ICON Journal of Engineering Applications of Artificial Intelligence
Volume 01 | Issue 01 | 2025
e-ISSN: 3051-3820
p-ISSN: 3051-3812
Journal homepage: https://iconpublishers.com/icon-j-eng-app-ai/

DOI: 10.5281/zenodo.16255214

Research Article

Artificial Intelligence in Smart Sensors and Actuators for Mechatronic Applications

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Received Date: 10 June 2025
Published Date: 21 July 2025

Abstract
Artificial intelligence (AI) is increasingly embedded within smart sensors and actuators to enable adaptive, autonomous, and predictive control in mechatronic systems. This review analyzes over 25 peer-reviewed studies, classifying methodologies by AI techniques, integration depth, and application context. Citation summaries highlight trends and future directions in robotics, manufacturing, soft systems, and embedded sensing. The study identifies research gaps, discusses deployment barriers (edge AI, standardization), and proposes an integration framework for next-generation AI-powered mechatronics.

Keywords: Artificial intelligence (AI), Smart Sensors, Mechatronics Applications, Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL).

I. INTRODUCTION

The convergence of Artificial Intelligence (AI) with mechatronics has introduced a new paradigm in the design and operation of intelligent systems. Mechatronic applications—ranging from industrial automation and robotics to wearable medical devices and autonomous vehicles—rely heavily on the integration of sensors, actuators, and control logic to function effectively in complex and dynamic environments. Traditionally, these systems have depended on predefined control algorithms and static behavior patterns. However, as systems become more interconnected, autonomous, and data-rich, traditional methods struggle to handle uncertainties, nonlinearities, and adaptive requirements.

Smart sensors and actuators are central to this transformation. Smart sensors not only detect environmental or internal system parameters but also preprocess data through embedded intelligence, allowing systems to perceive, interpret, and react to real-world conditions more effectively. Similarly, smart actuators are capable of executing actions with a degree of autonomy, often informed by real-time data streams or predictive models. These components become significantly more powerful when augmented with AI, enabling them to adapt to changing conditions, learn from experience, and interact with other subsystems in an intelligent, coordinated manner.

AI techniques such as machine learning (ML), deep learning (DL), reinforcement learning (RL), fuzzy logic, and hybrid AI models are increasingly being integrated with sensing and actuation mechanisms. These methods allow systems to go beyond reactive control, enabling capabilities such as predictive maintenance, adaptive decision-making, real-time optimization, and self-calibration. For instance, deep neural networks have been employed to fuse data from multiple sensors in robotic vision, while reinforcement learning has enabled autonomous robots to learn optimal control strategies in dynamic environments without explicit programming.

Moreover, the evolution of enabling technologies such as Edge AI, TinyML, and digital twins is accelerating the deployment of intelligent mechatronic systems. Edge computing allows AI algorithms to run directly on embedded devices close to the sensors and actuators, reducing latency and power consumption. Digital twins simulate real-time behavior of mechatronic systems, allowing AI models to be trained and tested in virtual environments before deployment.

Despite these advancements, several challenges remain. These include integrating AI models within the resource-constrained environments of sensors and actuators, ensuring reliability and explainability in safety-critical applications, and managing data quality and heterogeneity across different platforms. Additionally, the lack of standardized frameworks for AI-driven sensor–actuator systems present a barrier to scalability and interoperability.

This literature review aims to provide a comprehensive analysis of the current state-of-the-art in AI-enabled smart sensors and actuators for mechatronic applications. It categorizes key AI methodologies, highlights their practical implementations across various domains, and identifies emerging trends and future research directions. By synthesizing insights from over 25 peer-reviewed articles, the review seeks to guide researchers and practitioners in developing intelligent, responsive, and scalable mechatronic systems.

METHODOLOGY

AI Methodology	Function in Mechatronic Systems	Sensor Role	**Actuator Role**	**Example Studies**
Supervised Learning	Pattern recognition, fault detection	Data labeling, classification (e.g., vibrations)	Actuation based on classified states	[1], [4], [9]
Unsupervised Learning	Feature extraction, anomaly detection	Signal clustering	Health monitoring	[7], [18]
Reinforcement Learning (RL)	Online learning for control	Adaptive sensing feedback loops	Real-time trajectory and force control	[14], [17], [21]
Deep Learning (CNN/RNN)	Sensor fusion, temporal patterns	Visual/audio input processing	Motion prediction	[5], [12], [13]
Fuzzy Logic & Neuro-Fuzzy	Approximate reasoning	Noise tolerance in sensors	Haptic control, uncertainty handling	[3], [20]
Digital Twin + AI	Simulation-aided control	Real-time environment modeling	Predictive actuation control	[8], [19]
Edge AI / TinyML	On-device intelligence	Low-power data processing	Embedded actuation policies	[16], [23]
Hybrid AI (Physics + ML)	Model compensation	Drift estimation	Adaptive deformation response	[6], [22]

Citation Summaries of Key Literature

Ref	**Author(s)**	**Year**	**Title & Key Contributions**
[1]	Li et al.	2017	Surveyed AI-driven fusion of sensory input in automated manufacturing. Highlighted self-diagnosis in sensors.
[4]	Cherubini & Navarro-Alarcon	2020	Comprehensive review on multimodal AI sensors (vision, tactile) in collaborative robots.
[5]	You Li et al.	2020	Deep learning for inertial sensing and sensor calibration in wearable robotics.
[7]	Stassi et al.	2014	Fundamental soft tactile sensor technologies integrated with AI.
[8]	Huang et al.	2021	Proposed AI-based digital twins for closed-loop predictive control.
[9]	Zhao et al.	2024	Machine learning-enhanced wearable sensors for gesture recognition.
[12]	Amin et al.	2020	Edge-based deep learning coordination between sensors and actuators in Industry 4.0.
[14]	Lei et al.	2019	Reinforcement learning for AI-driven sensor-actuator optimization in IoT settings.
[17]	Guo	2023	Overview of AI in modular mechatronic architecture.
[20]	Chossat et al.	2013	Ionic liquid-based soft sensors for deformation recognition.
[22]	Xiao et al.	2023	Embedded magnetic sensing in soft actuators with AI feedback models.

DISCUSSION

The integration of Artificial Intelligence (AI) within smart sensors and actuators marks a fundamental shift in how mechatronic systems are designed, controlled, and evolved. The reviewed literature demonstrates that AI enhances mechatronic performance not only by improving sensor and actuator functionality independently, but more importantly by enabling seamless coordination between them through closed-loop feedback systems, data-driven control, and predictive intelligence.

1) Smart Sensors Enhanced by AI

Smart sensors embedded with AI capabilities move beyond simple data acquisition. They perform real-time preprocessing, feature extraction, anomaly detection, and context understanding at or near the edge. AI algorithms such as convolutional neural networks (CNNs) have enabled visual sensors to perform complex object recognition and tracking, essential in robotics and autonomous systems. Long Short-Term Memory (LSTM) networks and other recurrent architectures have demonstrated superior performance in temporal signal processing, such as electroencephalogram (EEG), electromyogram (EMG), and inertial measurement unit (IMU) data, facilitating accurate gesture recognition and movement intent detection in wearable systems and prosthetics.

Moreover, unsupervised and self-supervised learning models are emerging as solutions for applications where labeled data are scarce, enabling sensors to adapt and calibrate themselves over time without human intervention. These advances reduce the dependence on external computing infrastructure and make sensors more intelligent, robust, and context-aware.

2) Smart Actuators Driven by AI

AI integration in actuators has led to the emergence of intelligent actuation systems capable of learning optimal motion profiles, adapting to changing environments, and executing complex physical interactions with high precision. Deep reinforcement learning (DRL) has been particularly successful in enabling actuators to learn control policies through trial-and-error, a paradigm highly suitable for soft robotics, where dynamic modeling is difficult due to material nonlinearity.
In addition, fuzzy logic controllers and neuro-fuzzy systems are commonly employed to manage uncertainties and approximate reasoning in actuator control, especially in human–robot interaction (HRI) scenarios where safety and responsiveness are paramount. AI-enabled actuators are also used in fault detection and predictive maintenance, extending their operational lifetime and reducing downtime in industrial settings.

Hybrid approaches combining model-based physics with AI have shown potential in actuator performance prediction and optimization. These methods allow for interpretable and generalizable control strategies that balance accuracy with computational efficiency.

3) AI for Sensor–Actuator Feedback Loops

The most impactful applications arise when AI is used to tightly couple sensors and actuators in intelligent feedback loops. Reinforcement learning and adaptive control algorithms allow systems to adjust actuation in real time based on sensed conditions, environmental feedback, or predicted outcomes. This has been particularly effective in autonomous robots, exoskeletons, and drones, where dynamic adaptation is essential.

Sensor fusion plays a crucial role in these systems, allowing multiple sensor modalities (e.g., vision, tactile, inertial) to be combined using AI techniques to provide a holistic understanding of the environment. These fused signals are then used to drive actuator behavior with higher reliability and responsiveness. The ability of AI to extract complex, high-level features from raw sensor data and translate them into control commands is one of the key differentiators of intelligent mechatronic systems.

Furthermore, digital twins and virtual simulators powered by AI are being used to simulate sensor-actuator interactions in real time, allowing predictive modeling and preemptive control. These systems can train AI models in virtual space and deploy them in physical systems with high transfer fidelity, reducing testing costs and risks.

4) Cross-Domain Impact and Innovation

The application of AI-enhanced sensors and actuators spans several domains:

- **Industrial automation** benefits from AI's ability to predict failures, reduce downtime, and optimize energy usage.
- **Healthcare and assistive devices** leverage AI for interpreting bio signals and translating them into actuation patterns, e.g., controlling prosthetic limbs or robotic rehabilitation aids.
- **Soft robotics** uses AI to manage deformation sensing and shape actuation, critical in delicate manipulation tasks.
- **Autonomous systems**, such as drones and mobile robots, use AI to integrate multiple sensor feeds for real-time navigation and obstacle avoidance.

These innovations highlight the flexibility and scalability of AI-powered sensor-actuator frameworks and emphasize the need for standardization and efficient edge deployment.

Application in Mechatronics

Domain	AI Contribution	Examples
Industrial Automation	Predictive maintenance, anomaly detection	[1], [12], [14]
Robotics	Adaptive manipulation, sensor-guided motion	[4], [13], [17]
Wearables & Prosthetics	Biosignal-to-motion conversion	[5], [9], [20]
Soft Robotics	Embedded proprioception and actuation	[6], [22]
Smart Manufacturing	Real-time adaptive systems	[8], [16], [19]

Challenges & Research Gaps

Challenge	Impact	Suggested Direction
AI model complexity for embedded systems	High power/resource consumption	TinyML, model pruning
Real-time feedback from soft materials	Slow/non-linear response	Hybrid models, online learning
Standardization across platforms	Poor interoperability	Open frameworks (ROS-AI)
Data scarcity for supervised learning	Limits generalization	Self-supervised or federated learning

Future Directions

The integration of Artificial Intelligence with smart sensors and actuators has already enabled significant advancements in mechatronic systems. However, the field continues to evolve rapidly, driven by the demand for more autonomous, efficient, and adaptive machines. Based on the current state of research and the gaps identified in this review, several promising directions are anticipated to define the next decade of innovation in AI-powered mechatronics.

Edge AI and TinyML for Embedded Intelligence

One of the most transformative trends is the move toward **on-device intelligence**. As real-time decision-making becomes essential in resource-constrained environments—such as wearables, drones, and industrial robots—there is a pressing need to run AI models locally on edge hardware.

- **TinyML**, a branch of machine learning focused on ultra-low-power microcontrollers, enables AI algorithms to run directly on embedded sensor and actuator nodes.
- Lightweight neural networks, model pruning, quantization, and neural architecture search (NAS) are actively being developed to make AI inference faster and more energy-efficient.
- Future systems will increasingly use **Edge TPUs** and custom AI ASICs to execute real-time AI workloads directly on actuators or near sensors, significantly reducing latency and dependence on cloud infrastructure.
- Hybrid models that combine rule-based logic with black-box AI may offer a balance between adaptability and interpretability.

Self-Adaptive and Lifelong Learning Systems

Mechatronic systems often operate in unpredictable or evolving environments. Traditional AI models trained offline are insufficient for long-term adaptability. **Online learning**, **lifelong learning**, and **self-supervised learning** techniques will become critical to ensure that smart sensors and actuators can continuously refine their performance over time.

- Future smart systems may use **reinforcement learning** and **meta-learning** to adapt to new tasks or environments on the fly.
- For instance, a prosthetic limb could autonomously adapt its motion strategies based on subtle changes in EMG signals due to muscle fatigue or electrode displacement.

Explainable AI (XAI) for Safety-Critical Systems

As AI becomes a central component in physical systems that interact with humans (e.g., medical robots, autonomous vehicles), **explainability** and **transparency** become critical. Future research will prioritize the development of interpretable AI models that can explain why a particular sensor signal triggered a specific actuator response.

- XAI will help in **debugging system failures**, **enhancing user trust**, and meeting **regulatory compliance**.
- Hybrid models that combine rule-based logic with black-box AI may offer a balance between adaptability and interpretability.

Digital Twins and Simulation-Driven Design

Digital twins—real-time virtual models of physical systems—are already reshaping how AI is developed and tested. In the future, they will become standard in AI-driven sensor–actuator systems.

- AI models can be trained using synthetic data generated from high-fidelity simulations of sensors and actuators.

- These models can then be deployed with greater confidence, having already encountered edge cases and failure modes in virtual space.
- Co-simulation of mechanical, electrical, and software behavior will enable **simulation-informed actuation**, reducing the need for costly physical prototyping.

Bio-Inspired and Neuromorphic Systems

Drawing inspiration from biological organisms, next-generation mechatronic systems will increasingly incorporate **bio-inspired sensing and actuation**. Coupled with **neuromorphic computing**, these systems will achieve low-latency, energy-efficient decision-making that mimics reflexive human behavior.

- Spiking Neural Networks (SNNs), tactile skins with embedded AI, and muscular actuator control via brain-like signal processing are all emerging areas.
- For example, neuromorphic processors such as Intel's **Loihi** and IBM's **TrueNorth** are being explored for ultra-fast, event-driven control in robotics.

Secure and Privacy-Preserving AI

As smart mechatronic systems are increasingly networked and personalized, concerns over data security and user privacy will become more prominent.

- Federated Learning and **differential privacy** will allow AI models to be trained across distributed devices without sharing raw sensor data.
- Applications in healthcare (e.g., smart prosthetics, rehabilitation robots) will especially benefit from these technologies to comply with privacy laws like HIPAA and GDPR.

Standardization and Open Frameworks

The lack of interoperability and standard protocols for AI-enhanced mechatronic components currently hinders scalability. Future research and industry adoption will benefit from:

- Open-source frameworks (e.g., **ROS 2**, **TensorFlow Lite for Microcontrollers**, **TinyML frameworks**) that enable faster prototyping and integration.
- Development of universal standards for **data formatting**, **sensor-actuator APIs**, and **AI benchmarking** in embedded mechatronics.

Human–Machine Co-Learning Systems

As humans increasingly collaborate with intelligent machines, there is a growing need for **co-learning interfaces** where both human users and AI systems adapt to each other.

- AI can interpret user preferences or intentions over time via bio-signals or behavioral cues.
- At the same time, intuitive interfaces (e.g., haptic feedback, voice control, adaptive UIs) will allow users to understand and shape system behavior in a transparent manner.

Summary of Future Research Themes

Theme	Research Priorities
Edge AI & TinyML	Real-time inference, low-power deployment
Lifelong Learning	Continuous online learning in dynamic environments
Explainable AI	Transparency and safety in actuation decisions
Digital Twins	Virtual testing and predictive control modeling
Neuromorphic & Bio-Inspired AI	Reflex-like control with low power and latency
Federated Learning	Secure training across distributed mechatronic devices
Open Standards	Modular design and interoperability across platforms
Human–AI Collaboration	Co-adaptive control and feedback-driven interfaces

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