

TACTILE SENSING FOR MATERIAL IDENTIFICATION IN ROBOTICS: A REVIEW OF PIEZOELECTRIC, TRIBOELECTRIC AND MULTIMODAL APPROACHES

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KEYWORDS

Tactile sensors, piezoelectric, triboelectric, robotics, material identification, e-skin, machine learning.

ABSTRACT

Tactile sensing has become a key enabler of advanced robotic perception, complementing vision for manipulation and physical interaction. Material identification through touch—distinguishing plastics, glass, soil, or other substrates—relies on extracting mechanical and surface properties such as stiffness, friction, and texture. Recent advances in piezoelectric, triboelectric, capacitive, and multimodal tactile sensors allow contact dynamics and material-dependent interactions to be converted into electrical signals suitable for machine learning-based classification. This review presents recent progress in tactile sensing technologies for material recognition, detailing the physical principles of major sensor types and their integration into robotic systems. Applications in manipulation, prosthetics, and industrial robotics are discussed, along with key challenges including robustness, calibration, energy efficiency, and real-time processing. Finally, we highlight the growing role of multimodal sensing and artificial intelligence in enabling more adaptive and autonomous robotic touch perception.

1 INTRODUCTION

Robotic systems are increasingly deployed in complex and unstructured environments where physical interaction with objects is unavoidable (Wang et al., 2023; Shepherd et al., 2025). Although vision-based perception has advanced considerably, it remains insufficient for tasks requiring contact-level information such as grasp stability, surface texture recognition, and material identification (Park et al., 2022; Qu et al., 2022). Tactile sensing is therefore essential for enabling safe, adaptive, and reliable robotic interaction.

Human tactile perception provides a fundamental model for artificial systems. Mechanoreceptors embedded in the skin detect pressure, vibration, temperature, and texture,

allowing the brain to infer material properties and object characteristics (Deflorio et al., 2022; Ren et al., 2025). Inspired by this biological architecture, researchers have developed electronic skin (e-skin) and flexible tactile sensors based on piezoelectric, triboelectric, capacitive, and resistive principles (Wang et al., 2023; Qi et al., 2024). These technologies convert mechanical stimuli into electrical signals that encode contact dynamics, friction, deformation, and surface features.

Piezoelectric and triboelectric sensors are particularly attractive due to their strong sensitivity to dynamic events such as slip and vibration, and their potential for low-power or self-powered operation (Shepherd et al., 2025; Qu et al., 2022; Pal et al., 2024). The resulting electrical signatures can be processed using signal analysis and machine learning techniques to classify materials based on stiffness, roughness, and other physical properties (Xie et al., 2024; Song et al., 2022; Liu et al., 2025). Such capabilities are increasingly relevant in industrial automation, prosthetics, service robotics, and human–robot interaction.

Despite significant progress, important challenges remain, including mechanical robustness, long-term stability, real-time signal processing, controller integration, and the lack of standardized performance comparison across sensor technologies. Further systematic evaluation of tactile sensing approaches for material identification in robotics is therefore required.

This review examines recent advances in piezoelectric, triboelectric, and multimodal tactile sensing technologies. It discusses their physical principles, their integration into robotic systems, their applications in manipulation and material recognition, and the remaining technical challenges toward intelligent multimodal tactile perception, as shown in Figure 1. Unlike systematic surveys focused on exhaustive counting, this paper is a *perspective review*: we emphasize cross-technology interpretation, engineering trade-offs, and deployment implications for robotics.

Scope and Review Method

This perspective review was built from targeted searches in major scientific databases (IEEE Xplore, Scopus, Web of Science, and ScienceDirect), using combinations of

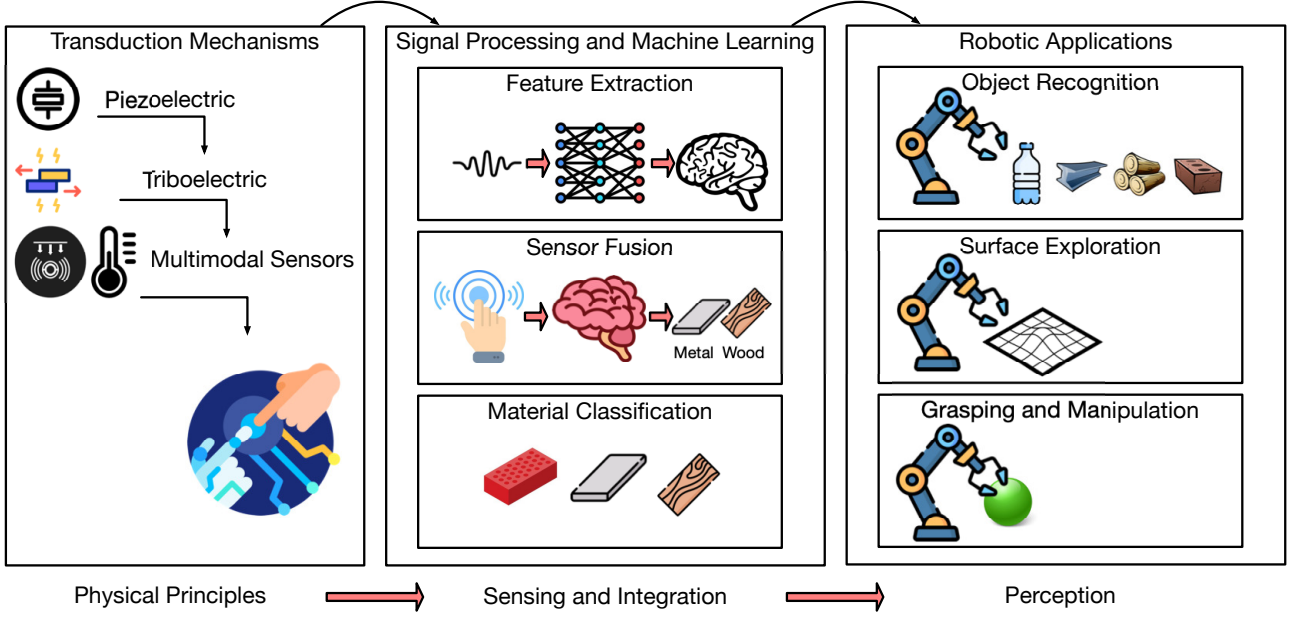


Figure 1: The idea of tactile sensing for material identification in robotics.

keywords related to tactile sensing, material classification, and robotic manipulation. Priority was given to recent and highly cited works, plus representative foundational papers. Studies were included when they provided explicit sensing principles, robotic implementation details, or quantitative material-recognition results.

2 HUMAN TACTILE PERCEPTION AND BIOMIMETIC APPROACHES

Human tactile perception is fundamental for object recognition, manipulation, and interaction. The skin contains specialised mechanoreceptors capable of detecting pressure, vibration, stretch, and texture, enabling the nervous system to infer material properties and contact dynamics. Mechanical stimuli are filtered through the layered structure of the epidermis, dermis, and subcutaneous tissues before being encoded into neural signals. Computational models of mechanoreceptor responses have demonstrated how skin deformation and neural encoding jointly shape tactile perception, providing a theoretical framework for artificial tactile system design (Deflorio et al., 2022).

Inspired by these biological mechanisms, biomimetic tactile sensors aim to replicate the distributed, multimodal, and hierarchical nature of human skin. Flexible electronic skin (e-skin) technologies integrate arrays capable of detecting pressure, temperature, vibration, and deformation, enhancing robotic and wearable systems in manipulation, prosthetics, and health monitoring applications (Wang et al., 2023). Advances in materials science and microfabrication have enabled highly sensitive and conformable devices that mimic the mechanical compliance and spatial resolution of biological tissue (Ren et al., 2025).

Beyond structural imitation, recent research focuses on

reproducing biological signal encoding strategies. Artificial mechanoreceptors and neuromorphic tactile sensors convert mechanical stimuli into spike-based electrical outputs, enabling efficient and event-driven tactile information processing (Kim et al., 2021). Intelligent bio-inspired mechanoreceptor systems further integrate synaptic-like functions, supporting adaptive perception and learning capabilities (Hong et al., 2025).

The integration of biomimetic tactile systems into robotic hands and soft manipulators has significantly improved dexterity, object property recognition, and adaptive grasp control. By emulating both the mechanical architecture and the neural encoding strategies of human skin, biomimetic approaches provide a robust foundation for intelligent tactile perception in robotics, where accurate interpretation of material properties and contact dynamics is essential.

3 PHYSICAL PRINCIPLES OF TACTILE SENSORS

3.1 Piezoelectric Sensors: Operating Principle, Materials, Advantages and Limitations

Piezoelectric tactile sensors convert mechanical deformation into electrical signals via the direct piezoelectric effect. Under applied stress, surface charges are generated, producing a measurable voltage. The linear constitutive relation is

$$\mathbf{D} = \mathbf{d} \boldsymbol{\sigma} + \epsilon \mathbf{E}, \quad (1)$$

where $\mathbf{D}$ is the electric displacement, $\mathbf{d}$ the piezoelectric coefficient matrix, $\boldsymbol{\sigma}$ the applied stress, ϵ the permittivity, and $\mathbf{E}$ the electric field.

Piezoelectric transduction is particularly effective for *dynamic* tactile events such as slip, tapping, and vibration,

which are essential for texture and friction recognition in robotics (Shepherd et al., 2025).

Operating Modes and Architectures

Flexible tactile devices typically employ PVDF-based films operating in d_{33} or d_{31} modes. Structural design plays a key role in sensitivity: rigid-in-soft architectures enhance force transfer and improve slip detection performance (Huang et al., 2024). Device-level amplification using piezotronics and OFET-based structures further improves signal-to-noise ratio while maintaining flexibility (Yin et al., 2023).

In robotic systems, piezoelectric layers are often embedded in fingertip or skin modules and combined with inertial sensing to capture vibration and contact-induced resonance (Shepherd et al., 2025).

Materials

PVDF and its composites dominate flexible tactile sensing due to compliance, processability, and chemical stability. Performance improvements focus on enhancing the β -phase content and microstructural engineering, including core-shell fibrous structures for improved robustness (Wei et al., 2023; Qi et al., 2024).

Ceramic materials such as PZT provide higher electromechanical coupling but suffer from brittleness, while ZnO and AlN thin films offer high-frequency response for microfabricated arrays.

Advantages and Limitations

Advantages:

- High bandwidth and sensitivity to dynamic events (slip, micro-vibrations) (Huang et al., 2024).
- Compact structure and compatibility with multimodal designs (Yin et al., 2023).
- Low-power, event-driven sensing capability (Kim et al., 2021; Qi et al., 2024).

Limitations:

- Poor static force measurement due to charge leakage (Qi et al., 2024).
- Need for high-impedance signal conditioning (Yin et al., 2023).
- Sensitivity to environmental factors and mechanical fatigue (Wei et al., 2023).

Recent developments in structural amplification and 3D force-sensitive PVDF architectures aim to overcome these limitations and move toward task-driven tactile perception systems (Huang et al., 2024; Li et al., 2025).

3.2 Triboelectric Sensors: Operating Principle, Materials, Advantages and Limitations

Triboelectric tactile sensors operate through contact electrification coupled with electrostatic induction. When two materials with different electron affinities contact and separate, interfacial charge transfer generates opposite surface charges and an induced potential difference. Unlike piezoelectric devices, triboelectric sensors rely on material-dependent electron exchange rather than crystal polarization, naturally encoding information about surface composition.

This mechanism is particularly effective for detecting dynamic interactions such as contact, sliding, and friction-induced vibrations, making triboelectric sensors highly suitable for material identification in robotics.

Operating Modes and Architectures

Triboelectric tactile devices are typically implemented as triboelectric nanogenerators (TENGs) operating in contact-separation, lateral sliding, single-electrode, or freestanding modes. For robotic applications, contact-separation and sliding modes are most relevant as they capture normal and shear interactions during grasping.

Micro or nano-structured surfaces are often introduced to enhance charge density and sensitivity. Sliding-mode devices are especially effective for material recognition, as friction-induced voltage waveforms contain rich spectral features that can be processed using machine learning classifiers.

Materials

Material selection follows the triboelectric series. Flexible polymers dominate due to compliance and tunability. Common negative materials include PTFE, FEP, and PDMS, while nylon or metals act as positive counterparts. Surface engineering (microstructures, porous layers, nanofillers) enhances contact area and output performance. Flexible conductive electrodes such as silver nanowires or graphene improve durability under deformation.

Advantages and Limitations

Advantages:

- Self-powered operation without external bias (Qu et al., 2022; Pal et al., 2024).
- Intrinsic sensitivity to material-dependent surface properties (Qu et al., 2022).
- High responsiveness to dynamic events and friction signals (Song et al., 2022).
- Mechanical flexibility suitable for robotic skins (Xie et al., 2024; Pal et al., 2024).

Limitations:

- Sensitivity to humidity and environmental conditions (Pal et al., 2024).
- Signal drift due to charge accumulation and surface degradation (Pal et al., 2024).
- Limited capability for static force measurement (Song et al., 2022).
- Calibration complexity due to coupled mechanical and material effects (Xie et al., 2024).

Hybrid and multimodal architectures increasingly address these challenges, improving robustness and classification accuracy in robotic material perception systems.

3.3 Capacitive and Piezoresistive Sensors

Capacitive and piezoresistive sensors are widely used in robotic tactile perception due to their reliability and suitability for static and quasi-static force measurement. Unlike piezoelectric and triboelectric sensors, which primarily capture dynamic interactions, these technologies provide stable pressure mapping and force estimation.

Capacitive Sensing

Capacitive tactile sensors measure variations in capacitance caused by deformation of a dielectric layer between electrodes. Changes in electrode spacing or dielectric properties enable accurate static force detection with high spatial resolution. Large-area robotic skins based on impedance tomography and deep learning reconstruction have demonstrated scalable and resilient tactile localization (Park et al., 2022).

However, capacitive sensors mainly measure mechanical deformation and do not intrinsically encode material-dependent electrical signatures, requiring feature extraction or multimodal fusion for material discrimination.

Piezoresistive Sensing

Piezoresistive sensors detect resistance changes induced by deformation of conductive composites. They offer simple readout, low cost, and compatibility with flexible substrates, making them effective for force mapping. When combined with deep learning, force-derived signals can support terrain and material classification with high accuracy (Liu et al., 2025).

Nevertheless, piezoresistive sensing reflects mechanical interaction rather than intrinsic surface charge properties.

Comparison with Piezoelectric and Triboelectric Sensors

Piezoelectric sensors provide high sensitivity to dynamic events but limited static detection, whereas triboelectric sensors generate material-specific voltage signatures through contact electrification (Qu et al., 2022; Song et al., 2022). Thermosensitive triboelectric systems further enhance material discrimination capabilities (Pal et al., 2024).

From a perception standpoint:

- Capacitive and piezoresistive sensors: strong static force mapping, limited intrinsic material specificity.
- Piezoelectric sensors: dynamic vibration sensitivity.
- Triboelectric sensors: self-powered, material-dependent electrical fingerprints.

Hybrid Architectures

Recent research increasingly combines static (capacitive/impedance) and dynamic (piezoelectric/triboelectric) mechanisms to enable simultaneous force, friction, and material characterization. Such multimodal platforms provide enhanced robustness and improved classification performance in robotic material identification.

Modeling and Simulation Opportunities

Modeling and simulation can support sensor design, calibration, and algorithm development across all tactile technologies. Piezoelectric sensors are often modeled with coupled electro-mechanical finite-element formulations to optimize geometry, stress transfer, and bandwidth. Triboelectric devices require multi-physics approximations combining contact mechanics and charge-transfer behavior; despite simplifications, these models are useful for sensitivity analysis and compensation strategies under humidity or wear. Capacitive and piezoresistive sensors are typically modeled with deformation-driven equivalent circuits or reduced-order finite-element models for static and quasi-static force reconstruction. At system level, digital twins of sensorized fingertips can link contact mechanics to learned classifiers, reducing experimental burden and improving controller tuning before hardware deployment.

Table 1 summarizes the main trade-offs between sensor families and highlights their typical robotic use cases.

3.4 Multimodal Sensors

Single-mode sensors provide only partial contact information, so recent systems combine capacitive/piezoresistive static channels with piezoelectric/triboelectric dynamic channels, sometimes augmented with acoustic or optical sensing (Xie et al., 2024; Song et al., 2022; Park et al., 2022; Gong et al., 2025). This fusion improves material recognition by jointly capturing force, friction, vibration, and subsurface cues.

In practice, multimodal platforms improve robustness and classification performance but introduce higher integration, calibration, and processing complexity. For this reason, fusion strategy and hardware–software co-design are as important as the sensing elements themselves.

4 MATERIAL IDENTIFICATION USING TACTILE SENSORS

Material identification through tactile sensing relies on extracting mechanical and interfacial properties during contact, such as stiffness, friction, elasticity, and surface

Table 1: Comparison of tactile sensor families for robotic material identification.

Sensor type	Principle	Advantages	Limitations	Applications
Piezoelectric	Stress-induced polarization and voltage generation	High dynamic sensitivity; good slip/vibration detection; compact integration	Weak static force response; high-impedance readout; fatigue sensitivity	Slip detection, texture sensing, dynamic grasp control
Triboelectric	Contact electrification and electrostatic induction	Self-powered; material-dependent electrical signatures; high dynamic response	Humidity sensitivity; signal drift; calibration complexity	Material classification, friction analysis, wearable tactile skins
Capacitive	Deformation-induced capacitance change	Accurate static/quasi-static force mapping; high spatial resolution	Limited intrinsic material specificity; parasitic capacitance sensitivity	Pressure mapping, compliant grasp control, robotic skin arrays
Piezoresistive	Resistance change under strain/deformation	Simple electronics; low cost; flexible implementation	Drift/hysteresis in some materials; mainly mechanical information	Force mapping, terrain/material support classification
Multimodal (hybrid)	Fusion of complementary transduction mechanisms	Simultaneous static and dynamic perception; improved robustness and accuracy	Increased integration complexity and data-fusion load	Advanced robotic manipulation, prosthetics, industrial inspection

morphology. These properties are converted into electrical signals whose patterns form distinctive material signatures. Advances in flexible electronics and multimodal sensing have significantly improved robotic material classification performance.

Table 2 summarizes representative works reviewed in this paper, highlighting the relation between sensor type, method, application, and reported outcomes.

4.1 Electrical Signatures of Materials

Different materials generate distinct electrical responses depending on the sensing mechanism. Triboelectric sensors produce material-dependent voltage signals through contact electrification, creating intrinsic electrical fingerprints linked to surface electron affinity (Qu et al., 2022). The signal magnitude and polarity enable discrimination between polymers, metals, and biomaterials (Pal et al., 2024).

Capacitive and piezoelectric sensors primarily capture mechanical responses such as stiffness and deformation. Capacitive arrays differentiate material moduli through dielectric variation (Berman et al., 2026), while hybrid triboelectric–capacitive systems improve classification by combining static deformation and dynamic surface interaction cues (Xie et al., 2024). Impedance-based robotic skins further enhance large-area material characterization (Park et al., 2022).

4.2 Surface Roughness and Texture Recognition

Texture recognition relies on friction-induced vibrations generated during sliding contact. Piezoelectric and triboelectric sensors capture these micro-vibrations, whose frequency content reflects surface roughness. Signal decomposition techniques enable simultaneous material and texture classification with high accuracy (Song et al., 2022).

Multimodal systems integrating ultrasound or vibration sensing extend perception to subsurface structures, improving robustness in complex environments (Gong et al., 2025). Similar principles have been applied in terrain classification for legged robots using force and vibration data (Liu et al., 2025).

4.3 Machine Learning for Classification

Tactile signals are typically processed using time–frequency analysis and feature extraction before classification. Deep learning architectures such as CNNs and CNN–LSTM models capture temporal and spectral patterns for reliable material recognition (Xie et al., 2024; Liu et al., 2025).

Wavelet-based decomposition further separates macro-scale mechanical features from micro-scale texture information, enhancing discrimination performance (Song et al., 2022). Multimodal learning frameworks integrating impedance, vibration, and triboelectric signals provide robust classification in robotic applications (Park et al., 2022).

Overall, combining physics-based sensing mechanisms with machine learning enables reliable material identification and adaptive robotic interaction in unstructured environments.

5 APPLICATIONS IN ROBOTICS

5.1 Robotic Manipulation

Tactile sensing is essential for stable grasping and object handling, especially when vision is insufficient (e.g., occlusions, deformable or transparent objects). For grasp stability, slip detection plays a central role. Piezoelectric and vibration-based sensors capture high-frequency micro-vibrations associated with incipient slip, enabling

Table 2: Representative literature on tactile material identification in robotics.

Paper	Sensor type	Method	Application	Key results
Qu et al. (2022) (Qu et al., 2022)	Triboelectric	Contact electrification + feature-based classification	Robotic material recognition	Material-dependent voltage fingerprints for multiple classes
Song et al. (2022) (Song et al., 2022)	Triboelectric + piezoelectric + piezoresistive	Wavelet decomposition + multimodal learning	Simultaneous texture/material recognition	High recognition performance with decoupled macro/micro features
Park et al. (2022) (Park et al., 2022)	Impedance/acoustic multimodal skin	EIT reconstruction + deep learning	Large-area robotic skin perception	Distributed localization and material characterization
Xie et al. (2024) (Xie et al., 2024)	Triboelectric + capacitive	Deep learning fusion (CNN-based)	Object/material recognition for manipulation	Improved robustness over single-modality sensing
Gong et al. (2025) (Gong et al., 2025)	Visuotactile + ultrasound (UltraTac)	Optoacoustic multimodal fusion + ML	Material/texture recognition	99.20% material-class accuracy; proximity-enhanced perception
Liu et al. (2025) (Liu et al., 2025)	Force-based tactile (piezoresistive/capacitive context)	CNN-LSTM temporal modeling	Terrain/material classification	96.94% accuracy across five ground classes

adaptive force control (Shepherd et al., 2025). Triboelectric sensors similarly provide dynamic contact waveforms and low-power operation for slip-aware grasp monitoring (Qu et al., 2022; Pal et al., 2024).

For object recognition during manipulation, tactile sensors enable identification of material class, stiffness, and surface properties directly at the fingertip. Triboelectric smart fingers demonstrate accurate material classification from contact-induced electrical signatures (Qu et al., 2022), while hybrid triboelectric–capacitive systems improve robustness through multimodal fusion (Xie et al., 2024). Large-area impedance-based skins further support distributed contact awareness during manipulation tasks (Park et al., 2022).

5.2 Robotic Hands and Prosthetics

Anthropomorphic robotic hands and prostheses require distributed tactile sensing for dexterity and adaptive grip control. Capacitive arrays estimate stiffness and pressure distribution for force modulation (Berman et al., 2026), while flexible piezoelectric sensors enhance slip detection during in-hand manipulation (Huang et al., 2024).

In prosthetics, biomimetic and neuromorphic tactile sensors aim to emulate mechanoreceptor encoding for efficient, low-latency signal processing (Deflorio et al., 2022; Kim et al., 2021). Triboelectric and multimodal tactile systems further improve material discrimination and enable low-power wearable integration (Qu et al., 2022; Pal et al., 2024).

5.3 Industrial Robotics

In industrial environments, tactile sensing supports material-based sorting and non-destructive quality control. Triboelectric sensors provide material-dependent electrical fingerprints suitable for automated classification (Qu

et al., 2022). Hybrid systems improve reliability under variable contact conditions (Xie et al., 2024).

Piezoelectric and vibration-based sensors enable surface inspection and defect detection through texture-related frequency signatures (Shepherd et al., 2025; Song et al., 2022). Capacitive arrays contribute to stiffness verification in soft or compliant components (Berman et al., 2026). Robust multimodal skins further enhance large-area monitoring capabilities (Park et al., 2022).

5.4 Medical and Wearable Robotics

Medical and wearable robotics demand flexible, biocompatible, and energy-efficient tactile systems. Flexible piezoelectric and capacitive sensors enable distributed pressure monitoring for rehabilitation and assistive devices (Qi et al., 2024). Biomimetic tactile architectures inspired by mechanoreceptors improve sensitivity and signal encoding efficiency (Ren et al., 2025; Hong et al., 2025).

For prosthetic interfaces, self-powered triboelectric sensing offers lightweight solutions for dynamic contact detection and potential sensory feedback integration (Qu et al., 2022). Multimodal tactile strategies are increasingly adopted to ensure safe and adaptive human–robot interaction.

6 MULTIMODAL SENSING AND ARTIFICIAL INTELLIGENCE

The increasing complexity of robotic interaction tasks has driven a shift from single-modality tactile sensing toward integrated multimodal perception systems supported by artificial intelligence. While individual sensing mechanisms provide partial information, their fusion enables a more complete understanding of contact events and material properties.

6.1 Sensor Fusion Strategies

Multimodal tactile sensing integrates complementary mechanisms within a unified platform. Hybrid triboelectric–capacitive devices combine static pressure information with dynamic material-dependent signals, improving recognition robustness (Xie et al., 2024). Other platforms combine electromechanical, acoustic, or optical channels to capture both surface and subsurface cues (Park et al., 2022; Gong et al., 2025; Song et al., 2022).

Sensor fusion can be implemented at multiple levels:

- **Data-level fusion:** raw signals from different modalities are concatenated and processed jointly.
- **Feature-level fusion:** extracted descriptors (e.g., frequency spectra, statistical features) are combined before classification.
- **Decision-level fusion:** independent classifiers are trained per modality and their outputs are merged using ensemble strategies.

Feature-level fusion is often preferred because it captures cross-modal correlations with manageable computational cost.

6.2 Deep Learning and Tactile Perception

Tactile signals depend on force, motion, surface geometry, and environment. Deep learning is therefore used to model nonlinear and temporal patterns: CNN-based models process spatial/time-frequency representations, while CNN–LSTM variants capture sliding dynamics (Liu et al., 2025; Xie et al., 2024). Wavelet-assisted pipelines improve material–texture decoupling (Song et al., 2022). Neuromorphic tactile concepts further reduce data and power at sensor level (Kim et al., 2021; Hong et al., 2025).

6.3 Autonomous Robotic Perception

The goal of multimodal tactile AI is autonomous perception and control. In manipulation, tactile feedback supports online force adaptation, slip prevention, and material-aware decisions (Qu et al., 2022; Pal et al., 2024). At system scale, multimodal skins improve distributed awareness and become most effective when fused with vision and proprioception (Park et al., 2022). Real-time deployment will rely on lightweight models, edge computing, and efficient sensor fusion pipelines.

7 CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress in tactile sensing technologies for material identification, several technical and practical challenges must be addressed before widespread deployment in real-world robotic systems can be achieved. These challenges concern mechanical robustness, calibration and reproducibility, scalability of sensor architectures, energy efficiency, and seamless integration into real-time robotic control frameworks.

7.1 Robustness, Calibration, and Scalability

Flexible tactile sensors, particularly those based on polymeric piezoelectric and triboelectric materials, are frequently subjected to repeated mechanical stress, bending, shear, and environmental exposure. Long-term durability remains a major concern, especially for robotic hands, wearable devices, and industrial manipulators operating in harsh environments. Material fatigue, delamination of electrodes, and surface degradation can lead to signal drift and reduced sensitivity over time (Wei et al., 2023; Huang et al., 2024).

Triboelectric sensors are additionally sensitive to environmental conditions such as humidity and temperature, which directly influence charge transfer efficiency and signal stability (Pal et al., 2024). Ensuring repeatable and stable performance therefore requires improved encapsulation strategies, surface engineering, and environmental compensation algorithms.

Calibration represents another critical challenge. Tactile signals depend not only on intrinsic material properties but also on contact force, velocity, angle, and sensor compliance. For instance, vibration-based texture recognition is sensitive to scanning speed and applied normal force (Shepherd et al., 2025). As a result, classification models trained under controlled laboratory conditions may not generalize well to dynamic robotic environments. Standardized benchmarking protocols and dataset sharing are necessary to improve reproducibility and fair comparison across sensing technologies.

Scalability is equally important for practical deployment. Large-area tactile skins, such as impedance-based or multimodal robotic skins, require efficient multiplexing, signal routing, and computationally efficient reconstruction algorithms (Park et al., 2022). As sensor density increases, managing wiring complexity, electromagnetic interference, and mechanical integration becomes increasingly challenging. Future research must therefore focus on scalable architectures with distributed processing capabilities.

7.2 Energy Consumption and Power Management

Energy efficiency is a key consideration, particularly for mobile robots and wearable systems. Capacitive and piezoresistive tactile sensors require continuous power supply and signal conditioning circuits, which may limit battery life in embedded systems. In contrast, triboelectric sensors offer self-powered operation by converting mechanical energy directly into electrical output (Qu et al., 2022; Pal et al., 2024). This property is especially advantageous for distributed sensing networks and low-power wearable applications.

However, even self-powered sensing elements require energy for signal amplification, processing, wireless transmission, and machine learning inference. The integration of low-power electronics, event-driven sensing strategies, and neuromorphic processing may help reduce overall system consumption. Artificial mechanoreceptors with built-

in synaptic functionality represent a promising direction for local preprocessing of tactile information, potentially decreasing the computational burden on central processors (Kim et al., 2021; Hong et al., 2025).

Future developments should emphasize energy-aware system design, including optimized duty cycles, adaptive sampling strategies, and hardware–software co-design for embedded intelligence.

7.3 Integration into Real-Time Robotic Systems

For tactile sensing to be fully effective, it must be tightly integrated into robotic perception and control loops. Real-time constraints impose strict requirements on latency, computational efficiency, and robustness. Multimodal tactile systems generate high-dimensional data streams, particularly when combining pressure maps, vibration signals, impedance data, and acoustic information (Xie et al., 2024; Song et al., 2022; Gong et al., 2025). Processing these signals in real time while maintaining stable control remains a significant engineering challenge.

Deep learning models improve classification accuracy but can introduce computational overhead. Lightweight neural architectures, edge computing solutions, and hardware acceleration (e.g., embedded GPUs or neuromorphic chips) are therefore critical for practical deployment. Furthermore, tactile perception must be synchronized with other sensory modalities such as vision and proprioception to enable coherent sensor fusion in autonomous systems.

Another challenge concerns the interaction between perception and control. Tactile information should not only support classification tasks but also inform adaptive grasp planning, force modulation, and motion control. Developing closed-loop frameworks that translate tactile features into actionable control policies remains an active area of research.

7.4 Outlook

Future research in tactile sensing for material identification will likely converge toward multimodal, intelligent, and distributed systems capable of operating reliably in unstructured environments. Advances in flexible materials, surface engineering, and self-powered sensing will improve robustness and durability. Simultaneously, progress in artificial intelligence, neuromorphic computing, and edge processing will enable efficient real-time interpretation of complex tactile data.

Ultimately, overcoming these challenges will allow tactile-enabled robots to achieve more human-like perception, adaptive manipulation, and safe interaction across industrial, medical, and service robotics applications.

8 CONCLUSION

Tactile sensing has become a fundamental component of advanced robotic perception, particularly for material identification and contact-aware manipulation. This review discussed the operating principles and recent advances in

piezoelectric, triboelectric, capacitive, piezoresistive, and multimodal tactile sensors, highlighting their respective strengths and limitations.

Piezoelectric and triboelectric technologies enable high-sensitivity detection of dynamic contact events and, in the case of triboelectric sensing, intrinsic material-dependent electrical signatures. Capacitive and piezoresistive sensors remain essential for static force estimation and pressure mapping. However, multimodal architectures that combine complementary sensing mechanisms provide the most comprehensive solution for robust material characterization.

The integration of artificial intelligence and sensor fusion strategies has significantly improved classification accuracy and real-time adaptability in robotic systems. Nevertheless, challenges related to robustness, calibration, scalability, energy efficiency, and real-time processing remain critical for large-scale deployment.

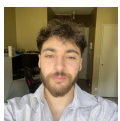
Future research should focus on durable, self-powered, and intelligent multimodal tactile skins, standardized evaluation protocols, and embedded processing solutions enabling efficient real-time perception. Advancements in these areas will further bridge the gap between artificial and human tactile capabilities, supporting safer and more autonomous robotic interaction with the physical world.

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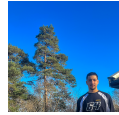
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