, limits dependence on cloud infrastructure, and supports more immediate responses in applications requiring real-time or near-real-time operation. At the same time, multimodal machine learning enables information from heterogeneous sources—such as images, sound, temperature measurements, motion signals, and other sensor data—to be integrated into more comprehensive representations of an environment [8].

These developments support a wide range of applications. In transportation and autonomous driving, AI-assisted perception helps machines evaluate environmental conditions and determine whether safe operation is possible [9]. UAVs and autonomous robots use intelligent sensing, computer vision, and decision-making algorithms to navigate and perform operations in agricultural, industrial, security, and hazardous environments [10]. In manufacturing and other industrial systems, digital twins provide virtual representations of physical processes that can be continuously updated using sensor data [11], while machine learning methods enable predictive maintenance by identifying faults and estimating equipment condition before failures occur [12]. Data-augmentation and synthetic-data-generation techniques can also improve the development of AI systems when representative real-world data are limited, difficult to acquire, or unevenly distributed [13].

Despite this progress, AI-assisted systems must operate under uncertainty, incomplete or noisy data, changing environmental conditions, limited computational resources, communication constraints, and safety requirements. Models developed under controlled conditions may not maintain the same performance when applied to new environments. Moreover, the increasing use of complex machine learning models makes it difficult for



Received: 14 July 2026

Accepted: 22 July 2026

Published: 24 July 2026

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users and system operators to understand how particular predictions or decisions are produced. Explainable AI therefore plays an important role in making model behavior more transparent and understandable [14,15]. More broadly, trustworthy AI requires attention not only to predictive performance but also to robustness, reliability, transparency, privacy, safety, and accountability [16]. Uncertainty estimation is particularly important because an AI-assisted system should be able to indicate when the available data do not support a sufficiently reliable prediction [17]. In autonomous decision-making, these concerns are closely related to safe learning and the prevention of actions that could result in harmful physical consequences [18].

This Special Issue, “AI-Assisted Machine–Environment Interaction”, brings together ten contributions that address these opportunities and challenges from different but complementary perspectives. The contributions cover multimodal data integration, IoT-based agroecology, thermal-image analysis, energy prediction, infrastructure inspection, autonomous robot navigation, sound-data augmentation, UAV-based situational awareness, precision agriculture, and predictive maintenance. Collectively, they demonstrate how intelligent sensing, machine learning, computer vision, autonomous systems, and data-driven decision-making can improve the ability of machines to perceive, interpret, and respond to complex physical environments.

2. An Overview of Published Articles

Kang et al. (List of Contributions, 1) proposed a Tri-CycleGAN-based approach for multi-domain data integration in plasma diagnostics for semiconductor manufacturing. The study shows how AI can combine heterogeneous diagnostic data sources to improve the interpretation of complex industrial processes.

Bouchemal et al. (List of Contributions, 2) presented an intelligent IoT platform for agroecology. Their work demonstrates how embedded sensing, communication technologies, and AI-based reasoning can support more sustainable and data-driven agricultural practices.

Arnal et al. (List of Contributions, 3) introduced an automated semantic segmentation methodology for infrared thermography analysis of the human hand. This contribution illustrates the value of AI-assisted image analysis for extracting meaningful information from thermal sensing data.

Colucci and Mahgoub (List of Contributions, 4) investigated solar irradiance prediction for battery operation optimization in IoT-based microgrid environments. Their study highlights the role of machine learning in improving energy management and environmental adaptation.

Molefe et al. (List of Contributions, 5) compared image-processing and machine learning methods for classifying rail-welding defects. This work shows how AI-assisted visual inspection can contribute to infrastructure monitoring and maintenance.

Shanmugaraja et al. (List of Contributions, 6) reviewed hybrid path-planning algorithms for autonomous mobile robots. Their review emphasizes the importance of combining different planning strategies to improve robot navigation in complex and dynamic environments.

Tsalera et al. (List of Contributions, 7) evaluated the impact of sound dataset augmentation and synthetic generation on classification accuracy. Their results show that data augmentation can improve AI performance, although the benefits depend on the model and data characteristics.

Rattanaamporn et al. (List of Contributions, 8) provided a systematic review of drone imaging and sensing for situational awareness in hazardous environments. This contribution highlights the growing role of UAVs and intelligent sensing in environments where human access may be dangerous or limited.

Meng et al. (List of Contributions, 9) introduced a multi-background UAV spraying behavior recognition dataset for precision agriculture. This dataset supports research on robust AI models capable of recognizing agricultural operations under diverse environmental backgrounds.

Finally, Botomba et al. (List of Contributions, 10) proposed an automatic fault detection and prediction approach for automated guided vehicle (AGV) magnetic tracks using machine learning and computer vision. Their study connects AI-assisted perception with predictive maintenance for autonomous industrial transport systems.

Collectively, these contributions illustrate the breadth of AI-assisted machine–environment interaction, spanning multimodal data integration, intelligent sensing, predictive modeling, autonomous navigation, synthetic data generation, situational awareness, and predictive maintenance. Despite their diverse application domains, they share a common objective: enabling machines to derive actionable knowledge from complex environments and use it to support more adaptive, efficient, and reliable operation.

3. Conclusions

The papers published in this Special Issue demonstrate the rapid development and multidisciplinary character of AI-assisted machine–environment interaction. The accepted contributions cover industrial diagnostics, agroecology, thermal imaging, renewable energy, railway inspection, autonomous navigation, acoustic classification, hazardous-environment monitoring, UAV-based agriculture, and AGV fault detection.

Together, these works demonstrate that AI can improve how machines perceive, interpret, and respond to their environments. They also show that the field is moving from isolated sensing or classification tasks toward more integrated systems combining sensing, learning, prediction, and decision support.

Future research should focus on robust and trustworthy AI systems capable of operating under real-world uncertainty. Important directions include multimodal sensor fusion, edge AI, explainable and uncertainty-aware models, continual learning, digital twins, synthetic data generation, autonomous decision-making, and human–AI collaboration. Particular attention should be given to reliability, generalization, safety, and sustainability, since AI-assisted systems are increasingly being deployed in physical environments where errors may have operational, safety, economic, or environmental consequences.

This Special Issue provides a representative view of current progress and future challenges in AI-assisted machine–environment interaction. It is hoped that the contributions collected here will encourage further research toward intelligent, adaptive, and trustworthy systems for complex real-world environments.

Acknowledgments: The Guest Editors would like to express their sincere gratitude to all authors who contributed their research to this Special Issue and to the reviewers for their careful evaluations and constructive comments, which helped ensure the scientific quality of the published articles. The Guest Editors also thank the editorial team of the Journal of Sensor and Actuator Networks for their continuous support throughout the preparation and completion of this Special Issue.

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

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