Machine Intelligence Research
www.mi-research.net

22(5), October 2025, 929-940
DOI: 10.1007/s11633-025-1550-8

AI, Machine Learning, and Deep Learning in Advanced Robotics: A Review of Current Innovations and Future Prospects

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Abstract: This narrative review addresses the applications of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in robotics. It explains the differences between these paradigms, generalises their use in the area, and determines new innovations and challenges that define the future trends. The literature in the last 20 years of peer-reviewed articles was synthesised through a narrative dissection. The sources were chosen from large databases concerning their relevance to technical underpinnings, field of application, sustainability, and human-robot interaction, as well as cross-disciplinary issues, such as ethics and governance. It was stressed on conceptual integration and comparative analysis at the expense of systematic protocol. The review finds that symbolic AI, ML, and DL provide complementary strengths: transparency, adaptability, and perception capabilities. They find use in surgical and rehabilitative systems of the medical field or in concurrent assembly and predictive maintenance of industrial systems, and have other applications in sustainable agriculture, waste disposal and energy efficiency. Affective computing and augmented reality contribute to the growth of human-robot interaction. Transformers, edge AI, digital twins, bio-inspired robotics, and others are all innovations that are changing the landscape, but explainability, power consumption, and control remain problematic. Robotics is evolving to integrated, hybrid AI solutions. Some of the priorities will be energy-efficient architectures, explainable models, and ethical frameworks of safe, sustainable deployment.

Keywords: Artificial Intelligence in Robotics; Machine Learning; Deep Learning; Human–Robot Interaction; Industry 4.0; Sustainable Robotics

Citation: Bao Thien Nguyen. AI, Machine Learning, and Deep Learning in Advanced Robotics: A Review of Current Innovations and Future Prospects. *Machine Intelligence Research*, vol.22, no.5, pp.929–940, 2025.

1 Introduction

Robots have been revolutionised because artificial intelligence (AI), machine learning (ML), and deep learning (DL) have led a revolution in the last 2 decades. The rule-based robots were predominant in the older robots since they were only able to operate in an environment under controlled instructions. Smart algorithms enable robot systems to have greater autonomy and dexterity and to make decisions (Fedele et al., 2024). Robots are no longer isolated industrial machines but complex helpers in different fields, including health care, industry, space exploration, and human life in general. As an example, the patients can now have surgical and rehabilitation robots that can detect the medical condition and perform certain complex sub-tasks during a surgical operation and provide specific assistance in helping the patient and improving

Research Article
Manuscript received on May 30, 2024; accepted on February 25, 2025
Recommended by Associate Editor Harish Garg
Colored figures are available in the online version at https://link.springer.com/journal/11633

the patient outcomes and safety. Similarly, bio-inspired computing (Huang et al., 2021), the digital twin concept and reinforcement learning are helping robots to respond appropriately to unstructured environments, which is common in Industry 4.0 applications. Such innovations are a radical departure from the inflexibility of hard-programmed systems to the flexibility of intelligent machines that form part of multi-layered social-technical systems.

This change is opportune since robotics is currently at the point of the technology curve - inflexion point - and it is no longer a specialised automation, but a general-purpose autonomous intelligence. Application numbers are expanding exponentially, and in health care and manufacturing, particularly, predictive maintenance or precision surgery is carried out by AI-enabled robotics (Pyzer-Knapp et al., 2022). It is one of the trends that the COVID-19 pandemic accelerated: disinfection, parent monitoring, and even logistics services, which were carried out by robots to limit human contact (Sarker et al., 2021). But this also implies that there are challenges that have accompanied the opportunities. Indeed, the issue of topics energy efficiency, ethics and morality, and the deficits of narrow AI to human-level intelligence are hotly contested(Peres et al., 2020). There are too numerous reviews of the field, however, due to the rapidity of the progress of robotic technology, the knowledge of it has become atomistic, and reviewers have remarked that there must be a more integrative perspective about its technical developments, clearly in the eyes of society and ethics.

This review provides an understanding of the transformations brought by AI, ML, and DL to the nature of robotics in four dimensions, namely: (1) The technical basis, such as supervised, unsupervised, and reinforcement learning; (2) application domains, namely, healthcare, manufacturing, waste management, and scientific discovery; (3) new directions such as collaborative robots, edge AI, digital twins, and soft robotics; and (4) cross-cutting issues such as sustainability, ethics, and the nature of machine intelligence. Combining these themes, the review provides a general review of the state of the art that develops our knowledge and where we have gaps in our knowledge base, which need more research and interdisciplinary work.

This scholarly literature is making contributions to several fields, resulting in successful convergence in healthcare and industrial robotics, and other inventions such as augmented reality and bio-inspired robotics. It connects the theoretical discussions, like the debate on artificial general intelligence, with practical developments in autonomous systems and soft robotics. It synthesises the knowledge, which has been frequently pursued separately, providing a more integrative image of AI-based robotics. Rather than focusing on specific technical scopes in their review, as their predecessors did, this narrative review focuses on how algorithms, applications and societal influences interact, giving researchers and practitioners a more general view of the direction robots are taking and where they are going.

2 Literature Review

The last 20 years have seen a historical change in robotics, which was mainly influenced by the combination of artificial intelligence (AI), machine learning (ML), and deep learning (DL). In contrast to the early systems of rules, which ran on strict and deterministic algorithms, modern robots take advantage of adaptive and data-based algorithms that enable them to perceive and learn as well as interact with unstructured environments. In 2020-24 specifically, fast digitalisation and the worldwide shocks of the COVID-19 pandemic, especially in healthcare, manufacturing, sustainability, and human-robot interaction fields, robotics studies have gained momentum (Sarker et al., 2021). This review examines these advances based on a narrative synthesis of the technical underpinnings of AI in the field of robotics, the scope of application areas, and the new innovations on the future of intelligent machines.

2.1 Technical Foundations of AI in Robotics

2.1.1 Artificial Intelligence Frameworks

Early robotics had been based on symbolic AI and rule-based systems, which were limited to obeying instructions that had been pre-written in advance. Although these systems were predictable and transparent, they were not flexible in the dynamic circumstances that existed in the real world (Fjelland, 2020). The development of AI systems in robotics has presented multi-layered perception, cognition, and action systems. They combine sensor fusion, probabilistic reasoning and decision-making models that facilitate the capability of robots to act independently in uncertain situations (Soori et al., 2023).

This has given rise to the hybrid models, which have been characterised as the integration of symbolic reasoning and flexible learning. One such application is the use of augmented reality (AR)-assisted robotics to combine the rule-based safe practices with the AI-based perception of the system, such that human-robot interaction becomes more explicit and reliable (Bassyouni & Elhajj, 2021). Hybrid models can help adjust and overcome drawbacks encountered with either approach based solely on rules or data; in other words, hybrid models will represent the future of a more integrated paradigm of robotic intelligence.

2.1.2 Machine Learning in Robotics

Machine learning is a significant change in the prescriptive control to experience-based learning, where robots extract patterns and draw conclusions from the data.

Supervised learning has found extensive application in robotics as an object detector, defect detector and diagnostic imaging. CNN-based models have been improved in terms of real-time fault detection in the manufacturing industry and accuracy in the segmentation of medical images (Gao et al., 2024; Hashimoto et al., 2020; Ng et al., 2021). Robotic nursing assistants in healthcare are currently based on supervised models to identify signs of distress in patients and react to them (Knudsen et al., 2024).

Learning without supervision is also a very important matter in detecting anomalies and adaptive navigation. Clustering and autoencoder-based models have been used in industrial robotics to enable them to identify abnormal behaviours without the need to have exhaustive labelled datasets. Unsupervised algorithms have been used in the context of sustainability, such as waste sorting, where the nature of materials causes unsupervised training to be more feasible (Wilts et al., 2021).

Robotic control and navigation have been shaken by reinforcement learning (RL). RL can be used to achieve a dextrous control of robots, optimise the paths of a tool in surgical robotics, and adjust to changing industrial conditions by enabling learning through trial-and-error in simulated or controlled environments (Yip et al., 2023). Insect-like navigation has been expanded further by bio-inspired RL models, which provide aerial robots with the ability to navigate with very few computational requirements.

Despite these successes, there are still problems. Supervised models are modelled with huge, labelled data sets, RL is sample inefficient, and unsupervised models are not easily interpretable (Soori et al., 2023). To combat this, one needs innovations in transfer learning, explainable AI and energy-efficient algorithms, which are core to the new generation of robotic intelligence.

2.1.3 Deep Learning for Perception and Control

Deep learning models have dominated contemporary robotics, especially those that require heavy perception. Convolutional Neural Networks (CNNs) are a popular tool in the interpretation of spatial data, which can be used to detect objects, faults, and guide surgery. Robotic surgery has been used to enhance the localisation of tumours and intraoperative guidance, and robotic assembly in industrial assembly lines to detect defects in real-time using CNNs (Yip et al., 2023).

RNNs and LSTMs are particularly useful in working with sequential data and thus are used to predict the trajectory, to control dynamic motion, and for predictive maintenance of industrial robots (Peres et al., 2020). RNNs have also been applied to forecast surgical outcomes with sequential patient data in the healthcare field (Rasouli et al., 2020). Transformers that were initially designed for natural language processing are finding their way into robotics due to their capability to model long-range relationships and context. They have been used in soft robotics, defect detection pipelines, and AR-assisted human-robot interaction systems (Bassyouni & Elhajj, 2021). Deep learning has provided exceptional innovations, but is resource-intensive, data-demanding, and non-transparent in its decision-making. According to the researchers, explainable and hybrid deep learning models need to be developed, which is the reason to implement robots in the safety-critical area of healthcare (Soori et al., 2023).

2.2 Applications of AI-Driven Robotics

2.2.1 Healthcare Robotics

Healthcare is one of the most revolutionary fields of AI-powered robotics. New surgical robots have CNNs and RL systems that can help in minimally invasive surgery, enhance the precision of in-operative accuracy, and decrease the variability in surgeon performance (Yip et al., 2023). Spine surgery predictive analytics is assisted by AI algorithms and helps with preoperative planning and risk detection (Rasouli et al., 2020).

Another promising use of robotics in anaesthesiology is available. The AI-powered systems will be able to track vital signs, change anaesthesia depth on the fly, and minimise human error during intricate procedures (Hashimoto et al., 2020). In addition to surgery, rehabilitation robotics and soft exoskeletons have been shown to be effective in assisting patients with mobility limitations, with assistance being tailored to the requirements of the user based on the DL models (Cao et al., 2024). Robotics in healthcare further increased in importance due to the COVID-19 pandemic. Healthcare professionals were at risk of exposure to COVID-19; autonomous robots were used to sanitise, deliver logistics, and provide care to patients. These advancements demonstrate the possibilities of AI-based healthcare robotics, as well as the urgency of the challenges in clinical practice that need to be considered in terms of ethical, interpretability, and safety matters.

2.2.2 Industrial and Manufacturing Robotics

Artificial intelligence has transformed industrial robotics as part of Industry 4.0. It can now be done by intelligent robots for predictive maintenance and to detect defects as well as dynamic scheduling, significantly reducing downtime and increasing productivity. Digital twins have been especially effective in terms of their influence, since now robots are able to model the production processes and optimise them in real time (Huang et al., 2021). High-volume, low-mix manufacturing requires the use of collaborative robots (cobots). Unlike traditional robots that can only work in closed spaces, cobots with AI can be quite dynamic and react to emergent tasks during an assembly process, which also leads to human-machine synergy. Bio-inspired cobots have been proposed based on insect intelligence in scenarios where precision work was required and lightweight and flexible systems were the requirements.

2.2.3 Robotics for Sustainability and the Circular Economy

In addition to healthcare and manufacturing, robotics has also been used to solve the sustainability issues.

AI-based waste sorting robots can also be capable of sorting heterogeneous waste materials and contributing to the realisation of the circular economy (Wilts et al., 2021). Bio-inspired robots are economic robots that offer designs that are light and energy-averse, with minimum environmental impact (Croon et al., 2022). These applications demonstrate the way AI and DL can be used to enhance efficiency and develop robotics in the capacity of sustainability.

2.2.4 Human–Robot Interaction and Affective Computing

The human-robot interaction (HRI) is an emerging field of serious focus, particularly in the fields of healthcare and shared production, which are sensitive. The conceptualisation of affective computing results in the concept of a robot, the human-reading, human-responding brain that makes situations of high risk more acceptable and bearable, e.g., surgery (Knudsen et al., 2024). This combination of augmented reality (AR) and artificial intelligence (AI) will overlay the human being with all-enlivening transparency and cooperation, as the person can observe the intention of a robot in real-time (Bassyouni & Elhajj, 2021). Cobot digital twins enable simulated interactions between the robot and workers in the industrial environment, which are safe and ergonomic (Huang, 2021). HRI was even further expanded by biologically inspired designs that allow robots to predict human movement and act in advance.

2.3 Emerging Innovations and Research Directions

There are a number of innovations that are transforming the path of robotics: Edge AI allows the robots to operate on the local data, instead of using cloud computing, and decreases the latency and increases the autonomy in the real-world context (Cao et al., 2024). The energy and scalability constraints of robotics based on the DL program potentially have a solution in quantum and neuromorphic computing, and may enable more rapid and sustainable robotic intelligence (Pyzer-Knapp et al., 2022). The problem of policy and regulation remains fierce, as the exposure to the set of ethics, safety standards, and rules about legal regulations puts the responsible use of intelligent robots at risk (Sutikno, 2024). A combination of these novelties and issues confirms that the use of AI-driven robotics is dual: a future promise that comes with enormous opportunities, and a threat to society unless handled responsibly and ensuring its sustainability.

2.4 Synthesis

The literature proves that robotics has developed in numerous directions. Under technical aspects, AI, ML and DL possess the philosophy of perception, decision-making, and control; hybrid solutions in these respects are becoming the compromise between symbolic reasoning and data-driven learning. The dominant frontier application areas on the healthcare and manufacturing side are still in use, whereas sustainability and HRI are new frontiers. The latest innovations include cobots, edge AI, and bio-inspired designs, which are signs of the robotics advancement, but also reveal the still unresolved issues in the spheres of interpretability, energy efficiency, and ethical governance (Fjelland, 2020). Bridging these different areas of knowledge, the narrative review recognises that the future of robotics is not as much about the technical breakthrough as it concerns itself with the creation of intelligent algorithms, human values and long-term design principles.

3 Comparative Analysis

Despite the similarities between artificial intelligence (AI), machine learning (ML), and deep learning (DL), all three theories reflect different innovations in the sphere of robotics, and each of them has its strong and weak sides, as well as uses. The comparative perspective allows for a more accurate perspective of how all these paradigms are present individually and collectively in the creation of robotic autonomy, adaptability, and trustworthiness.

3.1 Rule-Based AI versus Data-Driven AI

Classical AI in robotics was mainly rule-based since it was deterministic and based on symbolic reasoning. These methods provided interpretability and transparency, as every action was possible to be outlined by a particular rule (Fjelland, 2020). They were unable to cope in any unstructured or unexpected situations, where strict regulations were not generalised over other conditions. On the contrary, the concept of adaptability of ML and DL systems makes robots capable of learning through experience and becoming better with time. As the example is reinforcement learning (RL), it enables robots to optimise manipulation skills or navigation policies with no explicit instructions (Hua et al., 2021). Despite the flexibility of ML and DL, rule-based reasoning is still relevant. To illustrate, AR-based robotics tends to combine symbolic safety policies with perception-based learning, which guarantees flexibility and confidence in human-robot communication (Bassyouni & Elhajj, 2021). Such a comparison highlights a complementary nature: symbolic reasoning is more reliable, whereas the data-driven approaches add flexibility.

3.2 Supervised versus Unsupervised Learning

Robotics applications are largely dominated by supervised learning with labelled datasets available in large quantities. CNN-based vision systems that have been trained using annotated defect data can be used in industrial contexts to detect faults in real-time (Ng et al., 2021). CNNs can also be used in healthcare to improve intraoperative imaging and assist surgeons in more minimally invasive surgeries (Hashimoto et al., 2020). Supervised models are therefore useful in tasks that have clear inputs and outputs. Unsupervised learning, on the other hand, works in conditions when labelling is neither feasible nor economical. Robots in industries detect anomalies without labels with the help of clustering and autoencoders. The waste-sorting robots are based on unsupervised designs to detect the different materials in heterogeneous waste streams. Unsupervised clustering is useful in healthcare to provide patient risk stratification when there is a scarcity of labelled clinical outcomes (Rasouli et al., 2020). The disadvantage, though, is interpretability: unsupervised models tend to be less transparent; therefore, it is hard to justify their choices in safety-critical models (Moglia et al., 2021). The former is superior to the latter in areas that require accuracy and responsibility, whereas the latter succeeds in areas that are either exploratory or lack data.

3.3 Reinforcement Learning versus Other Paradigms

Reinforcement learning is a different paradigm from supervised and unsupervised learning. RL is highly useful in navigation and dexterous manipulation, and unlike models trained on static datasets, policies are optimised by interaction with the environment. In surgical robotics, RL provides the option of fine-tuning of tool paths in the process of performing minimally invasive surgery (Yip et al., 2023). In the case of industrial robotics, RL allows adaptive strategies of scheduling and maintenance. However, RL has sample inefficiency and computationally expensive problems. The complexity in the real world cannot be well represented in simulations, and thus, one can generally infer that there is poor generalisation of RL-trained policies to the physical robot world. These disadvantages notwithstanding, RL is essential in the future because of its capacity to attain emergent behaviours; thus, it is essential in future applications that involve high degrees of autonomy.

3.4 Deep Learning Architectures Compared

Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers are considered the most promising approaches to deep learning (DL), and each of them offers specific benefits in robotics. CNNs are best in perception-based applications and can detect objects and find defects, showing successful results in surgical imaging and with industrial inspection (Hashimoto et al., 2020; Ng et al., 2021). RNNs and RNN variants, e.g. long short-term memory (LSTM) networks, are specifically useful in sequential tasks, such as trajectory prediction and predictive maintenance, as they can model temporal dependencies that are complementary to the spatial capabilities of CNNs. Transformers have become a potent source of context-aware perception, which has the option of modelling long-range dependencies in a more efficient manner. They have not only been found to perform better than conventional CNN-RNN pipelines in industrial defect detection but also offer new possibilities in human-robot interaction, especially when used in conjunction with augmented reality (Bassyouni & Elhajj, 2021). Even though CNNs are the most popular architecture used in robotics, the recent increase in the use of transformers is an indication that more integrated, scalable, and context-sensitive robotic intelligence is being implemented.

3.5 Cross-Sectoral Comparisons

The weaknesses and strengths of AI, ML, and DL are more apparent across various segments of application. Deep learning-based precision of healthcare robotics is highly advantageous, and CNNs facilitate the use of advanced imaging and diagnostic functions, yet the issues of interpretability and ethical concerns remain (Knudsen et al., 2024). Supervised learning and reinforcement learning have also become particularly useful when it comes to optimisation of efficiency and reliability in industrial robotics, especially in defect detection, predictive maintenance, and workflow scheduling (Gao et al., 2024). On the contrary, robotics with sustainability concerns tends to be based on unmonitored methods because it is impractical or impossible to label such a heterogeneous flow of waste and environmental data, which is not available in the laboratory (Wilts et al., 2021). The analysis of human-robot interaction reveals the opportunity of hybrid AI systems, where symbolic rules are used to make them safer and more predictable and deep learning models and transformers are applied to make them more adaptable and context-aware. When combined, these instances show that every paradigm has a niche, although the most promising advances are achieved through integration of methods and not through adherence to a specific method.

3.6 Research Gaps and Opportunities

Although improvements have been made, several loopholes exist. One of its main difficulties is generalisation because models derived in controlled settings often do not perform in the real world. There is an issue of energy efficiency, since DL models require massive computational resources. Another technology-related aspect is ethical governance that also invokes issues of responsibility, bias and security in high-risk situations (Sutikno, 2024).

Opportunities include transfer learning, explainable AI, hybrid symbolic-sub-symbolic models and bio-inspired intelligence (Croon et al., 2022). Additional integration of quantum and neuromorphic computing would also allow the creation of scalable and energy-efficient robotics (Pyzer-Knapp et al., 2022). Interdisciplinary coordination of computer science, engineering, ethics, policy, etc, will be significant to deal with these challenges in their holistic approaches.

4 Discussion

The comparative analysis explains the interactions between the artificial intelligence (AI), machine learning (ML), and deep learning (DL) in the broader context of robotics and the influence of these interactions on the technical basis of the perception, control and decision making and the application of robotic systems in practice. What is born is an environment of speedy innovation, progressively cross-sectoral convergence and a delicate balance between technical competence and societal issues. The discussion is based on the analysis and its implications in the context of paradigm integration, sectoral implications, emergent innovations, ethical and governance issues, sustainability and future direction of the area of robotics.

4.1 Integration of Paradigms

A move towards hybrid and cross-cutting paradigms has been one of the most apparent types of development in robotics. In the past, robotic systems have been dominated by symbols of AI. The fact that these systems are interpretable and compliant, particularly in predictable and structured settings, is their strength in terms of rule-based approaches. The problem with these approaches is that they lack adaptability and probabilism, which have been increasingly applicable with the application of robotics to the medical field, to space, and to less disciplined environments.

Comparatively, ML and DL paradigms invoked algorithms that help the robots to be flexible and learning intelligence based on perception, allowing the robots to generalise based on data, and optimise their behaviour in real-time (Soori et al., 2023). There is, however, a trade-off with interpretability; the more a system can learn about data, the less interpretable the system becomes, and with a less interpretable system comes the black-box phenomenon. This leads to mistrust in safety-related conditions, including surgery (Knudsen et al., 2024).

The hybrid paradigms provide a way to proceed by combining symbolic logic with data learning. As an example, system transparency and system flexibility can be provided in augmented reality (AR) enhanced robotics, including rule-based safety, perception-based adaptability, and so on (Bassyouni and Elhajj, 2021). The focus of insect-inspired designs is navigation that is easy to carry and consumes relatively little in its use of resources, although they are being combined with DL pipelines to expand their applications (Croon et al., 2022).

The concept of paradigm integration is illustrative of the situation in modern settings: the robots must be accurate and versatile, yet clear and safe at the same time. As a result, hybrid models will not only facilitate a shift between autonomous and non-autonomous robots, but they will also be a premeditated aspect of the future world of robots.

4.2 Sectoral Implications

The second point may be made in the case when the relative benefits and limitations of AI, ML, and DL overlap in various fields of use. The niches of each of the paradigms may differ according to environmental needs.

Healthcare Robotics

Deep learning has arguably been the most significant for healthcare robotics. CNNs have changed the surgical imaging and intraoperative guidance by improving anatomical accuracy and reducing the variability of the surgeons (Hashimoto et al., 2020). Transformers go even further and offer context-sensitive perception of multi-modal data streams. The same systems also pose ethical concerns: opaque algorithms may be dangerous to use in case of labelling anomalies, and high-stakes surgical settings are the ones where this method can be especially hazardous to use. Prejudices in training data may be transmitted to clinical outcomes, and this is a concern that has been brought up regarding the dangers of applying AI assertions to general intelligence.

Industrial Robotics

The priorities are otherwise in industries. They are dominated by efficiency, reliability, and adaptability, so supervised and reinforcement learning are especially effective (Peres et al., 2020)(Peres et al., 2020). Supervised models are good in defect detection and predictive maintenance, whereas RL is flexible in scheduling and dynamic workflow optimisation. This flexibility is further improved through the integration of digital twins, which makes the real-time simulation and optimisation of the industrial processes possible (Huang et al., 2021). In industry, interpretability of models is not as urgent as in healthcare; however, efficiency and cost-effectiveness must matter, which determines the form of AI implementation.

Sustainability Robotics

In terms of unsupervised methods, they are especially promising for sustainability-oriented robotics. Physical systems where waste management and recycling must deal with unpredictable and heterogeneous materials, labelled training data is not feasible (Wilts et al., 2021). The use of unsupervised clustering and feature extraction is where the robots can recognise the type of material based on its dynamics and can advance to the procedures involved with the circular economy. Although unsupervised approaches may have interpretability issues, the associated risks are not as critical as they are in healthcare, and thus, these approaches fit the sustainability applications.

Human–Robot Interaction (HRI)

Another layer of complexity is presented by HRI, in which the safety and trust are at the centre stage. It is also promising that hybrid systems that combine rules of safety, which are symbolic, and adaptability, relying on DL, are considered (Bassyouni & Elhajj, 2021). The combination of AR and transformers can increase the level of transparency, as human beings can see what a robot wants to do in real time, and the use of affective computing can teach systems how to understand human emotions and act accordingly. The combination of paradigms in this industry should be encouraged; it’s mandatory, with human adoption dependent not just on the effective performance but also on reliability. In these fields, the implication is also very evident: no paradigm is more dominant than others in every field. Paradigms are instead chosen according to disciplinary priorities-accuracy in medicine, resourcefulness in business, scalability in environmental sustainability, and credibility in HRI.

4.3 Emerging Innovations

Robotics are becoming more innovative, and several technologies are transforming the field. One of the most revolutionary ones is edge AI. Edge AI will decrease latency by allowing robots to process data on board instead of sending it to a cloud service, increase privacy by preventing reliance on cloud computing, and enable real-time autonomy. This finds application especially in mobile, resource-constrained robots, i.e. insect-inspired aerial robots, which do not always need to be connected to a network (Croon et al., 2022). Edge AI in soft robotics enables an environment and human response in real-time, which makes the systems more responsive and adaptive.

Another significant innovation is digital twins, which are used to simulate industrial processes in real time for predictive maintenance, optimisation, and training (Huang, 2021). They are not only more efficient in industrial processes but also present new possibilities in studying robotics because simulated environments create risk-free and scalable environments to train RL models and then implement them in a real scenario.

Bio-inspired computing and robotics are progressing towards sustainability through the study of insect flight strategies. Insects possess lightweight yet energy-efficient autonomy, which has a form of resilience against the unpredictability of states (Croon et al., 2022). This kind of autonomy goes against the belief that it requires lots of computational power, and there will be attempts to find new models of efficiency. Lastly, transformers will mark a change to the concept of autonomy: context-aware robotics appears particularly effective in such systems because it can represent the long-range dependencies. With Augmented Reality (AR) systems, there will be a shift to the HRI that mimics transparency, co-operation, and trust (Cao et al., 2024). These tendencies allude to a scalable, context-sensitive, and sustainable intelligence in robotics.

4.4 Ethical, Safety, and Governance Challenges

While there has been technological progress, hardly any changes have been made in the frameworks of ethics and governance. The most important factor is bias in the training dataset, which contributes to inequitable or dysfunctional outcomes. In the sense of surgical procedures determined by DL systems in healthcare, biased inputs yield more health inequities or false diagnoses. In the industry, opaque models can miss low-frequency and important safety events.

Another burning issue is the accountability gap. Automation has non-technical risks to society. Loss of jobs, mass surveillance, and possible unethical use of autonomous robots in the military are only some examples of why these devices should be regulated. The lack of clear policies and standards may damage the confidence people have in robotics, as it may lead to the rejection of this technology even in those spheres where the advantages are high.

Healthcare is a highly sensitive field due to safety-related challenges that can put surgical results or anaesthesia monitoring at risk because the opaque models are unsafe in this field. These risks are to be addressed by explainable AI to make sure that the decision-making process can be transparent and verifiable. It also requires the presence of interdisciplinary control, and that is, engineers, ethicists, clinicians and policymakers will work together to bring about structures of trust.

4.5 Sustainability and Energy Efficiency

The other issue that has not been solved yet is the sustainability of AI-driven robotics. The process of training CNNs, RNNs, or transformers is extremely resource-intensive, which is concerning to the environment. To illustrate, transformer model training at a large scale may require the same energy as small data centres, which makes the research of robotics unsustainable.

Bio-inspired approaches offer a way to go about sustainability. Lightweight architectures can be illustrated by using insect-inspired navigation and show that robust autonomy can be achieved using such a system with very little energy. Another direction, which is promising, is neuromorphic computing, which tries to emulate the efficiency of the brain to provide low-power-based perception and control in real time.

The alignment of robotics and sustainability objectives will necessitate the co-design of algorithms and hardware. Development of algorithms should focus on giving importance to energy saving without performance degradation, and hardware should be redefined with sustainability as a fundamental value. The concept of Industry 4.0 represents an opportunity in this case because the implementation of AI in the industrial process can assure energy efficiency and environmental sustainability (Peres et al., 2020).

4.6 Future Trajectories

Going forward, robotics is at the point of convergence of various disruptive forces. The ability to solve complex optimisation problems, like multi-robot coordination or high-dimensional path planning, at scales that are not possible with classical computing can be done by quantum computing (Pyzer-Knapp et al., 2022). Equally, neuromorphic computing may provide brain efficiency, incorporating real-time smartness into soft robots with low-energy expenditures. The robotic autonomy is also likely to be redefined using transfer learning and meta-learning. The existing RL systems do not usually generalise environments (Hua et al., 2021). In comparison, transfer learning would allow robots to apply knowledge in one task to another, and meta-learning would increase adaptability more quickly by training robots to learn. Digital twins can offer a connector in this aspect, whereby simulated environments are available where transfer learning can be tried out prior to implementation in the real world. The future path of robotics will not just be a result of any technical achievements, but also the responsibility and sustainability of ethics. It will be a matter of the integration of these dimensions that will determine whether robots are viewed as transformative partners or disruptive dangers.

5 Conclusion

This review has identified the role of AI, ML and DL in transforming robotics, their different contributions, areas of application and the newer innovations. AI structures provide transparency in the form of symbolic reasoning, ML provides flexibility with supervised, unsupervised, and reinforcement paradigms, and DL provides strong perception in the form of CNNs, RNNs, and transformers. The advancement of robotics leverages all these methods, particularly in health care, in producing goods, in sustainability and in human-robot interaction.

As every paradigm has its positives as well as negatives, this comparative analysis puts forward that. For instance, rule-based AI is reliable but inflexible, supervised learning is more accurate but costs more data, unsupervised models are flexible but black box in RL models, resource-consuming, and neural networks are pushed in interpretability and energy consumption as well. Some upcoming technologies, such as cobots, edge AI, bio-inspired computing, and quantum or neuromorphic computing, pave the way to more adaptable, sustainable, and trustworthy robotics.

The importance of the narrative synthesis is that it is integrative. While other reviews just present themselves as domain-based, this review represents an interdisciplinary perspective among the technical paradigms, application domains, and governance questions, carving a path toward future ongoing studies in robotics. The three priorities are technical excellence through hybrid models and high-performance computing in robotics.

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