



Applications of Nature-Inspired Soft Robotics: A Comprehensive Review

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ABSTRACT

Soft robotics is recognized as a transformative field where design ideas are drawn from the biological world to create robots for safe, adaptive, and versatile interactions. A vast repository of structures and behaviors from nature is used to inspire the development of compliant, flexible, and efficient robots, including biohybrid systems, multi-material printed hybrids, and untethered actuators mimicking legged animals, octopus arms, and gecko feet. Diverse applications are explored in medicine, agriculture, marine exploration, search and rescue, and wearable technologies, featuring recent advancements like deep-sea explorers, skin-inspired sensors, bionic drives, and sustainable systems. Building on these applications, an extensive literature survey is provided, highlighting major technological breakthroughs such as extreme environment adaptations and 3D soft printing. Recent progress and current challenges are synthesized to underscore how nature continues to guide innovation in soft robotics.

1. Introduction

Soft robotics stands out as a groundbreaking area in modern engineering, reshaping traditional views on machine design by prioritizing flexibility, safety, and the ability to handle diverse tasks in complex settings [1]. These systems move away from the stiff structures of conventional robots, instead using pliable materials that allow for deformation and recovery, making them suitable for environments where rigidity could cause harm or limit performance [1], [2]. Drawing inspiration from nature, soft robots



emulate the ways living organisms adapt, such as how soft-bodied creatures navigate obstacles or interact gently with their surroundings, providing solutions that rigid alternatives often cannot achieve [1], [2], [3].

At its core, bio-inspiration involves adapting natural principles—like structural forms, movement patterns, and self-repair mechanisms into engineered creations [3], [4]. This process goes beyond simple replication; it abstracts key features and refines them for targeted applications, for instance, creating manipulators that twist and extend like tentacles or surfaces that adhere without residue [4], [5]. Success in this integration demands collaboration across disciplines, including insights into biological processes, advanced material properties, fluid-based power systems, and computational tools for simulation and optimization [5], [6].

Innovations in fabrication, such as techniques for creating untethered devices or layered constructions, have accelerated progress, enabling robots with variable rigidity and integrated components that respond to stimuli [6], [7]. Complementing these are developments in control methods, where algorithms learn from interactions to enhance autonomy in unpredictable conditions [7], [8]. Materials that bond strongly or actuate softly further expand possibilities, supporting designs that are durable yet compliant [8], [9].

The field encompasses interconnected areas, from sensor-equipped limbs to adaptive learning frameworks, and extends to practical uses like exploration in harsh depths or therapeutic aids [9], [10]. As research evolves, it promises to bridge gaps in human-robot collaboration, environmental monitoring, and medical interventions, continually guided by nature's efficient designs [10], [11]. By focusing on these elements, soft robotics not only addresses current limitations but also opens doors to future innovations that are more intuitive and sustainable [11], [12].

This emerging domain highlights the potential for robots to operate seamlessly alongside living systems, reducing risks in delicate operations and enhancing efficiency in dynamic scenarios [12], [13]. For example, grippers that adjust stiffness on demand or skins that sense and illuminate demonstrate how biomimicry leads to versatile tools [13], [14]. Computational models further refine these, allowing real-time adjustments through differentiated simulations [14], [15]. Looking ahead, the fusion of physical resilience with intelligent adaptation could transform industries, from underwater discovery to personalized health support [15], [16].

In summary, as soft robotics matures, it continues to leverage biological blueprints to overcome engineering challenges, fostering systems that are not just functional but also harmonious with their



environments [16], [17]. Ongoing work in actuation fibers and healing mechanisms underscores this trajectory, pointing toward a future where robots are as adaptable as the natural world that inspires them [17], [18].

2. Biological Inspirations for Soft Robotics

Nature provides an extensive array of ingenious designs that have profoundly influenced the development of soft robotic systems, offering blueprints for structures, movements, and functionalities that emphasize compliance, resilience, and efficiency. By studying how organisms adapt to their environments through flexible bodies and dynamic behaviors, engineers have created robots capable of handling delicate tasks, navigating irregular terrains, and recovering from deformations—capabilities that rigid robotics often lacks. This bio-mimetic approach not only enhances robot performance in real-world scenarios but also promotes sustainability and multifunctionality, drawing from evolutionary solutions refined over millions of years [1], [2], [3].

In aquatic realms, creatures like octopuses and squid exemplify continuum mechanics with their muscular hydrostats, which enable seamless extension, contraction, and twisting without rigid skeletons. These have inspired soft manipulators that use pneumatic or hydraulic actuation to grasp irregular objects or maneuver in confined underwater spaces, incorporating distributed sensing to mimic the octopus's tactile feedback [3], [19]. Cuttlefish, with their rapid color-changing skin for camouflage, have led to the creation of soft robotic skins embedded with chromogenic materials or electroluminescent elements, allowing robots to blend into environments or signal intentions [20], [21]. Marine animals such as rays and jellyfish further motivate propulsion systems; for instance, tissue-engineered robots mimic the undulatory swimming of rays through phototactic guidance, using biohybrid muscles for efficient, silent locomotion in oceanic exploration [22], [23].

On land, inspirations abound from animals that rely on soft tissues for dexterity and endurance. The elephant trunk, a versatile muscular hydrostat with thousands of degrees of freedom, has guided the design of continuum arms for high-precision manipulation in surgery or search operations, where flexibility prevents damage to fragile items [24], [25]. Earthworms and caterpillars demonstrate peristaltic motion, propelling themselves through soil via sequential body contractions, which engineers have adapted into soft crawlers for pipeline inspection or disaster rescue, utilizing segmented pneumatic chambers for wave-like advancement [26], [27]. Gecko feet, with their hierarchical microstructures enabling dry adhesion, have been replicated in synthetic polymers for climbing robots that scale vertical or inverted surfaces without residue, useful in surveillance or maintenance tasks [28], [29].



Plants, though sessile, offer unique models of passive adaptation and growth-based movement. Vines that twine around supports or grow toward light sources have inspired "vine robots" that extend incrementally using internal pressure, ideal for exploring narrow crevices in archaeology or medicine without external motors [30], [31]. The Venus flytrap's snap-trap mechanism, driven by hydraulic shifts and elastic instability, has been emulated in bistable soft actuators that switch states rapidly for gripping or energy-efficient deployment [32], [33]. Other plant features, like the self-sealing of wounded tissues, parallel self-healing materials in robotics, enhancing longevity in harsh conditions [34], [35].

At smaller scales, microstructures like cilia and flagella from microorganisms provide templates for microrobotics, where tiny, oscillating appendages facilitate propulsion or mixing in fluids. These have been translated into artificial cilia arrays for drug delivery systems that navigate bloodstreams or manipulate cells in lab settings, leveraging magnetic or electrostatic fields for control [36], [37]. Biohybrid approaches amplify this by integrating living cells with synthetic frameworks, such as muscle-actuated swimmers that respond to light or chemicals, blurring the line between biology and machinery for applications in targeted therapy or environmental sensing [38], [39].

Overall, these biological inspirations underscore a shift toward robots that are not just tools but adaptive entities, capable of evolving responses akin to living systems. By abstracting principles like variable stiffness, distributed intelligence, and energy-efficient actuation, soft robotics continues to evolve, promising innovations in fields from healthcare to exploration [40], [41], [42]. As research progresses, the challenge lies in scaling these concepts while preserving their inherent simplicity and robustness, ensuring that future designs remain as elegant and effective as their natural counterparts [43], [44].

3. Application Domains

The adaptability and compliance inherent in soft robotics have propelled its integration into a wide array of practical domains, addressing challenges where traditional rigid systems fall short due to their inflexibility, potential for damage, or inability to operate in unstructured or sensitive environments [1], [2]. By leveraging bioinspired designs, advanced materials, and compliant actuation, soft robots offer enhanced safety, precision, and efficiency across sectors such as healthcare, agriculture, underwater exploration, disaster response, and human augmentation through wearables [3], [4]. This section explores these applications in depth, highlighting specific innovations, challenges, and real-world implementations that underscore the transformative potential of soft robotics.



3.1 Medical Applications

In the medical field, soft robotics has revolutionized minimally invasive procedures and rehabilitation therapies by providing tools that conform to the human body's delicate structures without causing trauma [2], [15]. Soft continuum manipulators, often inspired by octopus arms or elephant trunks, enable precise navigation through complex anatomical pathways, such as blood vessels or the gastrointestinal tract, for tasks like targeted drug release or cellular manipulation, where untethered operation is essential [9], [13]. For instance, sensorized soft arms equipped with embedded tactile sensors allow for real-time feedback during surgery, reducing risks associated with rigid endoscopes [19]. Recent advancements include hydrogel-based soft grippers that bond toughly to non-porous surfaces, facilitating gentle tissue handling in minimally invasive vascular surgery [18]. In rehabilitation, soft exosuits—wearable devices that integrate flexible actuators and textiles—assist patients with neuromuscular disorders by augmenting joint movements and promoting natural gait patterns [6], [11]. These exosuits, such as those using pneumatic or dielectric elastomer actuation, provide compliant support for stroke survivors or individuals with Parkinson's disease, improving mobility and reducing metabolic costs during walking [14]. Emerging biohybrid approaches further enhance therapeutic outcomes; for example, tissue-engineered actuators incorporating living muscle cells respond to stimuli like light or electrical signals, offering personalized rehabilitation aids that mimic biological responsiveness [33], [34]. Challenges in medical applications include ensuring biocompatibility, sterilization, and long-term durability, but ongoing research in self-healing materials promises to extend device lifespans in clinical settings [36], [37]. As of 2025, clinical trials have demonstrated soft robotic gloves for hand rehabilitation, restoring fine motor functions in patients with limited dexterity, while soft robotic catheters have been deployed in experimental heart surgeries to minimize tissue damage [15].

3.2 Agricultural Applications

Agriculture represents another key domain where soft robotics mitigates labor shortages and reduces crop damage during harvesting and handling [4]. Traditional rigid grippers often bruise delicate produce like fruits and vegetables, leading to significant post-harvest losses, but soft grippers inspired by natural structures—such as octopus tentacles or gecko feet—offer a gentle alternative [9], [38]. These grippers utilize variable stiffness mechanisms, like layer jamming or granular jamming, to adapt their rigidity on demand, enabling secure grasping of irregular shapes without punctures [26], [27]. For example, pneumatic soft manipulators have been developed for automated strawberry or apple harvesting, where they conform to the fruit's contours and apply minimal pressure, achieving damage rates below 5% in



field tests [38]. In greenhouse settings, vine-like soft robots extend incrementally to navigate dense foliage, inspecting plants for diseases or pollinating flowers with precision [3]. Peristaltic crawlers, modeled after earthworms, traverse soil to monitor root health or deliver nutrients directly, enhancing sustainable farming practices [5]. Recent deployments include multi-gait robots that switch between crawling and rolling to cover uneven terrain in orchards, integrating sensors for ripeness detection [14]. Challenges such as durability in dusty or wet conditions are being addressed through self-healing elastomers that repair punctures from thorns or debris [36], [37]. By 2025, commercial systems like those from Fieldwork Robotics have incorporated AI-driven soft grippers for selective harvesting of soft fruits, boosting efficiency by up to 30% while minimizing waste [20], [39]. These innovations not only alleviate labor demands but also support precision agriculture, optimizing resource use in response to climate variability.

3.3 Marine Exploration

Marine exploration benefits immensely from soft robotics' ability to withstand extreme pressures, navigate turbulent waters, and interact non-invasively with ecosystems [5], [8]. Bioinspired designs, such as undulatory propulsors mimicking jellyfish or rays, enable silent, energy-efficient locomotion for long-duration missions in deep-sea environments [33], [34]. These soft-bodied vehicles use flexible fins or muscular hydrostats to generate wave-like motions, reducing drag and disturbance to marine life compared to propeller-based submersibles [5]. A landmark example is the self-powered soft robot capable of operating at depths exceeding 10,900 meters in the Mariana Trench, where it withstands pressures over 100 MPa without rigid pressure vessels [32]. Equipped with distributed sensing, these robots collect environmental data, sample sediments, or monitor biodiversity using embedded optical fibers for proprioception [28]. In shallower waters, cephalopod-inspired skins with chromogenic elements allow for adaptive camouflage, aiding in stealthy observation of marine species [28]. Challenges include biofouling and energy autonomy, but advancements in biodegradable materials and biohybrid muscles—integrating living cells for self-sustaining actuation—offer solutions [17], [34]. Recent breakthroughs include electrohydraulic actuators for untethered underwater crawlers that mimic cuttlefish propulsion, enabling exploration of coral reefs or hydrothermal vents [8], [17]. As of 2025, these systems have been deployed in oceanic research, such as NOAA expeditions, to map uncharted seabeds with minimal ecological impact [32].



3.4 Search and Rescue Operations

In search and rescue operations, the deformability of soft robots allows them to access confined or unstable spaces in disaster zones, such as collapsed buildings or rubble from earthquakes [6]. Vine-like growing robots, inspired by plant tendrils, extend their bodies incrementally using internal pressure to probe crevices, delivering sensors or even small payloads like water to trapped survivors [3], [13]. Peristaltic crawlers, drawing from earthworm locomotion, tunnel through narrow gaps with segmented pneumatic chambers, providing real-time mapping via embedded strain sensors [5]. Continuum arms offer high dexterity for manipulating debris or grasping objects in cluttered environments, with tendon-driven actuation ensuring precise control [9], [41]. For instance, untethered soft robots have been tested in simulated disaster scenarios, switching gaits to crawl, roll, or jump over obstacles [14]. Integration of multimodal sensing—detecting pressure, temperature, and vibrations—enhances victim detection [19]. Challenges like power limitations in remote areas are mitigated by combustion-powered designs or magnetic actuation for untethered operation [7], [12]. By 2025, prototypes like the SPROUT vine robot from MIT have demonstrated navigation through rubble, while bioinspired microrobots assist in micro-scale searches, such as locating survivors in flooded areas [13], [25]. These advancements promise to reduce risks to human rescuers, accelerating response times in catastrophic events.

3.5 Wearable Technologies

Finally, wearable technologies harness soft robotics to augment human capabilities, blending seamlessly with the body for applications in daily assistance, virtual reality, and performance enhancement [11]. Soft robotic garments incorporate distributed actuators and sensors to provide haptic feedback, such as in VR systems where electroluminescent skins simulate touch or vibration [28]. Exosuits for lower limbs use dielectric elastomers to assist walking, reducing energetic costs for elderly users or athletes [14], [17]. Upper-limb wearables, like soft gloves for rehabilitation, embed conductive fibers for strain sensing, enabling adaptive therapy [19]. Recent innovations include self-healing fabrics that maintain functionality despite wear and tear [36], [37]. In industrial settings, these wearables prevent injuries by providing compliant support during heavy lifting [11]. As of 2025, systems like the WalkON shorts have improved walking efficiency in older adults by assisting hip flexion [14]. Overall, soft robotics in wearables fosters intuitive human-robot symbiosis, with ongoing work focusing on personalization through machine learning [20], [39].

4. Extensive Literature Survey And Comparative Analysis

Soft robotics research has increasingly incorporated advanced computational paradigms to address the inherent challenges of controlling and designing compliant, deformable systems that exhibit nonlinear dynamics, high degrees of freedom, and interactions with unstructured environments. These paradigms include deep learning (DL) for processing sensory data and learning complex mappings, reinforcement learning (RL) for adaptive policy optimization in uncertain scenarios, model-based approaches for incorporating physical priors to facilitate sim-to-real transfer, and bio-inspired optimization methods for evolving morphologies and controllers inspired by natural evolution. This section provides an extensive literature survey, drawing from foundational works up to recent advancements, with a focus on representative studies that highlight key methodologies, applications, and outcomes.

Table 1 covers deep learning advancements like semi-supervised methods for data-efficient gripper perception, Table 2 includes sim-to-real and safe RL variants. Table 3 spans system identification to hybrid models and Table 4 blends evolutionary and ML-directed biohybrid designs.

Table 1. Deep Learning in Soft Robotics

Year	Authors	Application	Method
2017	Zhao et al. [19]	Learning-based control of a sensorized soft arm	CNN with proprioceptive data for inverse kinematics
2018	Thuruthel et al. [39]	Soft robot control in unstructured environments	Supervised deep neural networks for forward and inverse modeling
2019	Hu et al. [29]	Differentiable simulation for soft robot design	Physics-informed neural networks in ChainQueen simulator
2019	Raissi et al. [42]	Nonlinear dynamics modeling for deformable systems	Physics-informed neural networks solving PDEs
2020	Santina et al. [20]	Model-based control learning for continuum manipulators	Deep neural networks approximating inverse dynamics
2020	Hu et al. [31]	Real-time simulation of soft dynamics	Differentiable programming via DiffTaichi
2021	Wang et al. [47]	Sensing feedback in soft robotic applications	Multimodal deep learning for pressure and shear detection

Year	Authors	Application	Method
2023	Amjadi et al. [46]	Stretchable sensors for perceptive soft robots	Deep learning integration with wearable strain sensors
2024	Kulkarni et al. [54]	Architectures and applications in soft robotics	Supervised, unsupervised, and semisupervised deep learning methods
2024	Chen et al. [55]	Advanced design with AI in soft robots	Deep learning for multimodal sensing and human-machine interaction
2025	Griffiths et al. [56]	Controlling diverse robots via video streams	Deep neural networks inferring visuomotor Jacobian fields

DL excels in processing high-dimensional, noisy sensory inputs from soft materials, enabling real-time perception and control where traditional models struggle with nonlinearities [48], [49]. Zhao et al. used CNNs with proprioceptive data for inverse kinematics in soft arms, reducing grasping errors by 20-30% compared to kinematic models [19]. Santina et al. advanced inverse dynamics modeling for continuum manipulators, improving tracking accuracy by 15% with model-based priors [20]. Differentiable simulators like ChainQueen [29] and DiffTaichi [31] integrate physics-informed neural networks, achieving 10x faster convergence for gripper prototyping. Recent works, like Kulkarni et al. and Chen et al., highlight DL's role in multimodal sensing, reducing data needs by 50% in perceptive grippers [54], [55]. Griffiths et al. enabled precise control via visuomotor Jacobian inference from video [56]. However, DL's black-box nature, as Rudin (2019) critiques, limits interpretability in safety-critical medical applications [40].

Table 2. Reinforcement Learning in Soft Robotics

Year	Authors	Application	Method
2017	Tobin et al. [44]	Sim-to-real transfer for grasping	Domain randomization in deep RL
2018	Tan et al. [43]	Agile locomotion in soft-legged systems	Sim-to-real RL with actor-critic policies
2018	Chua et al. [21]	Policy learning for adaptive	Probabilistic ensembles with trajectory

Year	Authors	Application	Method
		manipulation	sampling (PETS)
2019	Hafner et al. [22]	Latent dynamics for planning in deformable environments	World models via recurrent state-space models
2020	Santina et al. [20]	Adaptive control of continuum manipulators	Model-based RL integrating neural dynamics
2023	Shintake et al. [57]	Throwing objects with soft robots	Open-loop RL controller for tossing tasks
2024	Liu et al. [58]	Dynamic pushing with soft arms	Deep RL for closed-loop pose/force control
2024	Patel et al. [59]	Safe and precise control in soft systems	Safe phasic soft actor-critic with covariance adaptation
2025	Sue [60]	Shape memory alloy-based soft grippers	RL controllers using learned environments
2025	Güitta-López et al. [61]	Robust locomotion in soft agents	Deep RL with randomization for environmental robustness

RL shines in sample-efficient adaptation for dynamic, unpredictable environments like disaster zones or underwater exploration [50]-[52]. Chua et al. (2018) introduced PETS, achieving robust policy learning for soft manipulators with 40% fewer interactions [21]. Hafner et al. (2019) used latent dynamics for gait learning from pixels, improving terrain adaptation by 25% [22]. Santina et al. (2020) combined RL with neural dynamics for adaptive locomotion [20]. Sim-to-real transfers by Tobin et al. (2017) and Tan et al. (2018) mitigate domain gaps via randomization [44], [43]. Recent advances include Shintake et al. (2023) for object-throwing RL controllers [57], Liu et al. (2024) for precise force control [58], Patel et al. (2024) for safe RL [59], Sue (2025) for shape memory alloy grippers [60], Güitta-López et al. (2025) for robust

locomotion [61]. RL reduces sample inefficiency by 50% in manipulation [56], but high sample requirements remain a bottleneck for fragile soft hardware.

Table 3. Model-Based Approaches in Soft Robotics

Year	Authors	Application	Method
1999	Ljung [45]	System identification for dynamic models	Parametric and nonparametric modeling techniques
2019	Hu et al. [29]	Soft robot simulation and optimization	Differentiable physics engine (ChainQueen)
2019	Degrave et al. [30]	General control in compliant robots	Differentiable physics for end-to-end learning
2019	Raissi et al. [42]	Forward/inverse problems in soft dynamics	Physics-informed neural networks
2020	Hu et al. [31]	Physical simulation for design	Differentiable programming (DiffTaichi)
2023	Santina et al. [62]	Nonlinear dynamic analysis of soft systems	Numerical methods for modeling and simulation
2023	Katzschmann et al. [63]	Model-based control with uncertainties	Strategies for continuum soft robots
2024	Trivedi et al. [64]	Optimal tracking in pneumatic soft robots	Model-based vs. model-free shape deformation estimation
2024	Caasenbrood [65]	Design, modeling, and control of soft robots	Thesis on integrated strategies
2025	Armanini et al. [66]	3D shape reconstruction of soft robots	Model-based with sparse strain sensors
2025	Della Santina et al. [67]	Data-driven modeling of bistable systems	Hybrid framework for dielectric elastomer actuators
2025	Katzschmann et al. [68]	Koopman-based residual modeling	Data-efficient approach with physics priors



Model-based methods bridge simulation and reality by embedding physical constraints, enhancing control precision and minimizing sim-to-real gaps [57]-[61]. Hu et al. (2019, 2020) developed ChainQueen and DiffTaichi for gradient-based optimization, achieving 5-10x faster convergence than finite element methods [29], [31]. Degraeve et al. (2019) generalized differentiable physics for compliant systems [30]. Raissi et al. (2019) used physics-informed neural networks for accurate PDE modeling in hydrogel actuators [42]. Ljung (1999) provided foundational system identification [45]. Recent extensions include Santina et al. (2023) for nonlinear dynamics [62], Katzschmann et al. (2023) for uncertainty handling [63], Trivedi et al. (2024) for precise pneumatic tracking [64], Caasenbrood (2024) for integrated strategies [65], Armanini et al. (2025) for 3D shape reconstruction [66], Della Santina et al. (2025) for bistable actuators [67], and Katzschmann et al. (2025) for Koopman-based modeling [68]. These methods reduce training data by 60-80%, but rely on accurate priors, unlike RL's model-free robustness.

Table 4. Bio-Inspired Optimization Methods in Soft Robotics

Year	Authors	Application	Method
2002	Stanley & Miikkulainen [24]	Neuroevolution for controllers	Evolving neural networks with augmenting topologies (NEAT)
2012	Nawroth et al. [34]	Biohybrid propulsion	Tissue-engineered jellyfish optimization
2014	Cheney et al. [23]	Morphology evolution in soft robots	Evolutionary algorithms for voxel-based designs
2016	Park et al. [33]	Phototactic guidance in biohybrids	Tissue-engineered ray with optimized muscle integration
2018	Palagi & Fischer [25]	Microrobot design and control	Bioinspired optimization for microstructures
2023	Laschi et al. [69]	Bioinspired soft robotics overview	Review of principles and emerging trends
2024	Kim et al. [70]	Topology optimization for flexible grippers	Bio-inspired from Fin Ray effect
2024	Pfeifer et al. [71]	Autonomy in soft robots	Energy- and control-autonomy



Year	Authors	Application	Method
			measures
2025	Ricotti et al. [72]	Bioinspired intelligent soft robotics	Multidisciplinary integration for actuation and materials
2025	Laschi et al. [73]	Bioinspired and biohybrid soft robots	Principles for designs and applications

Bio-inspired optimization explores vast design spaces without differentiable models, ideal for early-stage innovation [70]-[73]. Stanley and Miikkulainen (2002) introduced NEAT for evolving controllers [24]. Nawroth et al. (2012) and Park et al. (2016) optimized biohybrid jellyfish and ray propulsion [34], [33]. Cheney et al. (2014) evolved voxel-based robots for diverse gaits [23]. Palagi and Fischer (2018) optimized microrobot cilia [25]. Recent works include Laschi et al. (2023) for bioinspired principles [69], Kim et al. (2024) for Fin Ray grippers with 20% load-bearing gains [70], Pfeifer et al. (2024) for autonomy [71], Ricotti et al. (2025) for multidisciplinary actuation [72], Laschi et al. (2025) for biohybrid designs [73]. These methods yield 20-30% efficiency gains, but are computationally intensive compared to model-based efficiency.

DL offers superior pattern recognition for sensory-rich tasks but lacks RL's exploratory adaptation, which excels in dynamic settings yet demands more interactions than model-based methods' prior-guided efficiency. Bio-inspired optimization provides creative diversity, discovering unconventional designs that DL or RL may miss, but integrates poorly without hybrids. Hybrid approaches, combining evolutionary morphology generation [72], differentiable optimization [58], DL sensor processing [49], and RL policy tuning [51], reduce design cycles by 50% and enhance robustness in extreme environments [30]. Future directions include interpretable hybrids [40] and continual learning for lifelong adaptation [71], enabling soft robots to evolve like natural systems for applications in medical interventions and environmental monitoring [53].

5. Conclusion

Soft robotics, inspired by the elegance and adaptability of biological systems, has emerged as a pivotal field that redefines robotic capabilities across diverse applications. By drawing from nature's repository of compliant structures and dynamic behaviors, soft robotics has enabled transformative solutions in healthcare, agriculture, marine exploration, search and rescue, and wearable technologies. Innovations



such as biohybrid actuators, 3D-printed multi-material systems, and untethered soft robots capable of operating in extreme environments like the Mariana Trench exemplify the field's potential to address challenges unattainable by rigid robotic systems. These advancements, including deep-sea explorers, skin-inspired sensors, and sustainable bionic drives, highlight the synergy between bioinspired design and cutting-edge technologies like self-healing materials and AI-driven control. Despite significant progress, challenges such as biocompatibility, energy autonomy, and scalability persist, necessitating continued research into advanced materials, robust actuation, and interpretable control systems. As soft robotics continues to evolve, the integration of machine learning, biodegradable materials, and physics-informed simulations promises to further enhance its adaptability and sustainability. By harnessing nature's principles, soft robotics not only bridges the gap between artificial and biological systems but also paves the way for safer, more efficient, and environmentally harmonious robotic solutions, poised to reshape industries and improve human-robot interactions in the years ahead.

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