



Review Article

Bionic Skins and Biosensors: Machine Learning Applications of Soft Robotics

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Received: 24 November 2025

Accepted: 29 April 2026

Published online: 30 June 2026

Keywords: *bionics, biosensors, machine learning, prosthetics, rehabilitation*

The combination of soft robotics with biotechnology and advanced electronics has created a new era in digital healthcare through the invention of engineered bionic skins and smart biosensors. Bionic skin systems function as human skin by replicating its sensory and mechanical abilities while delivering essential features that include flexible design and self-healing abilities and biocompatibility for ongoing physiological signal observation. Biosensors operate alongside these systems by transforming biochemical and biomechanical signals into measurable electrical signals which support immediate health assessments and customized medical treatment decisions. Machine learning (ML) implementation in recent years has improved system performance through better signal processing and adaptive control and predictive analytics functions. ML approaches such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks and Reinforcement Learning (RL) have demonstrated strong potential in gesture recognition and anomaly detection and feature extraction and closed-loop prosthetic control. Deep learning architectures achieve better performance than traditional models when processing advanced multimodal biosignals because they can recognize both spatial and temporal relationships. The field experiences fast development progress yet must resolve persistent issues about long-term biocompatibility and data protection and power consumption and clinical practice regulatory compliance. The review traces the development of bionic skins and biosensors while studying their use with soft robotic systems and machine learning systems and developing future research paths toward multimodal patient-centered healthcare solutions.

Introduction

The integration of soft robotics with wearable bioelectronics and artificial intelligence is a vital force driving the development of healthcare technologies that deliver personalised, adaptive medical solutions through their data-driven capabilities [1]. The recent development of intelligent skin-interfaced systems brings about new opportunities which enable continuous physiological monitoring and rehabilitation support and improved human-machine interaction capabilities [2]. The healthcare system is currently undergoing a transformation that requires implementing predictive and preventive patient management systems rather than traditional reactive treatment methods [3]. Wearable health-monitoring systems require devices that meet four essential design criteria:

mechanical compliance, breathability, high sensitivity, and user comfort during extended operation [4-5]. Engineers encounter significant difficulties because they must develop all required properties in one product. The researchers developed bionic skin-inspired designs which integrate stretchable circuits together with nanomaterial-based sensing elements and multi-purpose bioelectronic patches which can monitor various physiological indicators [6]. This technology represents a fundamental breakthrough which enables artificial devices to replicate human skin's sensory and functional abilities [7]. The field of implantable and epidermal biosensors has advanced from its initial research stage to a point where it is clinically applicable [8].

The investigation has progressed through major advancements across five different scientific areas: material science, nanotechnology,

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<https://doi.org/10.65795/5qqzmq56>

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Figure 1: Various senses generated by body that can be converted to signals

wireless communication, micro-power systems, and biomedical informatics. The combined results of interdisciplinary research work together to develop biosensing systems which achieve high accuracy in detecting both biochemical signals and biomechanical signals [9]. The implementation of machine learning (ML) technology establishes a new intelligence system that operates alongside soft robotic systems and biosensing systems [10]. Automated biosensors contain biological elements that has capacity to express biological data as electric signals just like sense organs of the body thus supporting detailed health monitoring (figure 1).

Biosensors use ML models to improve their performance because the models provide automatic feature extraction and they detect anomalies in real time and they create control systems that adapt to changing conditions [11]. Support Vector Machines (SVMs) function as efficient tools for classifying structured biosignals while deep learning systems that include Convolutional Neural Networks (CNNs) and recurrent networks (LSTM-based models) excel at handling advanced multimodal and time-series physiological datasets [12-13]. The robotic system uses reinforcement learning to maintain closed-loop control of its prosthetic and exoskeleton operations by adjusting its movements according to the user's unique neuromuscular patterns [14]. Biosensor data processing now occurs on portable devices through edge intelligence which enables local data handling to minimize delays and safeguard user information while decreasing power usage [15]. Emerging directions in 2024–2025 highlight the increasing influence of foundation models and large-scale learning frameworks in robotic perception, sensor fusion, and autonomous healthcare assistance, signaling a shift toward more context-aware and self-optimizing bionic systems. The field has achieved major advancements; however, it still faces persistent difficulties which include establishing continuous compatibility with biological systems and maintaining sensor operational performance and protecting private medical information and transforming test models into actual medical applications [16-17]. The deployment of smart bionic skins and biosensors in medical fields will require researchers to solve existing technological constraints [18]. This review presents a complete analysis of bionic skin and biosensor development their combination with soft robotic systems and the increasing role of machine learning in creating personalized healthcare solutions.

Evolution of Biosensors and Bionic Skins

From rigid sensors to stretchable, skin-like devices

The field of biosensors and bionic skin technologies has advanced from initial rigid sensing technologies to current stretchable electronic systems which can be worn on the skin and accurately simulate human tissue movements and sensory abilities. The design of traditional biosensors uses inflexible materials which prevented their use in continuous body monitoring because these sensors could not adapt to the

natural shape and movement of human skin [19]. Researchers have developed new technology that allows electronic devices to flex and bend while maintaining their operational capabilities for extended time periods [20]. The development of electronic skins (e-skins) has emerged because existing electronic devices now combine flexible sensor arrays with either polymeric or nanocomposite substrates, which enable devices to function properly during active human movement [21]. The two systems have achieved full adoption in wearable health monitoring systems and prosthetic systems and robotic systems which need tactile sensing [22]. These sensors are combined on prosthetic hands or AI robots to re-develop the same sensing abilities as compared with skin for example pressure, touch, and temperature (figure 2).

The current e-skin technology platforms have built-in capabilities to recognize seven different sensory input types which include pressure and strain and temperature and biochemical detection [23]. The latest bionic skin technologies offer multiple detection abilities which function at higher spatial accuracy [24]. Material development has played the most important role in driving this advancement. The combination of conductive polymer gels with carbon nanotube composites and hydrogels and liquid-metal circuits has created materials which maintain their flexible performance while providing exceptional detection capabilities [25]. The existing situation involves multiple trade-offs that affect conductivity and long-term stability and fabrication complexity and biocompatibility. The sensors which use nanomaterials for their design show high signal fidelity yet people still worry about their skin irritation and toxic effects and their body will react to foreign materials during extended use. Stretchable bionic skins replace rigid sensors which create a new mechanical development that builds the base for complete wearable bioelectronic systems which enable healthcare monitoring and soft robotic interaction.

Integration of sensors in biological tissues: challenges and advances

The integration of biosensors and electronic skin systems into biological tissues represents one of the most critical challenges in bionic technology development which needs to achieve practical healthcare solutions. Tissue-interfaced sensors must function under real-world human body conditions which include persistent body movement and body moisture and body immune reactions and body damage and body parts which must work for extended periods [26]. Research efforts focus on achieving two objectives which involve maintaining stable system operation while ensuring complete biological compatibility with living systems. The first electronic skin systems suffered from a fundamental problem because their synthetic material components did not match the flexible properties of human soft tissue. Standard substrates did not provide the necessary elastic and breathable and adhesive properties which people need for continuous skin contact [27]. Recent developments in soft polymers and hydrogel materials and bio-inspired composite solutions have enhanced tissue compatibility because they decrease irrita-

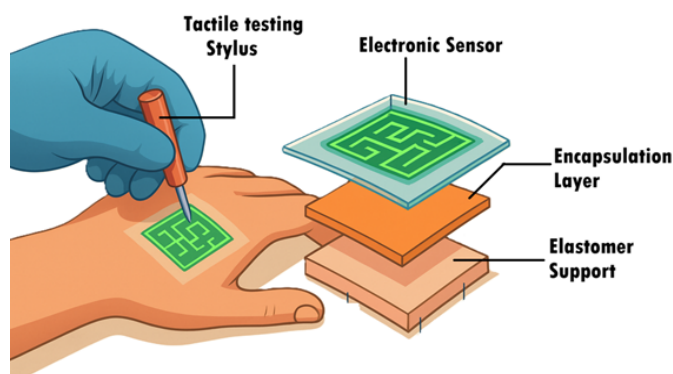


Figure 2: Schematic illustration of a conceptual bionic skin sensor on the human hand

Table 1: Comparison of Sensory Materials Commonly Used in Bionic Skins and Wearable Biosensors

Sensory Material / Platform	Typical Application in Bionic Skin	Key Advantages	Major Limitations / Challenges
Conductive Polymer Gels (e.g., PEDOT:PSS, ionic gels)	Stretchable pressure and strain sensors for prosthetics and soft robotics	High flexibility, good biocompatibility, skin-like mechanical properties	Reduced conductivity over long-term use, dehydration risk
Carbon Nanotube (CNT) Composites	High-sensitivity tactile sensing and multimodal e-skins	Excellent electrical conductivity, high sensitivity, scalable integration	Potential cytotoxicity concerns, complex fabrication processes
Graphene-Based Films	Flexible biochemical and biomechanical biosensors	Ultra-thin, strong mechanical durability, high signal fidelity	Expensive synthesis, challenges in reproducibility
Hydrogel-Based Sensors	Sweat-based biosensing (glucose, lactate, electrolytes)	Soft, breathable, highly biocompatible for epidermal contact	Mechanical instability, water loss during prolonged wear
Liquid Metal Circuits (e.g., eutectic gallium–indium)	Self-healing stretchable interconnects for wearable electronics	High conductivity, self-repair capability, extreme stretchability	Encapsulation difficulty, oxidation issues, long-term stability concerns
Piezoelectric Nanomaterials (e.g., ZnO, PVDF)	Self-powered motion and pressure sensing in robotics	Enables energy harvesting, high responsiveness, compact size	Fragility, limited flexibility under repeated deformation
Triboelectric Nanogenerators (TENGs)	Self-powered e-skins for continuous monitoring	Battery-free operation, strong signal generation under motion	Performance affected by humidity, requires material optimization
Bio-Inspired Composite Materials (e.g., spidroin-based, epidermis-mimicking layers)	Long-term implantable or wearable smart skins	Reduced foreign body response, enhanced comfort	Early-stage development, limited clinical translation so far

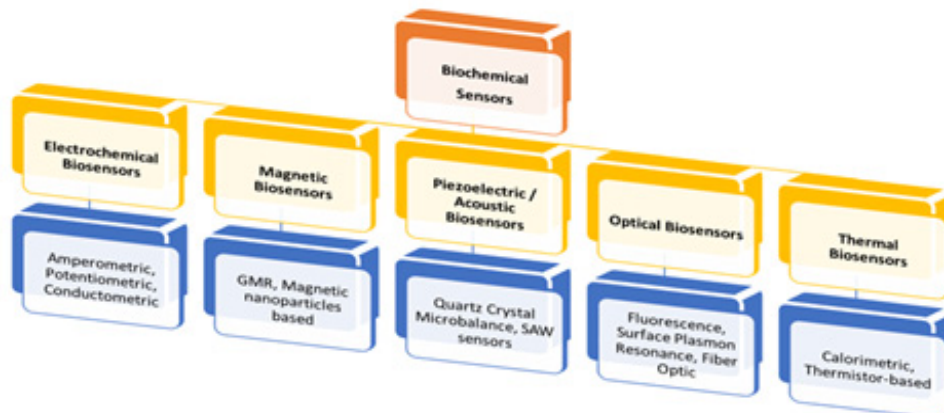
tion and provide better skin attachment [28]. Wearable biosensors can now monitor users continuously through their capacity to operate without creating significant discomfort to the users [29]. Sensors that stay in contact with the skin for extended periods will trigger an immune reaction which results in inflammation and fibrosis and signal loss [30]. The solution requires new techniques which include creating anti-inflammatory coatings and biomimetic surface treatments and wireless tactile systems that can be fully implanted which help restore sensory abilities while stopping immune system activation [31].

The development of smart wound-care biosensors has shown good clinical results because scientists make new technical advances in this field [32]. Wearable electrochemical and colorimetric platforms develop through recent research to monitor wound biomarker changes because these platforms offer visual and electrical output methods to detect early-stage infection [33]. Doctors can make remote clinical decisions because the system supports mobile and wireless technology, which helps create customized treatment programs [34]. The field has made progress, yet

engineers must solve multiple existing technological problems. The current design of most wearable biosensors depends on complex energy-storage systems, which restrict their ability to function continuously [35]. The development process of biosensors for new technologies like 3D bioprinted skin structures faces difficulties, which include creating proper vascular systems and maintaining safety for extended organ donation periods [36]. Active biosensor research has advanced to establish biosensors as practical tools for medical professionals, but scientists must conduct more research to improve material strength and compatibility with the human body and remote transmission and hospital use [37]. The upcoming generation of implantable and skin surface bionic devices requires solutions to multiple challenges before achieving continuous operation for medical treatment.

Machine Learning in Bio-sensing: An Overview

New bionic skin technology together with wearable biosensors now cre-

**Figure 4: Hierarchical representation of biochemical sensor types with their corresponding detection strategies**

ates complex physiological data sets which require advanced analytical methods beyond standard signal-processing methods for their analysis. The machine learning (ML) technology functions as a fundamental framework which enables biosensor systems to reach their full potential through automatic feature extraction and accurate classification and forecasting and dynamic system management. [38] The ML-based biosensing systems operate differently from traditional methods because they can learn to identify intricate connections between biomechanical and biochemical signals which enables improved health condition assessment and better customization of wearable medical devices. [39] The system demonstrates vital functionality within systems designed for gesture recognition and prosthetic operation and chronic disease assessment and rehabilitation robotics with closed-loop control.

ML techniques commonly used

Soft robotic biosensing systems use multiple ML algorithms which deliver different benefits according to specific biosignal types and application needs.

- Support Vector Machines (SVMs) in wearable diagnostics arises from their ability to handle small-to-medium datasets while delivering strong performance across structured classification tasks that include physiological state differentiation through electrochemical biosensor data [40].
- Convolutional Neural Networks (CNNs) have demonstrated superior performance in tactile sensing arrays and imaging-based biosensors, as they efficiently extract spatial features from pressure maps, fluorescence signals, or multimodal sensor grids. [41]
- Recurrent Neural Networks (RNNs) which include Long Short-Term Memory (LSTM) architectures serve as optimal solutions for processing sequential biosignal data which includes ECG EMG and respiratory patterns because these networks can detect long-duration time patterns within biological time series information [42].

Recent studies have found that Gated Recurrent Units (GRUs) deliver similar prediction results to LSTMs while using less system resources, which makes GRUs better suited for wearable biosensors that operate in edge environments with restricted memory and power capacities. Thus, model selection must balance performance with deployment constraints [43].

- Reinforcement Learning (RL) has emerged as a key technology for developing adaptive prosthetic systems and exoskeletons because these systems need to enhance their decision-making capabilities through ongoing access to neuromuscular information. RL provides valuable support to closed-loop robotic rehabilitation systems which create customized motor assistance plans for their patients [44].

The performance of deep learning models exceeds that of traditional algorithms when biosensor data exhibits multiple modes and high levels of noise and shifting patterns through time.

Data sources: biomechanical and biochemical signals

The research distinguishes between two learning methods which machine learning systems of bionic systems use for their operational functions. During the training process researchers use offline learning to study large collections of labeled data which they use to develop models for gesture classification and disease-state prediction and baseline biosignal modeling. The models enter operational use after their optimization process [45]. Prosthetic control and human-robot interaction depend on real-time adaptive learning which needs to handle continuous biosignal changes that occur during fatigue and electrode displacement and physiological condition shifts. The system needs to update its models in order to maintain effective closed-loop feedback operations [46]. The development of future wearable bionic intelligence systems requires a combination of offline system stability and personalized user experience which needs to maintain clinical operational effectiveness.

Table 2: Comparative Performance of Machine Learning Algorithms in Bionic Skin and Biosensing Applications

Machine Learning Algorithm	Typical Bionic /Biosensing Task	Key Strengths	Limitations	Reported Performance Range*
Support Vector Machines (SVMs)	Gesture classification, electrochemical biomarker detection	Strong performance on small datasets, good generalization	Limited scalability for high-dimensional multimodal signals	~85–92% accuracy
Random Forest / Ensemble Models	Biomarker classification, anomaly screening	Robust to noise, interpretable feature importance	Less effective for sequential/time-series dependencies	~80–90% accuracy
Convolutional Neural Networks (CNNs)	Tactile pressure mapping, imaging-based biosensing, sensor array pattern recognition	Excellent spatial feature extraction, high accuracy on complex inputs	Requires large datasets, computationally intensive	~90–97% accuracy
LSTM Networks	ECG/EMG time-series prediction, physiological trend monitoring	Captures long-term temporal dependencies, ideal for biosignals	High parameter cost, slower training	~93–98% accuracy
GRU Networks	Edge-based wearable time-series sensing	Comparable accuracy to LSTM with fewer parameters	Slightly reduced long-memory capability in some tasks	~92–97% accuracy
Autoencoders / Deep Anomaly Detection	Health anomaly detection, denoising biosensor signals	Effective in unsupervised settings, noise reduction	Interpretability challenges, needs careful tuning	~88–95% detection rate
Reinforcement Learning (RL)	Adaptive prosthetic control, exoskeleton gait optimization	Real-time decision-making, closed-loop personalization	Training complexity, safety constraints in clinical deployment	Task-dependent, high adaptability
Hybrid CNN–LSTM Models	Multimodal bionic skin systems combining tactile + physiological sensing	Joint spatial–temporal learning, superior multimodal accuracy	Higher computational demand, requires optimized hardware	~95–99% accuracy

Real-time v/s offline learning models in bionics

The bionics field shows its strengths and weaknesses through its two learning models which include instant learning and deferred learning. The system uses concurrent immediate-response models to create better user interaction results because it adjusts to user inputs in real time while offline models create the foundation for understanding user abilities before actual system operation begins. The upcoming sections of this document will provide complete information about these elements. Knowledge-based tutoring systems use real-time models to obtain user information which helps them deliver educational material according to the learner's emotional and cognitive states, which leads to better academic performance [47]. EMG-based NMIs enable time-critical applications to benefit from their strong offline capabilities by delivering faster system changes while decreasing mental demands during operational work [48-49]. The implementation of offline models in autonomous control systems improves their simulation robustness because developers create real-time applications with high-quality data [50-51]. The combination of real-time models which provide instant system changes and offline models which establish a solid basis for performance evaluation in bionic systems creates essential components for system development. The systems achieve better design and user experience because both methods are used to create a balance between them.

Types of Smart Bionic Sensors and Their Applications

These smart sensors are biocompatible in nature [52] and are sensitive as a self powered system engineered to incorporate, mimic as well as to improve the biological system [53]. These includes biomaterials integrated with sensor technology and electronics most often integrated with

AI algorithms for detection of mechanical movements, environmental variations as well as physiological impulses and expressing them as command signals [54-55].

Biomechanical sensors

These refers to sophisticated devices which are engineered for observing and examination of human physiology and locomotion. Sports, healthcare and human machine interface are some of its applications. These sensors assess cutting edge technologies for producing real time data to enhance performance as well as safety across a range of industrial sectors. Wearable robots namely Powered Ankle exoskeleton (PAEs) are intended in aiding gait rehabilitation and strength enhancement along with locomotion. These PAE also finds applications beyond assistance and rehabilitation. A robust augmentation PAE encourages healthy users for better performances as well as reducing the chances of injuries during motion [56]. A complete lower limb orthosis can be designed with the aid of bionic exoskeleton. Observing a passive degree of freedom and minimally restricting the user gait, it functions as a variable stiff regulator in all six joints that enables user specific assistance. These versatility of exoskeleton permits them to be used as both a single and a joint orthosis by using torque control [57]. Muscle triggered communication also make use of biomechanical sensors. These extremely sensitive sensors uses machine learning algorithms to translate muscle response into morse code permitting disabled users with accurate communication [58]. Soft mechanical sensors are wearable devices that analyses motion tracking and vital signs in real time characterised by wireless communication, stretchability and flexibility. These improve user's functionality and well-being [59]. Biomechanical sensors collects and analyse crucial biomechanical information to help in injury prevention and improve the accuracy of performance benchmarks of the athlete by pre-

Table 3: Types of Biomechanical sensors with their medical applications, advantages and disadvantages

Type of Biomechanical Sensor	Applications in Medicine	Advantages	Disadvantages
Strain Gauge Sensors	Monitoring joint movement, Prosthetic limb feedback, and muscle force measurement	High accuracy, simple design, reliable for continuous monitoring	Sensitive to temperature changes requires calibration
Piezoelectric Sensors	Heartbeat detection, respiration monitoring, orthopaedic implants, Gait analysis	High sensitivity, no external power needed for sensing, compact size	Fragile, limited flexibility, signal drift over time
Accelerometers	Fall detection in elderly patients, monitoring physical activity, gait and posture analysis	Portable, real-time monitoring, widely used in wearable devices	Susceptible to noise, limited accuracy for very small motions
Gyroscopes	Balance and vestibular function assessment, rehabilitation monitoring, prosthetics	Measures angular velocity, complements accelerometer for motion tracking	Higher cost, drift errors over time, complex calibration
Force / Pressure Sensors (Capacitive, Resistive, Optical)	Foot pressure distribution (diabetes care), prosthetics, rehabilitation robotics, orthopaedic implants	Detects subtle force variations, useful for gait and rehabilitation studies	Can wear out under long-term use, limited range for extreme forces
Tactile Sensors (Artificial skin, robotic-assisted surgery)	Prosthetic limb touch feedback, surgical robotics, rehabilitation devices	Mimics human touch, enhances feedback for prosthetics/surgeons	Complex fabrication, expensive, biocompatibility issues
Flexible / Stretchable Biomechanical Sensors (Polymer-based, nanomaterial composites)	Wearable health monitoring (pulse, breathing, muscle contraction), sports medicine	Comfortable, lightweight allows continuous non-invasive monitoring	Durability issues, lower accuracy than rigid sensors, signal variation with sweat/skin condition
Inertial Measurement Units (IMU) (Combination of accelerometer + gyroscope + magnetometer)	Motion analysis in sports medicine, Rehabilitation, and neurology (Parkinson's, tremors)	Provides comprehensive motion tracking, widely used in wearables	Power consumption, complex signal processing required

senting insights into athlete's physical conditions [60-61] Wearable biomechanical sensors collect data continuously in bio-systems for health management and tracking vital signs such as pulses and blood pressure, helping in diagnosis conditions like arteriosclerosis [62].

Biochemical sensors

Biochemical sensors are essential for the advancement of health monitoring and implantable devices. Since these sensors enable the routine assessment of critical biomarkers such as cortisol, lactate, and glucose, they are specifically of the enzymatic and electrochemical type and are useful in the prevention of disease management, especially for chronic conditions like diabetes and coronary artery diseases [63]. There are many different kinds of biosensors that operate on various principles (figure 4). Depending on their principle and mechanism, each of these biosensor types has pros and cons of its own (table 4). Biosensors, such as ingestible biosensors and implanted cardioverter defibrillators, are made to provide vital information with high accuracy for critical health changes, improving the quality of life for patients [64]. Smart tattoos and glucose meters are examples of devices that can monitor the health benchmarks to provide instant feedback for timely diagnostics of chronic diseases as well as personalised health insights [65-66].

Multimodal bionic skins

Soft robotics has advanced significantly in recent years, becoming a significant aspect of daily life by streamlining challenging tasks and enhancing human experience. In order to replicate human skin, these technologies make use of novel materials and prototypes. Its use in robotics, human-machine interaction, and healthcare is made possible by its integration of the ability to recognize both chemical and mechanical cues. Advanced e-skins make use of materials like liquid metals, polyurethane, and carbon nanotube fabrics that can simultaneously detect mechanical and chemical cues and improve stability without requiring complex power [67-68]. Robots with multimodal bionics exhibit more adaptable traits

to changes in their surroundings and greatly improve their ability to interact [69].

Machine Learning for Signal Processing and pattern recognition

It was discovered that the health care data sets were inherently complex and multifaceted. These are common in modern society, so their implications are necessary. The approaches are made to make it easier to identify and detect anomalous data points. These machine learning algorithms, which include a wide range of techniques such as Gaussian mixture models [70], sophisticated deep learning frameworks exemplified by convolutional neural networks [CNNs], one class support vector machine [SVM], and autoencoders, have proven to be transformative and groundbreaking tools in this context. All of these techniques play a critical role in the identification and analysis of anomalies that may serve as serious health complications. These are accomplished through a complex pattern recognition process [71].

ML for movement prediction and health anomaly detection

When it comes to identifying health abnormalities and predicting movement patterns, machine learning can be a reliable tool. Wearable sensors and machine learning models can be used to monitor patient kinetics and physiological parameters in real time. Early detection of possible health issues, such as stress-induced heart strokes, is made possible by IoT devices [72]. IoT sensors that gather moment data can help improve patient safety by identifying differences between abnormal and normal activities [73].

Noise reduction and signal enhancement

By removing noise from complex signals, a variety of deep learning models, including convolutional neural networks (CNNs), can increase the accuracy of biometric measurements in dynamic environments [74].

Table 4: Applications of Biochemical Sensor with their Advantages and Disadvantages

Type of Biochemical Sensor	Applications in Medicine	Advantages	Disadvantages
Electrochemical Biosensors (Amperometric, Potentiometric, Conductometric)	Blood glucose monitoring (glucometers), detection of lactate, cholesterol, urea	High sensitivity, fast response, portable, low cost	Limited stability of biological element (enzyme/protein), possible interference from other electroactive species
Optical Biosensors (Fluorescence, Surface Plasmon Resonance, Fiber Optic)	Detection of pathogens, cancer biomarkers, drug interactions, oxygen monitoring	Non-invasive, real-time detection, high specificity	Expensive instrumentation, sensitive to environmental factors (temperature, light)
Piezoelectric / Acoustic Biosensors (Quartz Crystal Microbalance, SAW sensors)	Detection of viruses, antibodies, toxins, and biomolecular interactions	Label-free detection, high sensitivity, miniaturization possible	Fragile crystals, interference from viscosity and temperature changes
Thermal Biosensors (Calorimetric, Thermistor-based)	Monitoring enzyme activity, DNA hybridization, immunoassays	Direct measurement of heat change, simple design, reusable	Low sensitivity compared to other types, affected by environmental temperature fluctuations
Wearable Biosensors (Integrated electrochemical /optical on skin patches or implants)	Continuous glucose monitoring, sweat analysis (electrolytes, cortisol), heart disease markers	Continuous monitoring, patient-friendly, real-time health data	Biocompatibility issues, limited lifespan, requires wireless power/data systems
Magnetic Biosensors (GMR, Magnetic nanoparticles based)	Detection of cancer cells, cardiac biomarkers, bacterial pathogens	High sensitivity, no optical background interference, miniaturizable	Requires external magnetic fields, relatively costly
Nanomaterial-based Biosensors (CNT, Graphene, Quantum dots)	Cancer diagnostics, early disease detection, drug monitoring	Ultra-sensitive, potential for multiplex detection, rapid analysis	High fabrication cost, reproducibility issues, biocompatibility concerns

Adaptive filtering and Bayesian modeling are two ML techniques that help biomedical and audio processing improve signal processing and reduce noise.

Feature extraction and selection

Accurate pattern recognition depends on the extraction of pertinent features from complex data using sophisticated machine learning algorithms [75]. K-means and support vector machines are used to improve classification performance [76].

Human Machine Interaction and Closed-Loop Feedback Systems

In order to facilitate smooth communication between humans and machines, Human Machine Interaction seeks to replicate natural interactions and focuses on interface optimization for the use of technologies like voice recognition and augmented reality [77]. In order to improve usability, the Closed-Loop Feedback System evaluates real-time data and makes adjustments based on user feedback [78]. To improve decision-making in dynamic environments, these systems are able to assess sensory inputs and produce adaptive responses [79].

Real-time decision making in bionic devices

Making decisions in real time using closed-loop feedback and human-machine interactions is a difficult process that calls for methods like VAE-Enhanced Demonstration Learning and RL-Enhanced Interaction Learning that increase efficiency, adaptability, and obstacle avoidance. A closed-loop system that combines perception, reasoning, and decision-making is necessary for ongoing feedback and modifications based on real-time data [80]. A hierarchical decision-making design in human-machine interaction in an intelligent system enables manual intervention when mistakes occur, preventing cascading failures in decision-making processes and guaranteeing dependability [81]. By combining AI capabilities with human inputs and working in real time with software programs that are autonomous, adaptive, reactive, communicative, and persistent in carrying out their task - known as intelligent agents - these systems are able to react dynamically to changing environmental conditions [82].

ML for adaptive control in smart prosthetics

Neuromorphic chips help people with severe disabilities improve their mobility and control. These chips, which are based on the neural architecture of the brain, allow for effective learning and self-adaptation in prosthetics, allowing for smooth integration with the human nervous system to help paralyzed people regain their mobility [82]. Adaptive linear regression enhances natural movement through closed-loop training protocols for simultaneous control of several degrees of freedom [83].

Challenges and Limitations

The remarkable progress of bionic skins and wearable biosensors and ML-enabled soft robotic healthcare systems faces multiple critical challenges that restrict their ability to achieve large-scale clinical use. The limitations of this system extend beyond its technical issues because it encounters multiple biological and computational and regulatory challenges. The development of intelligent patient-centered bionic technologies requires the removal of existing obstacles.

Real-time data collection and processing constraints

The process of real-time physiological monitoring needs ongoing biomedical signal acquisition together with signal analysis to handle high-frequency biomechanical and biochemical biosignals. The operational capacity of wearable devices gets restricted because of their insufficient storage space and processing power and their need to meet time constraints. The system faces more critical challenges because multimodal systems produce extensive data which needs to be processed without delay to enable prosthetic performance assessment and to identify system faults. Research has turned towards edge AI frameworks because

these systems enable machine learning inference to take place on wearable devices without needing cloud computation. Edge computing technology decreases system response time while safeguarding user data and boosting system dependability for prosthetic devices that operate in closed-loop systems. Researchers are creating lightweight systems which include GRUs and compressed deep-learning models to enable real-time performance under low power usage conditions.

Power efficiency and wireless data transmission

The first challenge of continuous biosensing operations requires its energy sustainability solution to function as the core solution. The operational capacity of traditional battery-operated wearable devices needs to recharge their batteries frequently while their devices become heavier. Biosensor data transmission through wireless methods creates additional power usage problems and introduces potential security risks. The latest advancements in self-powered sensing technologies now provide usable solutions through their ability to collect biomechanical motion energy from human movements through triboelectric and piezoelectric nanogenerator systems. The systems enable development of bionic skins which can operate without batteries while providing constant observation. The next generation of prosthetic intelligence systems will depend on low-energy wireless protocols together with ultra-low-power neuromorphic chips as their primary functional elements.

Biocompatibility, toxicology and long-term wearability

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Data Privacy, Security, and Regulatory Translation

The wearable biosensors which gather sensitive health data throughout their operation essential requirements for cybersecurity and ethical standards. AI-driven bionic healthcare systems need to implement three essential components which include methods for privacy-preserving learning and encrypted wireless communication and frameworks for transparent algorithmic decision-making. The process of translating regulations into practical applications presents significant challenges. The majority of advanced bionic skin prototypes remain limited to laboratory testing because they face difficulties in reaching required standards for medical-device approval and testing both scalability and reproducibility. The future of research needs to focus on interdisciplinary partnership between engineers and clinicians and regulatory authorities to speed up the process of clinical implementation.

Conclusion

The emerging field of digital healthcare will be transformed through bionic skins and advanced biosensor technologies which provide continuous non-invasive monitoring of physiological states using biomechanical and biochemical methods. Stretchable electronics have been successfully integrated with soft robotic platforms to develop skin-like sensing systems which enable rehabilitation, prosthetic feedback, chronic disease management, and advanced human-machine interaction. The integration of machine learning into these systems improves their capabilities because it provides automatic feature extraction, multimodal biosignal analysis, anomaly detection, and adaptive closed-loop control.

In complex wearable sensing environments deep learning architectures which include CNN-LSTM hybrid models and reinforcement learning methods show better results when real-time personalization is needed. Existing technologies still face four major challenges which include establishing long-term biocompatibility, developing sustainable power systems, implementing secure data handling methods, and achieving regulatory approval for clinical applications. The progress of intelligent bionic skin technology from laboratory testing to mainstream healthcare applications depends on solving these particular challenges.

Roadmap for the next five years (2026–2030)

The future research of bionic skins biosensors and ML-enabled soft robotics must follow these specific research directions to achieve both faster progress and clinical development.

- **Multimodal Intelligent E-Skins:** The next-generation platforms will provide wearable systems which combine tactile, thermal, biochemical and electrophysiological sensing for complete health assessment throughout all times.
- **Edge AI and On-Device Learning:** The transition to edge-based intelligence will create better security and faster response times while enabling persistent learning of prosthetic and rehabilitation systems which operate without cloud service needs.
- **Self-Powered and Energy-Autonomous Biosensors:** The new triboelectric and piezoelectric nanogenerators will create battery-free wearable devices which enable continuous monitoring through their ability to capture biomechanical energy.
- **Bio-Inspired Materials and Immune-Compatible Interfaces:** The development of biomimetic coatings together with hydrogel-based interfaces and skin-like composites will reduce body reaction to foreign materials while enhancing comfort during extended use.
- **Clinical Translation and Regulatory Readiness:** Future studies must prioritize scalable manufacturing, standardized benchmarking datasets, and clinical trials to ensure regulatory approval and real-world healthcare adoption.

The integration of soft robotics with biosensing and machine learning creates new healthcare solutions which operate through adaptive patient-centered and intelligent systems. The interdisciplinary field will establish bionic skins together with smart biosensors as essential elements for personalized medicine and human-robot collaboration in the future.

Although these sensors display strong potential in wearable technology, these two faces some notable limitations namely data precision, bio compatibility, production cost and durability. The major restraints faced by all these biosensors in our skins is that it has fundamental nature to oppose the body from surroundings as an immune defence. Moreover seamless integration of biosensors into healthcare needs resolving concerns viz. wireless connectivity, energy efficiency and wearer comfort. Since these sensing technologies merged with ML and AI models along with IoT, they are poised to enhance analytical efficiency, minimised errors and also facilitating adaptive healthcare systems. This fusion has promising action to transform personalised health care systems and yielding intelligent solutions.

Acknowledgement

All authors want to thanks Graphic era deemed to be university in publication of this work.

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