International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 58, No. 5, May, 2025, pp. 913-921
Journal homepage: http://iieta.org/journals/jesa

Advancing Autonomous Systems: A Review of Emerging Trends in Robotics

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https://doi.org/10.18280/jesa.580505

Received: 3 April 2025
Revised: 12 May 2025
Accepted: 23 May 2025
Available online: 31 May 2025

Keywords:
autonomous systems, robotics, artificial intelligence, path planning, human–robot interaction, reinforcement learning

ABSTRACT

Autonomous systems are transforming robotics by enabling machines to operate with minimal human intervention. These systems are now applied across a wide range of domains, including industry, healthcare, agriculture, and defence. This review presents a comprehensive analysis of emerging trends and technologies driving the evolution of autonomous systems. Key areas explored include perception, localization, path planning, learning, control, and human–robot interaction. We examine how artificial intelligence and machine learning are used for robust decision-making, as well as recent advances in sensor fusion and Simultaneous Localization and Mapping for environment mapping. Innovative techniques in motion planning and intuitive interfaces are also discussed. Special attention is given to swarm robotics and bio-inspired algorithms that enable scalable and decentralized coordination. The review includes comparative analyses of algorithms, hardware platforms, and real-world use cases. These comparisons highlight current capabilities and existing limitations. Despite considerable progress, challenges remain in ensuring scalability, achieving real-time responsiveness, and maintaining robustness in unstructured environments. Ethical and legal concerns also present ongoing barriers to deployment. Looking ahead, several transformative technologies are emerging. These include quantum computing for solving complex optimization tasks, edge AI for localized intelligence, and 6G connectivity for ultra-fast communication. Together, these technologies are expected to open new frontiers in autonomy and system integration. This paper underscores the need for interdisciplinary research to build autonomous systems that are intelligent, resilient, and socially responsible.

1. INTRODUCTION

Autonomous systems are intelligent machines or software agents capable of performing tasks with minimal or no human intervention. These systems leverage advancements in artificial intelligence (AI), machine learning (ML), sensor fusion, and real-time decision-making to perceive, interpret, and respond to dynamic environments [1, 2]. Their growing sophistication enables them to operate across various levels of autonomy ranging from semi-autonomous assistance to full autonomy making them critical in modern technological ecosystems.

Over the past decade, robotics and autonomous systems [3-6] have witnessed a significant rise across diverse sectors. In industrial manufacturing, autonomous systems have optimized production processes, enabling flexibility, precision, and cost-efficiency [7, 8]. In healthcare, surgical robots and assistive systems have transformed diagnostics and minimally invasive procedures, enhancing accuracy and patient outcomes [9, 10]. Defence applications have benefited from robust unmanned systems for reconnaissance, logistics, and combat support [11]. Meanwhile, agriculture has embraced smart farming through AI-driven robotics that support crop monitoring, harvesting, and yield prediction [12, 13]. Other domains such as food supply chains [14], logistics [15], and social environments [16] are increasingly integrating autonomous capabilities for enhanced efficiency and resilience.

The goal of this review is to examine the most recent trends and breakthroughs in autonomous robotics, focusing on the technological, functional, and application-driven aspects. By synthesizing findings from a wide range of domains and highlighting emerging technologies such as soft robotics [17], swarm intelligence [18], and AI-enhanced control systems [19], this paper aims to provide a panoramic view of where the field is heading. The review also identifies persisting challenges in reliability, safety, ethics, and system integration key hurdles to widespread adoption and scalability [20, 21].

This paper is organized as follows: Section 2 presents the technological foundations of autonomous systems, covering areas such as artificial intelligence (AI), machine learning (ML), embedded systems, and sensing technologies. Section 3 explores the diverse application domains of autonomous systems, including healthcare, agriculture, defence, logistics, and industrial automation. Section 4 discusses current challenges facing the field, such as issues of trust, ethics, energy efficiency, and the need for supportive regulatory frameworks. Section 5 reviews emerging paradigms that are shaping the next generation of autonomous systems, including soft robotics, neuromorphic computing, swarm robotics, and the concept of Industry 5.0. Finally, Section 6 concludes the paper by offering insights into future directions, identifying key research gaps, and highlighting potential breakthroughs that could drive the field forward.

2. BACKGROUND AND DEFINITIONS

To understand the advancements in autonomous systems, it is essential to first define the foundational concepts that underpin robotic autonomy and the classification of autonomous systems.

2.1 Key concepts

Autonomy in robotics refers to the degree to which a robot can perform tasks independently of human control or input. Autonomous systems perceive their environment, make decisions, and execute actions using algorithms, sensor data, and actuators. The concept extends beyond mere automation by enabling autonomous systems to adapt to dynamic and unstructured environments [1, 22].

Levels of Autonomy vary across a spectrum from fully manual systems to fully autonomous ones. These levels are often categorized similarly to the SAE levels for autonomous vehicles, ranging from:

- Level 0 (no autonomy),
- Level 1–2 (assistive and semi-autonomous),
- Level 3–4 (conditional to high autonomy),
- Level 5 (full autonomy without any human intervention) [23, 24].

Autonomous operation relies on several core functional modules:

- Perception: The robot's ability to interpret its environment using sensors such as cameras, LiDAR, radar, and tactile inputs in Balestrieri et al. [25]. Perception enables object detection, scene understanding, and obstacle recognition.
- Localization: The process by which a robot determines its position within a known or unknown environment. Techniques like SLAM (Simultaneous Localization and Mapping) and GPS-based tracking are widely used [26].
- Planning: Decision-making processes that guide the robot in pathfinding, trajectory planning, and task execution. Planning can be reactive (short-term response) or deliberative (goal-oriented) [27].
- Control: The execution of planned actions using actuators and feedback loops. Control algorithms maintain stability, precision, and compliance with physical constraints.
- Learning: Many modern systems incorporate machine learning and reinforcement learning to improve performance over time, particularly in complex or uncertain environments [28, 29].

2.2 Classification of autonomous systems

Autonomous systems come in diverse forms based on their structure, mobility, and application. The primary classes include:

- Mobile autonomous systems: These include ground-based platforms such as autonomous delivery robots, warehouse robots, and service robots. Mobile robots may be wheeled, tracked, or legged, and operate in dynamic environments [30, 31].
- Manipulators: Often used in industrial settings, these stationary or articulated robotic arms perform precision tasks such as assembly, welding, and material handling. With increasing integration of AI, modern manipulators are also capable of adaptive and collaborative operations [7, 8].
- Aerial Robot autonomous systems: Also known as Unmanned Aerial Vehicles (UAVs), these systems are employed in surveillance, mapping, agriculture, and disaster response. Their ability to cover large and inaccessible areas has made them crucial in environmental and commercial domains [32].
- Underwater autonomous systems: Used in marine research, inspection, and offshore exploration, these systems must operate autonomously in GPS-denied environments and withstand high pressure and salinity [33].
- Humanoid autonomous systems: Designed to mimic human appearance and behavior, these are often used in social, assistive, or experimental roles. Though not yet widely adopted for industrial tasks, humanoids represent a frontier in human–robot interaction [16].
- Soft autonomous systems: Inspired by biological systems, soft robots use flexible materials and actuators to navigate delicate or constrained environments. They are especially relevant in medical, agricultural, and wearable robotics [17, 34].
- Swarm autonomous systems: This category includes systems composed of many simple agents that coordinate to perform complex tasks collectively. Applications include search and rescue, environmental monitoring, and distributed sensing [18].

Each robotic system type is tailored to specific challenges and environments, contributing to the broader landscape of autonomy.

3. EMERGING TRENDS IN AUTONOMOUS ROBOTICS

Autonomous robotics has seen significant evolution driven by advances in machine learning, perception, control systems, and collaborative intelligence. This section presents key technological trends that are shaping the future of autonomous systems.

3.1 Machine learning and AI in autonomy

The integration of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized autonomy, enabling autonomous systems to perceive, decide, and act more effectively in complex environments.

3.1.1 Deep learning for perception

Deep learning techniques, particularly convolutional neural networks (CNNs), have significantly improved robot perception by enhancing capabilities in object detection, semantic segmentation, and scene understanding [1, 19]. These advancements allow autonomous systems to interpret noisy or unstructured data from cameras, LiDAR, and other sensors with higher accuracy and reliability.

3.1.2 Reinforcement learning for decision-making

Reinforcement learning (RL) enables autonomous systems to learn optimal behaviours through trial and error, offering solutions for navigation, manipulation, and human-robot interaction. RL is particularly valuable in environments where traditional rule-based systems fail due to unpredictability [28, 29]. Hybrid models combining deep learning [19] with RL often referred to as Deep RL are increasingly used in autonomous vehicles, drones, and robotic games.

3.2 Sensor fusion and SLAM

3.2.1 Multi-sensor integration

Modern SLAM systems rely on sensor fusion, combining data from cameras, IMUs, LiDAR, and GPS to improve robustness and accuracy in challenging conditions [14, 25]. Redundancy and complementary sensing enhance autonomy in low-light, dusty, or GPS-denied environments. A notable real-world example is Boston Dynamics' Spot, which integrates stereo cameras, 3D LiDAR, and IMUs using visual-inertial SLAM to achieve centimetre-level localization accuracy in dynamic industrial sites such as construction zones, power plants, and underground tunnels. This multi-sensor approach allows the robot to maintain stable navigation even in cluttered and unstructured environments.

Similarly, Clear path Robotics' Husky UGV employs sensor fusion with RGB-D cameras, LiDAR, and RTAB-Map-based SLAM to enable precise autonomous navigation in outdoor field robotics tasks such as mining surveys and precision agriculture. By fusing GPS with local SLAM inputs, the system mitigates drift and maintains accuracy over large, uneven terrains.

3.2.2 Advances in visual-inertial odometry

Visual-Inertial Odometry (VIO) techniques integrate visual and inertial data for real-time pose estimation. These have seen rapid improvements due to more efficient algorithms and dedicated hardware, contributing to robust indoor and outdoor navigation [26]; Liu [2]. For instance, drones like the DJI Matrice 300 RTK use VIO in conjunction with real-time kinematic GPS and LiDAR to operate in complex airspace environments, including near infrastructure and beneath tree canopies, where conventional GPS signals are degraded. This fusion enables real-time trajectory planning, obstacle avoidance, and terrain-adaptive flight paths.

These industry applications demonstrate how sensor fusion and SLAM are no longer confined to academic settings but are being actively deployed in mission-critical systems across diverse domains.

3.3 Motion planning and navigation

Autonomous navigation depends on the robot's ability to plan and follow paths dynamically in real-world environments.

3.3.1 Dynamic path planning

Autonomous systems must plan trajectories that avoid obstacles, minimize time, and adapt to changes in real-time. Algorithms like RRT*, A*, and D* Lite remain prevalent but are increasingly enhanced with predictive models and context-awareness [24, 27].

3.3.2 Learning-based planners

Emerging motion planning approaches integrate learning-based methods, allowing autonomous systems to generalize from past experiences. For example, imitation learning enables autonomous systems to replicate expert demonstrations, while RL-based planners optimize for reward-driven behaviours in uncertain conditions [28, 29].

3.4 Human–robot interaction

As autonomous systems [35] move into shared spaces, interaction with humans becomes critical to their acceptance and effectiveness.

3.4.1 Intuitive interfaces

The development of natural interfaces such as voice commands, gesture recognition, and AR/VR tools makes autonomous systems more accessible and operable by non-experts. Social autonomous systems and assistive systems often use emotional cues and expressive behaviours to enhance communication [16, 36].

3.4.2 Trust and safety in shared workspaces

Building trust in autonomous systems requires transparency, predictability, and safety assurance. Research has shown that human trust increases when autonomous systems explain their actions or intentions [20, 37]. Collaborative autonomous systems (cobots) are increasingly equipped with safety protocols and force-limited actuators to enable close human interaction without risk.

3.5 Swarm and multi-agent systems

Swarm robotics leverages decentralized control and local interactions to coordinate large groups of simple agents.

3.5.1 Decentralized control

Swarm systems operate without a central controller, using algorithms inspired by nature (e.g., ants, birds) to achieve complex collective behaviours such as formation flying, area coverage, and object transport [12, 18].

3.5.2 Bio-inspired algorithms

Bio-inspired strategies such as particle swarm optimization, ant colony algorithms, and neural-based coordination improve robustness and fault tolerance. These methods are especially suited for environments where scalability and redundancy are critical [17, 28].

3.6 Applications and case studies

Autonomous systems have become integral across several domains, each showcasing unique requirements and challenges.

3.6.1 Autonomous vehicles

Autonomous vehicles (AVs) incorporate advanced perception, planning, and control systems. Key challenges include perception under adverse weather, ethical decision-making, and regulatory compliance [24, 36]. The use of AI, V2X communication, and predictive QoS is driving rapid innovation [38].

3.6.2 Service autonomous systems in healthcare

Healthcare autonomous systems assist in surgery, rehabilitation, eldercare, and disinfection tasks. Surgical autonomous systems [39] now support semi- and fully autonomous operations, improving precision and reducing fatigue [9, 11]. Human-centric design and compliance with medical standards remain critical.

3.6.3 Agricultural robotics

In agriculture, autonomous systems perform crop monitoring, weeding, harvesting, and soil analysis. These autonomous systems rely heavily on machine vision, AI, and mobility for operation in unstructured environments [14, 40]. Smart farming integrates these systems into broader IoT ecosystems for precision agriculture.

4. COMPARATIVE ANALYSIS

A meaningful understanding of autonomous systems [41, 42] necessitates evaluating their core components algorithms, hardware, and real-world applications through systematic comparison. This section synthesizes insights from the literature to highlight trade-offs, strengths, and ongoing challenges across key dimensions.

4.1 Algorithm comparison

Table 1 provides a comparative overview of key algorithm types used in autonomy, detailing their purposes, advantages, limitations, and typical real-world use cases.

4.2 Hardware platform comparison

The hardware platforms powering these systems also vary significantly in sensor configuration, processing capacity, and mobility. Table 2 summarizes commonly used platforms across different domains.

Table 1. Comparative overview

Algorithm Type	Purpose	Advantages	Limitations	Typical Use Cases
Deep CNNs (e.g., YOLO, ResNet)	Visual perception, object detection	High accuracy; real-time capable with hardware	Requires >10,000 labelled images for effective training; performance drops in low-light/noisy environments	LiDAR-based obstacle detection in urban autonomous vehicles; pedestrian recognition in hospital assistance robots; object classification in UAV surveillance
SLAM (e.g., ORB-SLAM, RTAB-Map)	Mapping and localization	Robust in unknown environments	Degrades under >30% dynamic scene changes; sensitive to <20 lux lighting conditions	Indoor navigation for warehouse robots; real-time localization in AR headsets; terrain mapping by agricultural drones
RRT*, A*	Motion planning	Efficient pathfinding; well-studied	Suboptimal in dynamic environments; replanning latency ~100–300 ms	Path planning for industrial AGVs in dynamic factory layouts; obstacle avoidance for delivery drones in urban airspace
Deep RL (e.g., PPO, DQN) [30]	Policy learning and control	Learns from interaction; generalizes behavior	Requires >1M environment steps for convergence; performance unstable under sparse rewards	Robotic manipulation of irregular objects in warehouses; autonomous vehicle lane-merging on highways; adaptive NPC behavior in interactive robotics
Kalman/Particle Filters	Sensor fusion, localization	Proven mathematical model; real-time capable	Assumes linearity or Gaussian noise; tracking error increases >15% with >10% sensor dropouts	Pose estimation for UAVs flying in GPS-denied tunnels; wearable motion tracking for assistive exoskeletons; indoor SLAM for mobile service robots
Behavior Trees/FSMs	Decision logic	Easy to implement; modular	Limited adaptivity; hard-coded logic can't handle >10 concurrent context switches	Task scheduling in home assistant robots (e.g., cleaning, fetching); patrol routines in security robots; game AI in robotic companions

Table 2. Hardware platform comparison

Platform	Sensors	Processing	Mobility Type	Primary Applications	Notable Models
Mobile Robots [30]	LiDAR, cameras, IMU, GPS	Jetson TX2/Xavier, Raspberry Pi, Intel NUC	Wheeled or legged	Indoor logistics, surveillance	TurtleBot 4, Boston Dynamics Spot
Manipulators	Force/torque, encoders, cameras	Onboard microcontrollers or external PC	Fixed base or mobile	Industrial automation, surgery	UR5, Kinova Gen3, da Vinci system
Aerial Robots [32]	IMU, barometer, cameras	PX4, Jetson Nano	Multirotor	Mapping, delivery, monitoring	DJI M300 RTK, Parrot Anafi, Skydio
Underwater Robots	Sonar, depth sensors, DVL	Embedded systems	Propeller-based	Inspection, marine biology	BlueROV2, OceanOne, Iver3
Swarm Agents [18]	Minimal (IR, RF, IMU)	Lightweight MCU	Wheeled, flying	Research, collective tasks	Kilobot, Crazyflie 2.1

Table 3. Use case matrix

Use Case	Key Technologies	Performance Metrics	Challenges
Autonomous Vehicles [43]	CNNs, LiDAR, SLAM, V2X	Precision, reaction time, safety rate	Urban complexity, ethical decision-making
Surgical Robotics [44, 45]	Precision actuation, vision-guided manipulation	Accuracy (sub-mm), safety, latency	Regulatory approval, high costs
Warehouse Automation	Navigation, planning, barcode/RFID processing	Throughput, uptime, adaptability	Dynamic inventory layout
Elderly Care Robots	Voice interfaces, person recognition, safety systems	Responsiveness, user trust, emotion detection	Ethical concerns, personalization
Agricultural Robotics [40]	Multispectral vision, terrain navigation, AI analysis	Yield boost, weed detection accuracy	Outdoor variability, crop generalization

Table 4. Common benchmark datasets

Dataset	Focus Area	Usage	Remarks
KITTI	AV perception and SLAM	Object detection, tracking, odometry	Widely used; stereo and LiDAR data
TUM RGB-D	Visual SLAM, indoor nav	Pose estimation, mapping	Real-time indoor RGB-D sequences
COCO / ImageNet	General computer vision	Object recognition, segmentation	Rich, diverse annotations
AirSim	Aerial robotics, simulation	Reinforcement learning, control	Realistic physics; drone platform
Robot@Home	Service robots	Semantic mapping, HRI	Real-world domestic environments

4.3 Use case matrix

Table 3 outlines major use cases for autonomous systems, highlighting key technologies, performance criteria, and major deployment challenges.

4.4 Benchmarks and datasets

Table 4 compiles key benchmark datasets and performance metrics commonly used to evaluate SLAM, perception, and navigation systems.

Performance Benchmarks

- Accuracy: Measured in terms of trajectory error (for SLAM) or classification accuracy (for perception).
- Latency: Critical in real-time applications like AVs and surgical robotics.
- Robustness: Evaluated under noise, dynamic environments, or occlusion.
- Energy Efficiency: Particularly important for aerial and swarm robots.

5. CHALLENGES AND OPEN RESEARCH PROBLEMS

Despite impressive advances, autonomous robotics still faces significant challenges that hinder its widespread deployment and general-purpose applicability. These challenges span technical, environmental, and societal domains [46].

5.1 Scalability

Current autonomous systems frequently encounter scalability challenges when transitioning from controlled laboratory environments to complex, real-world applications. These issues become particularly evident in multi-agent coordination scenarios, such as swarm robotics, where maintaining synchronized behavior across numerous units is difficult. Similarly, distributed decision-making within large fleets of autonomous agents introduces significant complexity in terms of communication, consensus, and real-time responsiveness. As the range of tasks and operational environments diversifies, the overall system complexity escalates, making it harder to maintain robustness, efficiency, and generalizability across different contexts.

5.2 Real-time performance

Autonomous systems [6] demand low-latency decision-making capabilities for critical tasks such as collision avoidance, real-time manipulation, and seamless human interaction. However, achieving this remains challenging due to several technical barriers. One major obstacle is the high computational load associated with processing large volumes of sensor data and performing complex AI inference tasks. Additionally, bandwidth limitations and latency issues hinder effective offloading to edge or cloud platforms, especially in scenarios requiring rapid response. Meeting strict real-time performance guarantees becomes even more difficult in dynamic, unpredictable environments where delays or missed decisions can compromise safety and effectiveness.

5.3 Robustness in unstructured environments

Most robots remain brittle when operating outside of structured or pre-mapped environments. They face significant challenges such as handling perceptual noise, managing occlusions, and coping with sensor failures. Environmental variability including changes in weather, terrain, or the appearance of unexpected obstacles further complicates reliable operation. Additionally, a major hurdle lies in enabling robots to generalize learned policies and behaviours to unfamiliar domains or tasks, which limits their adaptability and robustness in real-world applications.

5.4 Ethical and legal issues in deployment

As autonomous systems increasingly operate in public, personal, and critical infrastructure spaces, ethical and legal considerations become central to their development and deployment. While ethical discourse has traditionally focused on abstract concepts such as fairness, accountability, and transparency, recent international efforts have produced more concrete guidelines and regulatory frameworks to guide ethical AI and autonomous system design.

One prominent example is the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, which outlines principles such as transparency, accountability, privacy, and algorithmic bias mitigation. These guidelines advocate for value-based design, emphasizing that systems should respect human rights, cultural norms, and environmental sustainability from the outset. For instance, IEEE recommends embedding explainability into autonomous decision-making, allowing stakeholders to understand and contest a system's output especially critical in healthcare robotics or autonomous vehicles.

In a parallel effort, the European Union's AI Act (2021) classifies AI-based systems, including autonomous systems, into different risk categories (unacceptable, high-risk, limited-risk, and minimal-risk). High-risk systems, such as autonomous vehicles and biometric surveillance robots, are required to undergo rigorous conformity assessments, maintain human oversight mechanisms, and ensure traceability of decisions. This risk-based approach provides a pragmatic framework for aligning ethical and legal compliance with application contexts.

Additionally, case-based concerns are emerging in real-world deployments. For example, in autonomous vehicle accidents, establishing accountability remains complex should liability rest with the manufacturer, the algorithm designer, or the user? In social robotics, privacy concerns arise when domestic assistant systems continuously collect audio-visual data, often without explicit consent or adequate data protection. To ensure ethical deployment, autonomous systems must be developed with interdisciplinary input, combining insights from law, ethics, computer science, and human-computer interaction. A shift toward proactive governance, backed by enforceable standards and contextual testing, is necessary to foster public trust and responsible innovation.

5.5 Emerging role of generative AI in autonomous systems

A growing trend in autonomous robotics is the integration of Generative AI, particularly large language models (LLMs) such as GPT-4, into robotic perception, planning, and decision-making. These models, originally designed for natural language understanding and generation, are increasingly being adapted for task decomposition, semantic understanding, and human–robot interaction.

For instance, LLMs can convert high-level human commands ("Clean the lab and return to the charging station") into a series of context-aware subtasks, enabling robots to reason about sequences, tools, and environmental constraints without explicit pre-programmed logic. Research prototypes from institutions like OpenAI, Google DeepMind, and Stanford have shown that LLMs can assist in zero-shot task planning, scene interpretation, and even natural-language-based policy learning for manipulation tasks.

In practical deployments, generative models are being used to improve multimodal interfaces, allowing robots to process and integrate spoken commands, visual cues, and sensor feedback simultaneously. This is particularly relevant for assistive robots, warehouse automation, and field robotics, where adaptability to unstructured instructions is critical.

Moreover, combining LLMs with robotics frameworks (e.g., ROS with LLM plug-ins or APIs) opens new possibilities for intention prediction, error recovery, and explainability, making autonomous systems more intuitive and human-centric. As these models become more efficient and hardware-friendly, their real-time use in embedded robotics systems is expected to increase.

Generative AI thus represents a paradigm shift in autonomy from rule-based planning to language-informed, reasoning-driven behavior synthesis, laying the groundwork for more general-purpose, conversationally operable autonomous systems.

6. FUTURE DIRECTIONS

Autonomous robotics [27] is rapidly evolving, and several emerging technologies promise to transform the field in the coming decades:

6.1 Integration of quantum computing, 6G, and edge AI

Quantum computing could dramatically accelerate computationally intensive tasks such as motion planning, Simultaneous Localization and Mapping (SLAM), and control by solving complex optimization problems far more efficiently than classical approaches. The advent of 6G networks is expected to revolutionize communication in autonomous systems by providing ultra-low-latency and high-throughput connectivity, which will enable real-time cloud-based robotic operations and seamless coordination among large-scale swarms. Additionally, the rise of Edge AI will facilitate more robust, on-device intelligence by processing data locally. This not only reduces reliance on potentially unstable cloud connections but also enhances system resilience and ensures greater privacy in sensitive applications.

Quantum computing could dramatically accelerate computationally intensive tasks such as motion planning, Simultaneous Localization and Mapping (SLAM), and control by solving complex optimization problems far more efficiently than classical approaches. Recent research highlights the potential of Quantum Approximate Optimization Algorithms (QAOA) in solving SLAM-related challenges, such as graph-based map merging and non-linear pose estimation. For example, Dalyac [47] demonstrated how QAOA can reduce the complexity of SLAM optimization by leveraging quantum superposition and entanglement to explore multiple hypotheses in parallel.

A real-world illustration of quantum application is Volkswagen's quantum routing initiative, which used quantum algorithms to optimize taxi fleet movements in urban environments. This approach is directly relevant to autonomous multi-robot systems requiring dynamic task allocation and route optimization under resource constraints. Furthermore, exploratory work in quantum machine learning (QML) is emerging to improve sensor data interpretation in robotic vision and perception pipelines.

The advent of 6G networks is also expected to revolutionize communication in autonomous systems by offering ultra-low-latency and high-throughput connectivity. Industry whitepapers from [48] envision 6G as a foundational enabler for real-time collaborative robotics, especially in scenarios involving robot swarms, autonomous vehicles, and distributed decision-making. These networks will support massive machine-type communications (mMTC) and ultra-reliable low-latency communication (URLLC), which are essential for coordinating robots in dynamic, mission-critical environments.

Additionally, the rise of Edge AI will facilitate more robust, on-device intelligence by processing data locally. This not only reduces reliance on potentially unstable cloud connections but also enhances system resilience and ensures greater privacy in sensitive applications. Together, the convergence of quantum computing, 6G, and Edge AI is poised to unlock unprecedented capabilities in autonomy by addressing the key bottlenecks of computational efficiency, communication latency, and adaptive intelligence.

6.2 Next-generation systems

Future autonomous systems are anticipated to incorporate self-repairing and self-adaptive hardware, enabled by breakthroughs in soft robotics and modular architectures, allowing machines to recover from damage and adjust to changing environments. These systems will also feature lifelong learning agents capable of continuous adaptation without suffering from catastrophic forgetting, ensuring sustained performance in dynamic settings. A significant development will be the emergence of unified cognitive architectures that integrate symbolic reasoning with neural networks, combining the strengths of rule-based logic and data-driven learning. Furthermore, there will be a strong emphasis on human-centric design, prioritizing transparency, trust, and ethical compliance to facilitate safe and effective collaboration between humans and robots.

6.3 Convergence with other fields

Robotics will continue to advance through interdisciplinary collaboration, drawing heavily from neuroscience and cognitive science to develop more accurate models of perception, learning, and decision-making. Materials science will play a pivotal role in creating energy-efficient and resilient autonomous systems, enabling enhanced durability and sustainability. Additionally, research in human-computer interaction will contribute significantly to the development of intuitive interfaces and collaborative frameworks, improving how humans and robots communicate and work together in diverse environments.

7. CONCLUSION

Autonomous robotics is undergoing a paradigm shift driven by breakthroughs in AI, sensors, computation, and interdisciplinary integration. This review has examined the fundamental concepts, emerging trends, and critical challenges shaping the field. As robots increasingly permeate domains such as healthcare, transportation, agriculture, and defence, the importance of interdisciplinary research becomes ever more vital. Future progress will depend not only on technical innovation but also on careful consideration of societal implications, regulatory alignment, and ethical deployment. Through collaborative efforts spanning engineering, computer science, law, ethics, and human factors, we can build autonomous systems that are not only intelligent but also responsible, scalable, and trustworthy.

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