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Recent advancements in wearable sensors: integration with machine learning for human–machine interaction

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Wearable sensors have emerged as a transformative technology, enabling real-time monitoring and advanced functionality in various fields, including healthcare, human–machine interaction, and environmental sensing. This review provides a comprehensive overview of the latest advancements in wearable sensor technologies, focusing on innovations in sensor design, material flexibility, and integration with machine learning. We explore the feasibility of wearable electronics in achieving high-performance, flexible devices and discuss their potential to enhance human–machine interactions through intelligent data processing and decision-making. The combination of wearable electronics and machine learning offers immense potential for applications requiring real-time responsiveness and advanced analytics. By analyzing recent developments of sensors, this review aims to inspire further innovations in this rapidly evolving field, paving the way for the next generation of wearable technologies.

1. Introduction

Flexible electronics, as an emerging technology that overcomes the limitations of traditional rigid electronic devices, has garnered widespread global attention and experienced rapid development in recent years. This technology, based on flexible materials and processes, enables devices to bend, stretch, and fold, thus opening up immense opportunities for innovation in fields such as wearable devices, health monitoring, electronic skin, flexible displays, and smart sensors.[1–3] The key materials for flexible electronics currently include conductive polymers, graphene, MXene, and other two-dimensional materials, as well as flexible inorganic thin films. These materials, with their exceptional mechanical flexibility and electrical properties, have been successfully applied in various novel electronic devices.[4] Additionally, advancements in manufacturing techniques, such as printed electronics, roll-to-roll processing, and flexible packaging technology, have further driven the large-scale production and application of flexible electronics. Despite significant progress, flexible electronics still face a series of challenges that demand urgent solutions, such as balancing mechanical stability and electrical performance, ensuring device reliability under extreme conditions, and achieving consistency and cost control in large-scale manufacturing processes.[5] However, with the ongoing exploration of new materials, the deep integration of interdisciplinary research, and the incorporation of technologies like artificial intelligence (AI), the potential of flexible electronics remains immense. In the future, flexible electronics are expected to integrate deeply with the Internet of Things (IoT), AI, and renewable energy technologies, paving the way for a smarter, greener, and more efficient society.[6]

The application of AI in higher education has become an irreversible trend, encompassing various aspects from learning management systems and automated assessments to intelligent tutoring systems. AI-enabled personalized learning, teaching quality evaluation, and the construction of knowledge graphs are driving the transition of higher education from traditional models to intelligent paradigms.[7] However, the integration of AI technology with new materials technology, such as flexible electronic materials, is providing new possibilities for teaching devices and laboratory operations. University educators are innovating teaching interactions through new devices like flexible displays and smart writing boards, while students can engage in real-time interactions with AI systems using portable devices, enhancing the personalization and engagement of their learning experiences.[8]

Flexible electronic materials, especially flexible films and nanomaterials, have garnered widespread attention in fields such as electronic products, wearable devices, and medical equipment due to their flexibility and broad application prospects. Devices like flexible displays and sensors not only change user interfaces but can also be embedded in teaching and experimental equipment, enhancing the interactivity and experience of education. In the education sector, the application of flexible materials can contribute to creating immersive

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learning environments, improving the precision of experimental equipment, and reducing costs. Fig. 1 illustrates the application scenarios of flexible electronics in motion detection, and intelligent monitoring. As the largest organ of the human body, the skin not only protects internal systems from environmental disturbances but also plays a crucial role in perceiving various external signals such as temperature, humidity, and tactile stimuli. Similar to the hierarchical processing of human somatosensory perception, the combination of artificial intelligence (AI) algorithms and biomimetic skin capable of detecting tactile signals holds great significance for various closed-loop robotic control tasks (Fig. 1B). For instance, Lu *et al.*[9] introduced a flexible tactile sensor based on a triboelectric nanogenerator (TENG), which leverages machine learning (ML) for optimized device design, including output signal selection and manufacturing parameter refinement. By

Fig. 1 (A) Next-generation intelligent sensing integrated with AI signal processing.[22] (B) The similarity between human brain learning and deep learning.[23] (C) Schematic diagram of sensor design assisted by machine learning through parameter optimization.[9]

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co-designing tactile performance through ML and manufacturing parameters, the sensor achieved an impressive classification accuracy of approximately 99.58%. This tactile sensor has been successfully applied to handwriting recognition of various English letters and sentences.[10]

By integrating physical signals from various sensors with AI, intelligent detection and feedback can be achieved, enabling applications such as smart homes and AI-driven robots. As a foundational principle, various sensing mechanisms have been developed, ranging from highly sensitive piezoresistive and capacitive sensors to piezoelectric and triboelectric sensors, which offer the significant advantage of zero power consumption. These mechanical sensors are used to record different physical parameters, enabling the perception of external stimuli with diverse sensing characteristics such as sensitivity, operating range, linearity, and robustness, thus allowing their application in various scenarios.[11] Moreover, to build an intelligent sensing system capable of not only detection but also analysis and decision-making, advanced data processing methods are integrated with flexible mechanical sensing technologies. Notably, machine learning algorithms are widely reported for conducting more sophisticated and comprehensive analyses of raw data collected from flexible sensors.[12] These algorithms can extract useful information far beyond the interpretability of traditional methods. Trained models in machine learning have been applied to classify, identify, and predict values based on the specific tasks of single or multiple/multimodal sensors in target applications. AI-driven interactions powered by machine learning can also be utilized in the education sector for teaching and interactive learning.[13]

By integrating various flexible acoustic pressure sensors to enhance functionality, machine learning algorithms have been introduced into voice communication.[14] To capture the full frequency range of human speech, researchers have developed a seven-channel flexible piezoelectric acoustic sensor capable of speaker recognition using machine learning algorithms. This approach demonstrated that multichannel audio inputs provide richer speech information. Subsequently, the same team further expanded the resonant bandwidth of piezoelectric acoustic sensors by adopting a biomimetic frequency band control method. This enhancement not only improved sensitivity in miniaturized dimensions but also enabled accurate biometric authentication using the same machine learning algorithms. The ability to recognize and analyze sound holds significant potential for applications in the education sector, offering innovative possibilities for teaching and learning interactions.[15]

Research and development in the field of flexible electronics will continue to advance toward higher performance, broader functionality, and larger-scale integration.[16] On one hand, exploring new two-dimensional materials, such as MXene and transition metal sulfides, and their applications in heterojunction structures can further enhance the conductivity, sensitivity, and stability of flexible devices.[17–19] On the other hand, micro-nano fabrication techniques based on flexible substrates, such as laser processing, nanoimprinting, and high-precision printing, will drive flexible devices toward ultra-thin, highly integrated, and multifunctional designs. At the same time, the integration of flexible electronics with biomedical applications presents tremendous potential. For instance, flexible biosensors and implantable medical devices can enable real-time monitoring of human physiological signals, offering critical support for personalized healthcare. Additionally, the development of flexible energy storage devices, such as flexible supercapacitors and lithium batteries, will provide reliable power supplies for flexible electronics, further expanding their application scenarios. In the future, a key step will be driving the industrial application of flexible electronics.[20] By optimizing material synthesis and processing techniques, reducing manufacturing costs, and building a complete research and development chain from fundamental studies to practical applications, flexible electronics are poised to occupy a central position in areas such as smart wearables, green energy, smart cities, and the industrial IoT. Thus, the development of flexible electronics is not only a frontier of science and technology but also a vital engine for fostering a more intelligent and convenient future society.[21]

2. Discussion

2.1. The development between flexible sensors and machine learning

Flexible electronics technology refers to the use of bendable and stretchable materials to create electronic devices and systems that can adapt to changing shapes while maintaining high performance. The core advantages of this technology lie in its flexibility, lightweight nature, and excellent electrical properties, particularly in fields such as sensing, energy storage, and display technologies. For example, sensors and flexible displays based on two-dimensional materials like graphene and MXene have been widely researched and are gradually being applied in wearable devices, smart homes, and medical monitoring.[24] With the continuous development of flexible electronic materials, especially the application of two-dimensional materials (such as MXene, graphene, black phosphorus, *etc.*) in flexible electronics, this technology is advancing towards high performance and multifunctionality. Researchers have successfully developed flexible sensors and electronic skins that can withstand large strains and operate stably over extended periods, opening up more possibilities for flexible electronics in medical, health monitoring, and educational applications.[25,26]

In recent years, the combination of flexible electronics and AI has demonstrated significant application potential in various fields, especially in education. Flexible electronics, with its unique advantages of bendability, high sensitivity, and lightweight nature, are widely used in smart sensors, wearable devices, and dynamic feedback systems. Meanwhile, AI enhances education through deep learning and data analysis capabilities, providing a data-driven personalized learning experience. The synergy of flexible electronics and AI technology enables the education sector to offer a more personalized and immersive learning environment. However, despite the broad prospects for their combination, many technical and societal

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Table 1 Summarizing different types of wearable sensors, their key features, advantages, limitations, and the role of machine learning in their applications

Sensor type	Key features	Advantages	Limitations	Role of machine learning
Electrochemical sensors	High sensitivity, real-time monitoring, selective detection	Fast response, low power consumption, suitable for biochemical sensing	Limited lifespan, susceptible to environmental conditions	Enhances signal processing, improves selectivity and sensitivity
Piezoelectric sensors	Converts mechanical stress into electrical signals	High precision, no external power needed	Limited flexibility, material degradation over time	Optimizes signal interpretation for motion tracking
Capacitive sensors	Measures changes in capacitance due to deformation	High flexibility, lightweight, low energy consumption	Sensitivity to environmental factors (humidity, temperature)	Machine learning aids in noise reduction and pattern recognition
Resistive sensors	Resistance changes with strain or pressure	Simple structure, low cost, easy integration	Limited sensitivity, hysteresis effects	ML helps in real-time compensation of drift and non-linearity
Optical sensors	Uses light-based detection (*e.g.*, photodetectors)	High accuracy, non-invasive	Bulkier designs, sensitive to external light interference	ML enhances data interpretation and compensates for noise
Thermoelectric sensors	Detects temperature variations through thermoelectric effects	No power supply required, reliable	Slow response time, low sensitivity in some applications	ML improves temperature compensation and predictive modeling

challenges remain in practical applications. This review will explore the current status, potential, and obstacles of flexible electronics and AI technology in the education sector and propose future directions for development. We first summarize the advantages and disadvantages of several types of sensors and their applications in machine learning in Table 1.

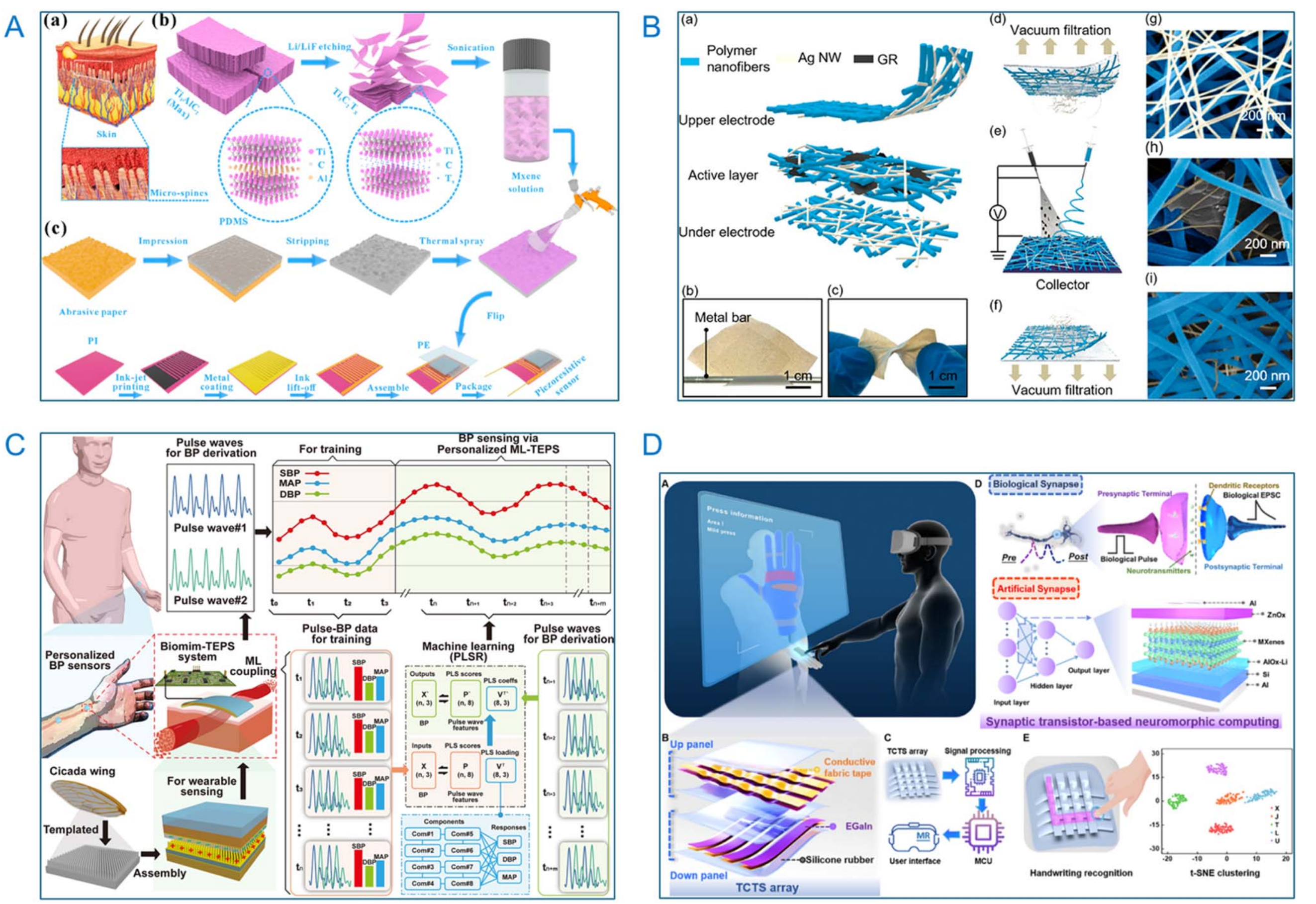

Fig. 2 (A) Flexible pressure sensor based on MXene nanomaterials.[27] (B) Fabric sensor based on Ag nanofibers.[28] (C) Pulse sensor for continuous blood pressure monitoring.[29] (D) Machine learning-assisted triboelectric-capacitive coupled tactile sensor.[22]

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As shown in Fig. 2A, Cheng *et al.* demonstrated a highly sensitive flexible pressure sensor based on MXene for wearable and human activity monitoring applications, biomedical research, and AI interaction.[27] This sensor is fabricated using simple manufacturing processes to create microstructures with high sensitivity, enabling pressure sensing with a wide range of functions (Table 2). Such sensors play an indispensable role in future wearable electronics, enabling pulse detection, human–machine interaction, and even applications in educational settings to detect students' learning states or interactions with teachers. In summary, these sensors exhibit great potential, enhancing the functionality of educational sensor technologies. Fig. 2B reports a flexible piezoresistive sensor with high sensitivity and a wide detection range, developed by Li *et al.*[28] This ultra-thin sensor is based on a multilayer nanonetwork structure composed of silver nanowires (Ag NWs), graphene (GR), and polyamide nanofibers (PANF). The Ag NWs are evenly distributed in the PANF network, forming conductive pathways. This skin sensor is crucial for flexible wearable electronics, actively used in medical diagnostics and healthcare monitoring. Additionally, the nanofibers can be integrated into wearable clothing, showcasing incredible potential in education, such as creating school uniforms or other educational materials that promote effective student learning. Fig. 2C shows a wearable electronic device developed by Yao *et al.* that can continuously monitor blood pressure fluctuations based on pulse signals.[29] Their bionic nanopillar-layered wearable triboelectric pulse sensor has great potential for medical use, tracking patients' pulse fluctuations and enabling real-time prediction and management of emergencies. Another promising application is in detecting psychological conditions, which could be valuable for medical and psychological assessments.

2.2. Scalable applications of flexible electronics

As shown in Fig. 3A, the pressure sensor is integrated into an intelligent robot to monitor its movements. The flexible sensor is fixed onto the robot's joints with PI tape, successfully detecting its motion and demonstrating its feasibility as a proof of concept. The distinct peak variations in the sensor's output indicate its ability to sensitively capture the robot's movements, suggesting its broad potential for future applications in AI devices. Additionally, by connecting the sensor with a Bluetooth system (a digital multimeter with Bluetooth functionality), a miniature circuit is formed, exploring its applications in portable devices. The system converts current changes into wireless electromagnetic signals, precisely identifying and recording finger tapping actions, making it a typical example of portable sensor applications. The successful integration of this flexible pressure sensor not only demonstrates its direct application in robot motion monitoring but also highlights its enormous potential in future smart devices and human–robot interaction.

High-resolution, large-area flexible sensor arrays have garnered considerable attention in wearable devices and human–machine interface applications, especially given the increasing demand for testing spatial pressure distribution. Therefore, developing a simple and efficient method for fabricating high-performance pressure sensor arrays is crucial. As shown in Fig. 3B, a resistive skin sensor array consisting of 64 pixels was successfully fabricated by employing patterned electrodes. The array measures the relative resistance changes of each pixel to achieve precise pressure distribution detection. An 8×8 high-resolution conductive square array electrode is tightly adhered to the surface of a ping pong ball, with each pixel measuring approximately 6.25 mm^2. The SEM image in Fig. 5C shows the detailed structure of the conductive array, clearly displaying its regular boundaries. In experiments, when 1 g, 2 g, and 5 g weights are placed on the sensor matrix, the corresponding current responses accurately reflect the location and pressure of the weights. Furthermore, because the skin sensor array relies on patterned electrodes rather than fixed sensor matrices, its pixel structure and size can be easily adjusted, providing greater flexibility and adaptability.[30]

Table 2 Common machine learning algorithms used

Algorithm	Application in sensor data	Advantages	Limitations
Support vector machines (SVM)	Classification of sensor signals (*e.g.*, stress detection, fatigue monitoring)	Effective for small datasets, high accuracy	Computationally intensive, requires careful tuning
Random forest (RF)	Feature selection and classification for multi-modal sensor data	Handles large datasets well, robust to overfitting	Less interpretable compared to simpler models
Artificial neural networks (ANNs)	Pattern recognition in physiological and motion sensor data	High accuracy, adapts to complex data patterns	Requires large training data, risk of overfitting
Convolutional neural networks (CNNs)	Image-based sensor data (*e.g.*, optical and thermal sensors)	Extracts spatial features efficiently	High computational cost
Long short-term memory (LSTM) networks	Time-series data analysis for wearable health monitoring	Captures temporal dependencies, useful for predicting trends	Requires extensive training, sensitive to hyperparameters
k-Nearest neighbors (*k*-NN)	Simple classification of sensor data patterns	Easy to implement, works well for small datasets	Computationally expensive for large datasets
Principal component analysis (PCA)	Dimensionality reduction for sensor data processing	Reduces computational cost, removes redundant features	May lose some information in compression

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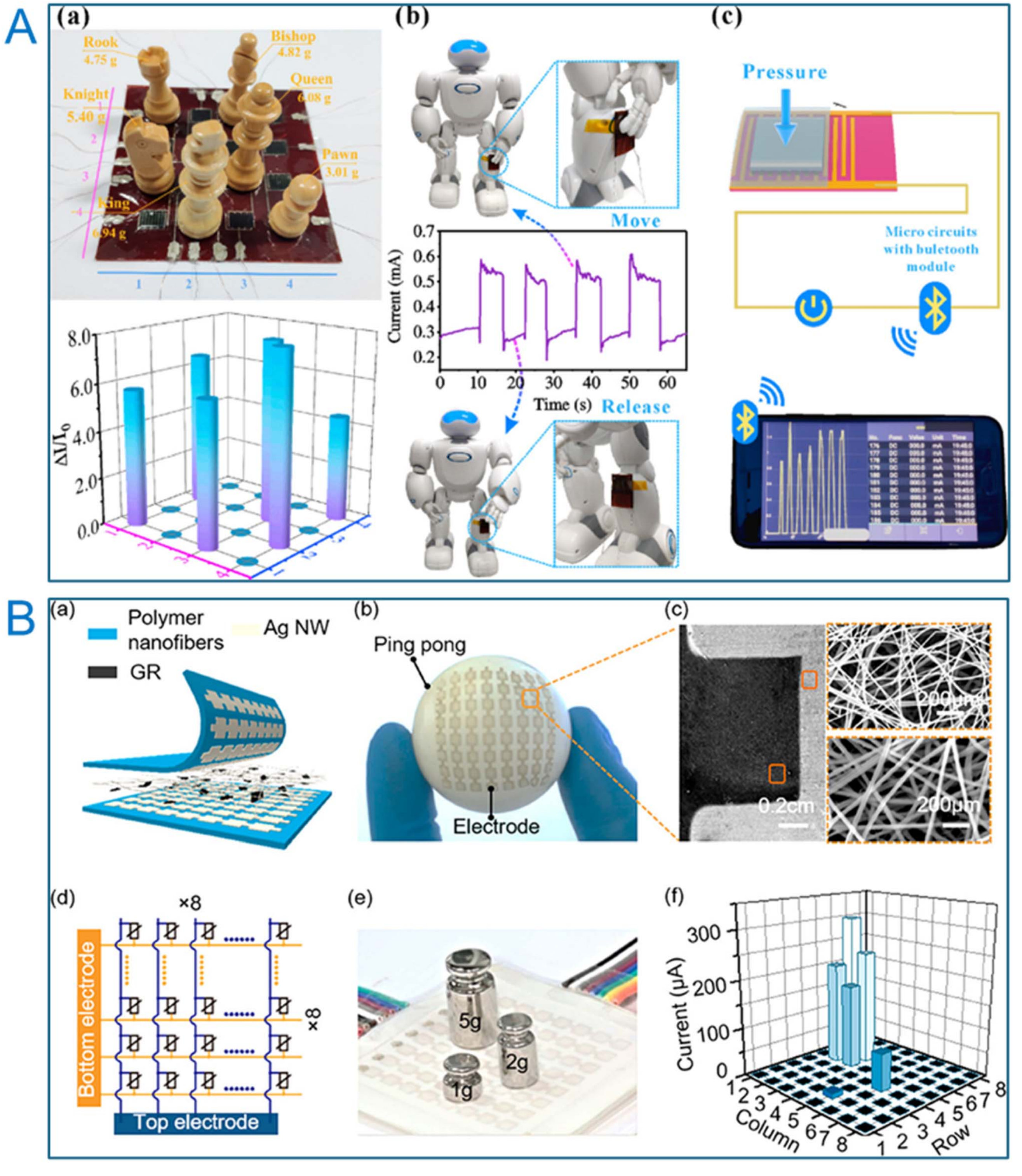

Fig. 3 (A) Flexible pressure sensor for array pressure distribution and human–robot interaction.[27] (B) Fiber electronics for pressure detection and learning in table tennis.[28]

Compared to traditional rigid sensors, this flexible sensor offers several unique advantages and significance. Adaptability to complex surfaces: the flexible sensor can conform to complex surfaces, such as robot joints or human skin, expanding its applicability in wearable devices and biomimetics. The sensor can capture minute mechanical changes in real-time, such as finger taps, showcasing its superior performance in precision motion detection and feedback systems. By integrating with wireless technologies like Bluetooth, the sensor offers high portability, providing solutions for mobile devices and remote

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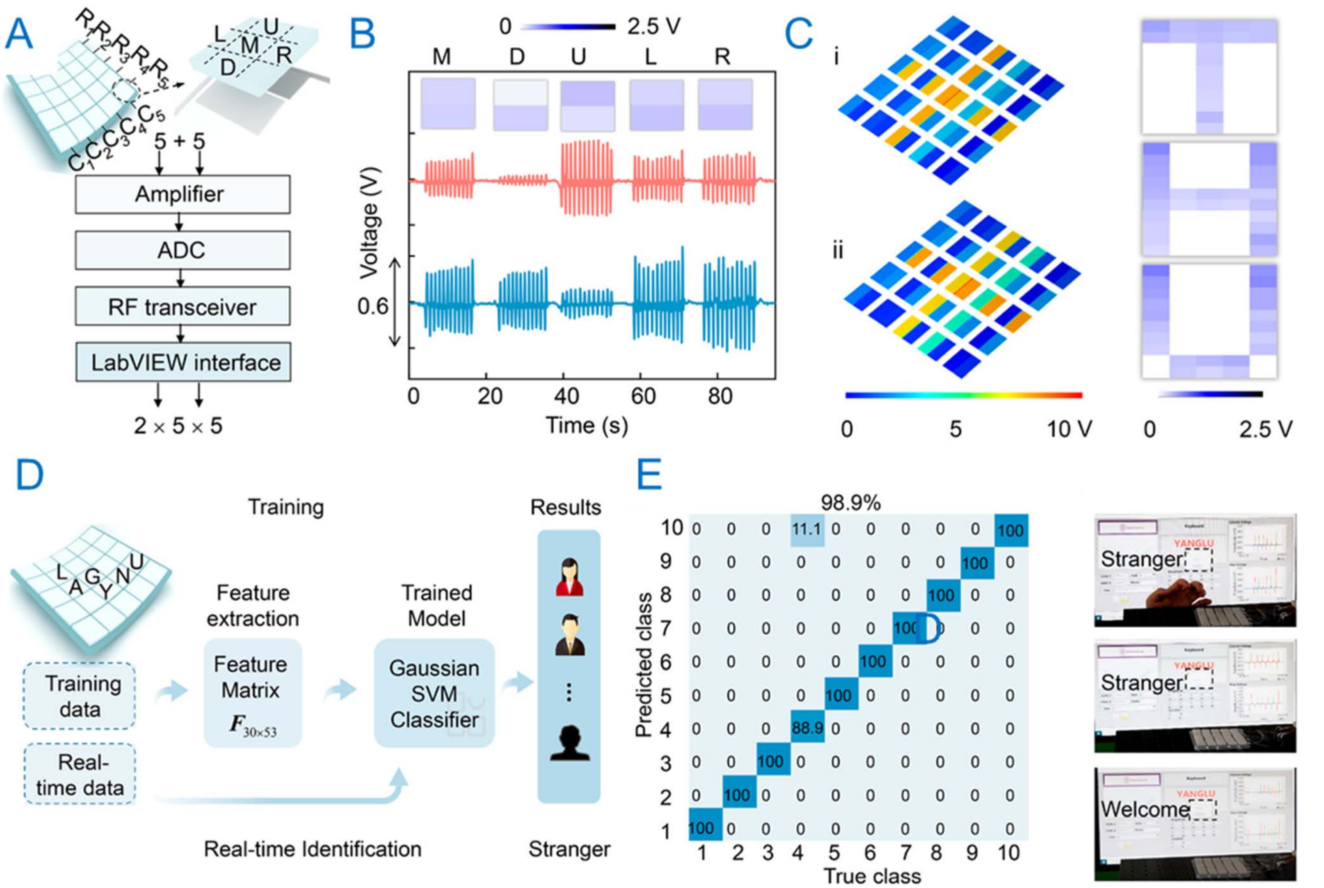

Fig. 4 Single-pixel sensing for machine learning-assisted individual identification. (A) Signal acquisition and processing system diagram. (B) Single-pixel tactile voltage signal during contact. (C) Theoretical simulation of voltage signal distribution. (D) Training and real-time identification process. (E) Classification of 10 individuals and video snapshots of real-time personal identification.[34]

monitoring scenarios, such as telemedicine and sports monitoring. In the future, it plays an essential role in remote education, interactive teaching, and monitoring student mental health and medical conditions in educational settings. With its simple fabrication method, high-resolution pressure detection capability, and adjustable pixel structure, this flexible sensor array provides reliable solutions for epidermal health monitoring, human–machine interaction, and wearable devices. It presents vast commercial potential and technological promotion value.

The continuous advancement of IoT technology has driven strong interest in building large-scale immersive sensor networks, particularly in smart homes, smart manufacturing, and industrial automation. With the ongoing evolution of environmental sensing technologies, sensor networks are becoming increasingly widespread in these contexts, especially in individual and object recognition, showing great potential and value. However, current technologies still face numerous challenges, prompting researchers to explore new solutions to meet the high demands of future smart environments. In the field of object recognition, current technologies largely rely on methods such as vision, laser, and ultrasound. For instance, vision-based monitoring technologies are widely applied in both home and industrial environments, enabling the detection and recognition of objects by capturing their shapes and movements through cameras. However, these methods have significant drawbacks: they are prone to environmental interference (such as changes in lighting or occlusion by obstacles) and may raise privacy concerns. Additionally, vision-based systems, which rely on bulky equipment, are expensive and energy-intensive, limiting their widespread application.[31]

Similarly, laser- and ultrasound-based sensing technologies also have comparable limitations. While they can provide relatively accurate distance and position data, their high power consumption, device complexity, and sensitivity to environmental factors restrict their applicability. As a result, individual and object recognition technologies in IoT require breakthroughs to overcome the limitations of current methods and seek more efficient, cost-effective, and reliable solutions.[32] To overcome the limitations of traditional technologies, tactile sensor technology has gradually become a hot research topic in object recognition. These sensors can sense the presence and characteristics of objects through pressure-based signals, with common sensing effects including magnetic, capacitive, and piezoresistive effects. For example, by embedding pressure sensors into tactile interactive interfaces, more precise object recognition and interactive responses can be achieved. This multimodal sensing approach effectively compensates for the shortcomings of vision and laser sensors in certain scenarios,

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providing a more comprehensive environmental sensing capability.[33]

2.3. Application prospects of sensors combined with artificial intelligence

As shown in Fig. 4, Luo *et al.*[34] developed a single-pixel sensor array that, combined with machine learning, can be used for array distribution. By touching the corresponding letter pattern, the corresponding voltage signal can be obtained. Fig. 4C displays the potential distribution under the corresponding theoretical simulation model, which can be used to predict the pressure distribution sensed. Fig. 4D demonstrates how the model can be trained to identify the corresponding pressure. Through machine learning, datasets and signals can be precisely identified, which holds great promise for the future of wearable electronics. This technology can also be applied in areas such as educational recognition, enabling precise identification systems.

Soft interfaces with self-sensing capabilities are gradually becoming the core technology in environmental perception and response systems. These soft interfaces can simulate the self-sensing abilities of biological systems and show broad application prospects in fields such as smart homes, industrial automation, and healthcare. However, with the deep integration of materials science and sensor system design, breaking through the technical bottlenecks in the sensor integration process has become the main challenge in current research. Through flexible array sensors (Fig. 5A) and machine learning, visualized data recognition can be achieved, playing a crucial role in the wearable electronics field. Additionally, machine learning in wearable electronics can be applied to human–computer interaction learning (Fig. 5B), such as in education, sports, identity recognition, interactive learning, *etc.*

2.4. Future development trends of artificial intelligence

Flexible sensors generate complex, dynamic signals that are often influenced by environmental factors such as humidity, temperature, and mechanical deformation. Traditional data processing methods struggle to handle these variations effectively. Machine learning algorithms play a crucial role in addressing these challenges by enhancing signal processing, noise reduction, and feature extraction. They enable real-time

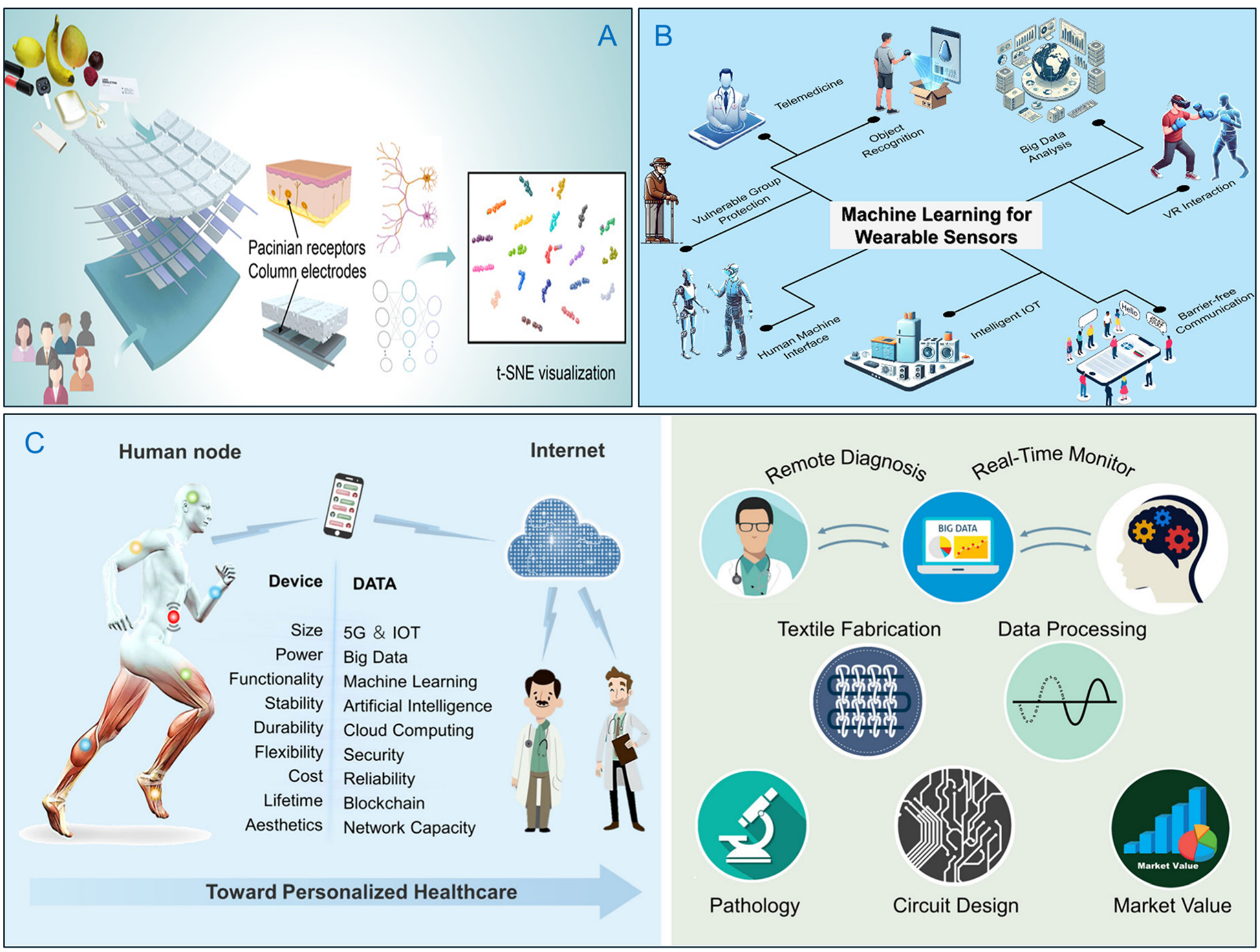

Fig. 5 (A) Bionic soft sensor based on machine learning for user and object recognition.[34] (B) Prospects for the future development of machine learning-assisted wearable sensors. (C) Future analysis and development trends of wearable sensor machine learning.[35]

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adaptive calibration, improve sensitivity and selectivity, and facilitate pattern recognition for health monitoring, human motion tracking, and wearable electronics. By integrating machine learning, flexible sensors can achieve higher accuracy, reliability, and intelligence, making them more practical for real-world applications. Here, we introduce several commonly used algorithms along with their advantages and disadvantages.

In recent years, with the rapid development of wearable sensors and bioelectronics, the role of machine learning in real-time sensor data analysis has become increasingly prominent.[36] These technologies not only improve the efficiency of data processing and analysis but also provide clinical-level information support for personalized healthcare, making health monitoring and disease management more accurate and intelligent (Fig. 5C). Furthermore, wearable electronics' data analysis and processing can be combined with various industries, playing an indispensable role in fields like biometrics, market analysis, circuit design, *etc.* Future wearable sensors will integrate flexible electronics technology, allowing devices to conform to the body for a seamless wear experience. This design not only improves user comfort but also expands the sensor's ability to capture physiological signals. For example, in addition to traditional ECG and sleep monitoring, sensors may also cover multimodal data such as body temperature, blood glucose levels, and blood oxygen saturation, providing support for comprehensive health assessments.

3. Conclusions

This review aims to provide a comprehensive overview of the latest advancements in the field of wearable sensors, with a particular focus on innovations in sensor design and their potential applications in machine learning. Initially, we examined the current technologies in wearable electronics, emphasizing their feasibility in achieving flexible and functional devices. Advanced research efforts in this domain were then discussed to highlight cutting-edge progress. Subsequently, we explored the unique advantages of wearable electronic devices in enhancing human–machine interaction and analyzed how machine learning empowers these devices to handle real-time data processing and intelligent decision-making in complex environments. The integration of wearable electronics with machine learning opens up vast opportunities for applications, enabling wearable devices with advanced functionalities across diverse fields. By synthesizing the exciting and rapidly evolving developments in this field, we hope this review serves as a valuable resource, providing insights and guidance for future research and practical applications. The synergy between wearable electronics and machine learning is poised to revolutionize areas such as personalized healthcare, human–computer interaction, and beyond.

Data availability

This article is a review of recent advancements in wearable sensors and their integration with machine learning, and it does not involve the generation or analysis of original datasets. All data presented in this manuscript are derived from previously published studies, which are cited appropriately within the text. Additional details can be obtained from the referenced publications.

Author contributions

Conceptualization, G. M.; validation, Z. Y., and Y. Z.; formal analysis, Q. Y.; investigation, Q. W.; writing—original draft preparation, G. M.; writing—review and editing, G. M.; supervision, G. M.; all authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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