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VIEW

REVIEW

Artificial intelligence-enhanced skin-like sensors based on flexible nanogenerators

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Abstract

Artificial intelligence-enhanced skin-like sensors based on flexible nanogenerators have been widely used in physiological signal acquisition, artificial organ, sensory simulation, human movement status recognition, and other biomedical related fields due to their excellent biocompatibility, comfortable wearing experience, high sensing accuracy, and low power consumption. In this paper, the working principle, evolution process, and several established general strategies of artificial intelligence-enhanced skin-like sensors are summarized in detail. More importantly, this paper further reviews several recent important advances on artificial intelligence enhanced skin-like sensor, and systematically analyzes and compares these works according to their principles and application directions. In the discussion section, we also list the current concerns of stress adaptation, stretchability–conductivity, algorithm optimization, function integration, and propose potential solutions to these problems. We hope that the deep integration of artificial intelligence and flexible nanogenerators can bring more enlightenment to the progress of biomedical engineering in the future.

KEYWORDS
artificial intelligence, piezoelectric nanogenerator, skin-like sensor, triboelectric nanogenerator

1 | INTRODUCTION

Skin-like sensors (SLSs) are a new type of electronic device that can sense external pressure, temperature, and humidity by simulating the real skin. SLSs mainly contain special geometric designs or are made by flexible organic materials, and their specific fabrication strategies include implanting conductive fillers on flexible substrates, applying conductive polymer hydrogels, and encapsulating liquid metals. SLSs have been widely used in the field of health monitoring, including body fluid sensing,[1] bioelectric signal sensing,[2,3] and biomechanical signal sensing.[4,5] For example, Pu et al. developed a flexible transparent sensor based on triboelectric nanogenerator (TENG), which can effectively capture blink motion with ultra-high signal level.[3] In addition, a large number of neuromimetic devices have also been derived based on the SLS signal transmission method.

Due to the demand for energy supply and high-precision sensing, the design of SLSs has gradually incorporated novel micro-nano devices, among which nanogenerator (NG)-based SLSs have become an important branch. NG is a device that can harvest mechanical, thermal, and other forms of energies from the environment and convert them into electrical energy outputs. Generally, NGs can be classified into three categories: TENG, piezoelectric nanogenerator (PENG), and pyroelectric nanogenerator (PrNG), among which TENG has a wider range of applications due to its advantages of simple structure, easy fabrication, and inexpensive cost.[6] Based on these superiorities mentioned above, TENG has currently become a research hotspot in the field of energy harvesting and sensors. On the one hand, TENG, as a self-powered device, can replace traditional power generation or energy storage equipment, especially in specific application scenarios with high difficulty in battery replacement (such as pacemakers[7]) and expensive maintenance expenses (such as sensors in the outdoor environment[8]). On the other hand, in addition to power supply, TENG has low power consumption, high sensitivity, and high stability of electrostatic induction capability, and can also be used as a self-powered sensor to monitor the natural environment and human activities. NG has a wide range material selectivity; whether it is a flexible polymer material, a liquid ionic conductor, or even a liquid metal, it can be used as the friction layer material of the NG. In addition, NG has multiple working modes and various structural designs, which can meet the needs of SLS in both structure and function. Therefore, when the concept of NG was first proposed, it has been realized that NG as an SLS has great research significance and application value.

NG-based SLSs enable long-term uninterrupted monitoring; however, the consequent generation of large amounts of data increases the difficulty of processing and analysis. To date, artificial intelligence (AI) has been gradually used in the research of physical sciences, and its powerful signal processing and data analysis capabilities are suitable for solving regression or classification problems that SLSs need to solve. As an emerging branch of computer science, AI is a technical science that studies theories, methods, and applications for simulating and extending human intelligence. The term AI has been developed for 65 years since it was first proposed by John McCarthy and Marvin L. Minsky at Dartmouth College in 1956.[9] However, the development process of AI was not smooth. Restricted by material science and mathematics, the development of AI has been at a low point for a long time. In recent years, due to the significant improvement of computing power, the development of AI has entered an explosive period, and it has been widely used in the fields of identity recognition,[10,11] smart medical,[12] and smart cities.[13] SLSs lack effective means to process and analyze data, while AI requires big data to build accurate, anomalous-resistant models. The combination of these two technologies will greatly expand the application functions and performance of SLSs, thereby promoting the development and practical value of AI.

2 | FUNDAMENTALS AND ESTABLISHMENT STRATEGIES

2.1 | The principle and classification of nanogenerators

The concept of NG was first proposed in 2006 by Professor Zhong-Lin Wang, who fabricated the first PENG based on zinc oxide (ZnO) nanowire arrays.[14] Materials with piezoelectric effect, such as ZnO and polyvinylidene difluoride (PVDF), are used in PENG. Piezoelectric materials must satisfy two preconditions: one is that a single unit can generate a dipole moment under mechanical loading; and the other is that it should have an oriented and ordered internal structure. Therefore, some special preparation or processing methods are required to obtain materials with piezoelectric effect. For example, PVDF films need to be polarized, and ZnO requires directional growth to obtain nanowire arrays. As the most classical piezoelectric material, when subject to a mechanical load perpendicular to the substrate, their positive and negative charge centers of ZnO are shifted, and a piezoelectric potential is generated macroscopically at the tip of the ZnO nanowires. Mechanical loads in different directions (such as stretching and squeezing) lead to opposite induced potentials (Figure 1B).

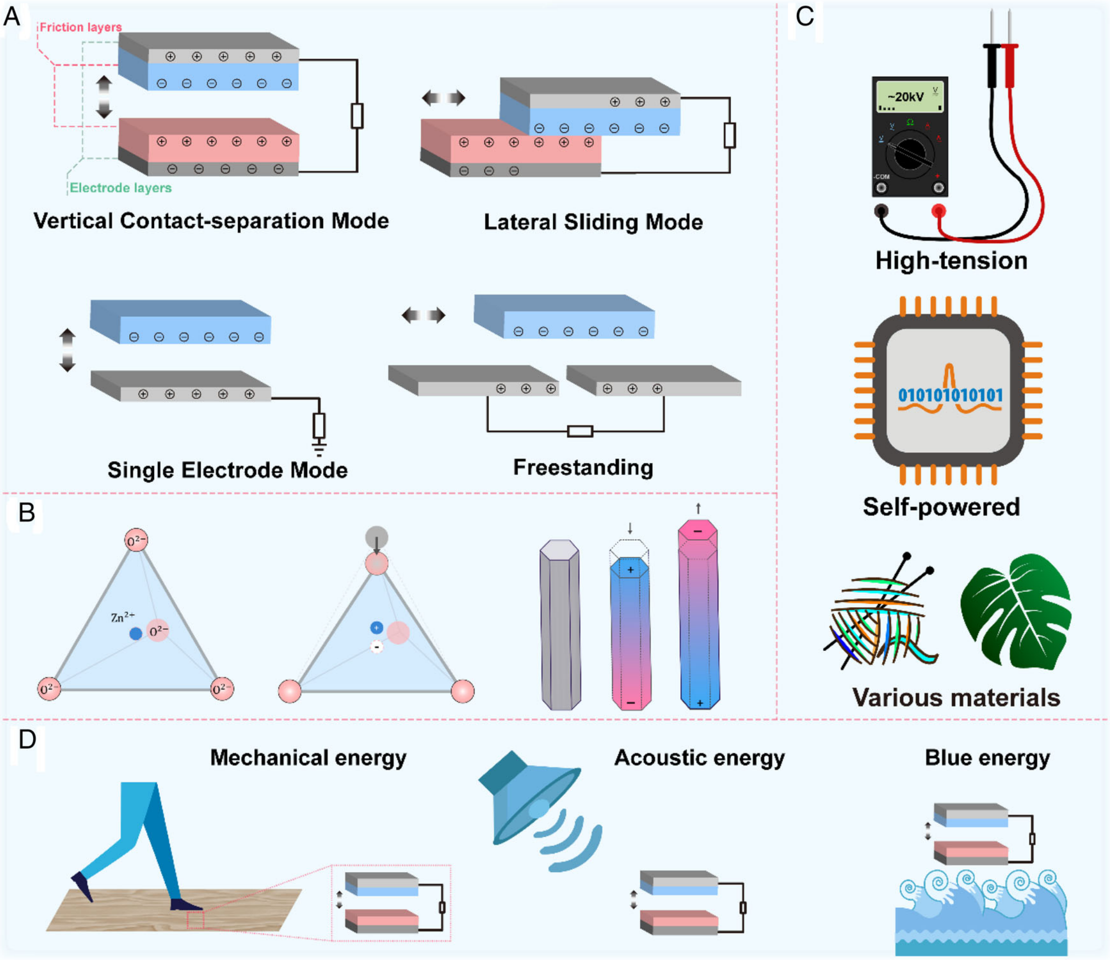

FIGURE 1 The working principle of nanogenerator (NG). (A) Four working modes of triboelectric nanogenerator (TENG). (B) The working principle of piezoelectric nanogenerator (PENG). (C) Features and advantages of NG. (D) The major source form of NG energy

TENG was also first proposed by Prof. Zhong-Lin Wang in 2012.[15] TENG is an energy-harvesting device based on triboelectrification and electrostatic induction effects, which efficiently convert mechanical energy into electrical energy with Maxwell's displacement current as the driving force. Due to the difference in ability of the two materials to acquire electrons, the surfaces of the two friction layers will carry equal amounts of opposite charges after contact and separation. This phenomenon is called triboelectrification. The phenomenon of electrostatic induction occurs when the sensing layers, which are closely connected with the friction layers, are connected by an external circuit. With the contact and separation of the friction layer, the internal charges of the induction layers will be redistributed, resulting in the generation of an induced current.[6] TENG can be divided into four categories based on the contact method of the two friction materials and the external circuit connection method.: vertical contact-separation mode, lateral sliding mode, single-electrode mode, and freestanding mode (Figure 1A). NG has the advantages of self-powered, high-voltage output, and a wide range of material selection in the fields of environmental energy harvesting and real-time signal sensing (Figure 1C).[16] NG can harvest a wide range of mechanical energy, including acoustic energy, blue energy,[17] and motion energy of living organisms (Figure 1D), and has great application potential for infrastructure monitoring,[9] physiological signal collection,[16] and human–computer interface.[18–20] Since NG can be manufactured from materials with good flexibility and biocompatibility, it is suitable for use in wearable and implantable devices.[21]

2.2 | Definition of artificial intelligence and common algorithms

AI is a branch of computer science that enables computers to accomplish complicated tasks like humans.[22] There are some technical terms in the field of AI, such as machine learning (ML), neural network, and deep learning (DL), which are confusing and highly related, but not interchangeable. As shown in Figure 2A, AI is a large research

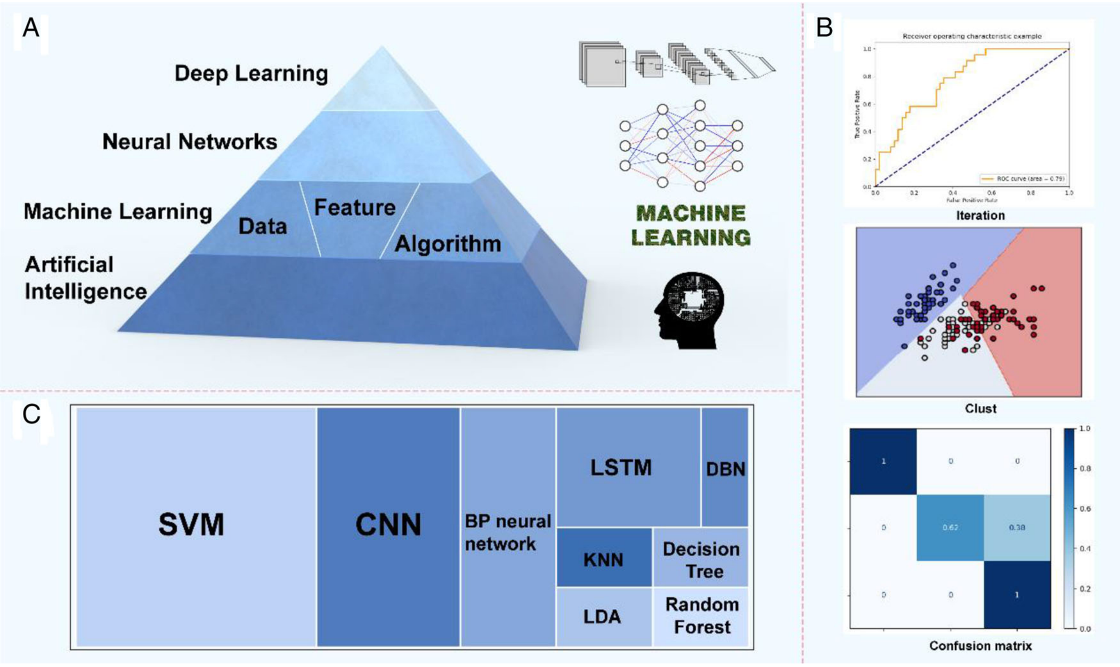

FIGURE 2 Detailed introduction of artificial intelligence (AI). (A) Diagram of the relationship between AI, machine learning (ML), neural networks, and deep learning (DL). (B) Common characterization diagrams of AI. (C) Rectangular tree diagram for AI algorithms

field; ML is a goal of AI and provides many algorithms; and neural network is a successful and widely used algorithm in ML. As a part of the neural network, DL is currently a research method with broad utilization.

Specifically, ML allows computers to learn directly from data features and build mathematical models to perform specific tasks without understanding the inherent logic between features and labels.[23] ML has been mainstream since 1980s and is currently applied to most daily life scenarios, such as spam identification,[24] personalized search.[25] Neural network is a specific method for realizing ML tasks.[26] It is a network structure composed of many simple neurons. This network structure, similar to the biological nervous system, is used to model the relationship between input layers and output layers. In 1986, Rumelhart et al. proposed a multilayer network backpropagation (BP) algorithm.[27] BP algorithm is crucial and is the theoretical basis to neural network. From model to algorithm, the BP algorithm promotes neural network research and lays the foundation for the commercialization of neural network computers. DL is the latest research achievement based on neural network optimization. In the early stages of neural networks, only very shallow and small networks were used in applications. With the increase of generated data and computing resources, and the continuous development and optimization of algorithms, the number of layers of neural networks is increasing, and the learning difficulty is also improved.

Hinton first proposed the concept of a deep belief net (DBN) in 2006, pushing DL into academia and making it a popular research direction in the current AI field. DL is essentially a multi-layer neural network; but in practice, its effect is superior to that of traditional neural networks and does not involve feature engineering. By increasing the number of layers of neural networks, the steps of artificial feature extraction can be avoided, and the feature extraction differences caused by individual cognitive differences can also be eliminated. In addition, DL is highly adaptable and easy to transfer, which can be more easily applied to different fields and applications. However, DL is not a panacea. In order to achieve high performance, DL requires very large datasets. Because DL techniques are inextricably linked to large amounts of training data, large-scale DL system usually necessitates millions of data.[28] For many applications, such large datasets are time-consuming, expensive, and difficult to gather. Therefore, for smaller datasets, traditional ML techniques are usually preferable to DL algorithms.

As shown in Figure (2B), the commonly used method for AI to improve the convergence accuracy is iteration. AI is mainly used to solve clustering problems, and the accuracy of the algorithm is intuitively displayed through the confusion matrix. As shown in the rectangular tree diagram (Figure 2C), the algorithms commonly employed in AI are counted, and the area of this figure represents the number of times the algorithm is used. Most researchers used support vector machine (SVM), convolutional neural

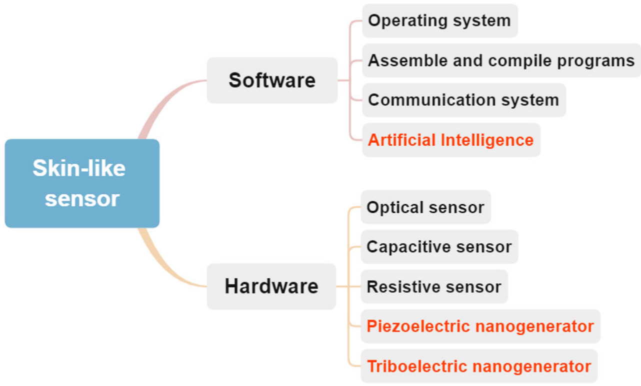

FIGURE 3 Composition of skin-like sensor (SLS). The software technology and hardware technology involved in the SLS

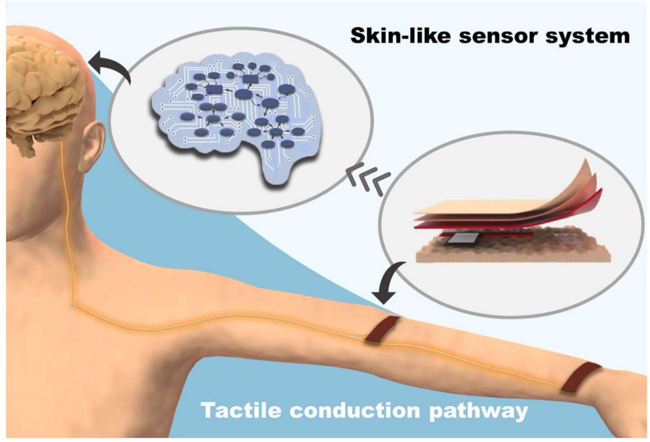

FIGURE 4 Schematic diagram of typical artificial intelligence (AI)-enhanced flexible skin-like sensor (SLS) system and tactile conduction pathway

network (CNN), and BP neural networks as their primary approaches in the field of NG.

2.3 | Establishment strategies of artificial intelligence-enhanced skin-like sensors based on flexible nanogeneratorss

The establishment strategies of SLSs are inspired by the tactile information transduction pathway. The tactile information transduction pathway is divided into the following steps. First, it needs to perceive external stimuli through various tactile sensors on the skin surface, such as Merkel cells, Meissner corpuscles, Ruffini corpuscles, and Pacinian corpuscles. Second, it needs to transmit this information to the tactile perception center of the brain through nerves, and finally the brain will use this information to comprehensively judge the size, texture, and temperature of the contacted object (Figure 3). Similarly, the SLSs, or more precisely, the skin-like sensing system, is also composed of two parts. One part is the hardware side responsible for collecting sensor signals, and the other part is the software side responsible for processing the collected information and making comprehensive judgments. The constructed skin-like sensing systems usually use various types of sensors to collect signals, which are based on different principles, including optical sensors,[29] piezoresistive sensors,[30,31] capacitive sensors,[32,33] TENG[13,34–36] and PENG.[37] The software side is based on AI as the brain to realize comprehensive analysis and judgment (Figure 4).

To more intuitively demonstrate the connection and research status between NG, AI, and SLSs (more broadly, electronic-skin). We used VOSviewer to plot citations and keywords based on the citation information from the web of science. The size of the bubble represents the reference frequency of the article, and different colors reflect different clusters. If these articles are frequently cited by other publications, they would be closer in distance and color in the figure.[38] As shown in Figure 5, the three different colors cluster generally represent different types of research directions. AI obviously occupies a large proportion, indicating that there are many research works related to AI. The distance between NG and electronic skin is relatively close, and the dense connection lines between the two clusters indicate that the two disciplines have a strong combination. According to this method, scholars can intuitively observe the current research hotspots, understand the possibility of combining different technologies, and find a settlement point of the specific combination.

This work reviews recent research progress in the intersection of AI, SLSs, and flexible NGs (Table 1), which can be summarized as the following commonalities. First, in terms of application scenes, the AI-enhanced, NG-based SLSs have promising prospects in handwriting recognition, image recognition, smart glove, and human behavior monitoring. Second, SVM, BP neural network, and CNN are very compatible with NG, and all algorithms are widely accepted by researchers. Third, in order to adapt to different application scenarios, the most suitable algorithms are selected, these typical working models have good accuracy. Some models adopt pre-training methods, and some studies even use more than two algorithms for comparison. Fourth, for the selection of NGs, the use of TENGs dominates in these works. The typical TENG positive electrode friction layer is generally made by copper, because it is easy to lose electrons and has good electrical conductivity. Polydimethylsiloxane (PDMS) and polytetrafluoroethylene (PTFE) with higher electronegativity are widely used in the negative electrode friction layer. Finally, in the selection of the TENG working mode, most studies choose the vertical contact separation mode TENG because of its simple structure, ease of preparation, and excellent

TABLE 1 Summary of typical application research of AI algorithm in SLSs

Years	Application	Materials	Type	Mode	Sensitivity	Algorithm	Accuracy	References
2021	Physiological signal acquisition	Ecoflex–thermoplastic fluorescent mat	TENG	Vertical contact-separation mode				[38]
2021	Physiological signal acquisition	PTFE–carbon black/TPU	TENG	Single electrode mode				[39]
2021	Olfactory simulation	PTFE–PMMA	TENG	Freestanding mode		CNN	48.21%	[54]
2021	Visual simulation	PTFE–Cu	TENG	Vertical contact-separation mode		BP neural network	92.00%	[56]
2020	Artificial neuron	ZnO	PENG	`				[47]
2020	Tactile simulation	Polyethylene naphthalate– PTFE	TENG	Vertical contact-separation mode	1.63 kPa^{-1}	Deep learning	99.10%	[27]
2020	Tactile simulation	PVDF NFs	PENG	`	0.18 V kPa^{-1}			[30]
2020	Tactile simulation	Silicone rubber	TENG	Single electrode mode	34 mV Pa^{-1}			[28]
2020	Tactile simulation	Tetrafluoroethylene–hexafluoropropylene-vinylide /cyclic olefin copolymer	PENG	`	30 mV Pa^{-1}			[29]
2020	Data glove	CNTs/TPE–Ecoflex	TENG	Vertical contact-separation mode		CNN	95.23%	[10]
2020	Writing recognition	Copper–PDMS	TENG	Vertical contact-separation mode		SVM	99.66%	[61]
2020	Writing recognition	Copper–PDMS	TENG	Vertical contact-separation mode		SVM	93.50%	[62]
2020	Writing recognition	Skin–FEP	TENG	Vertical contact-separation mode and lateral sliding mode		CNN	93.60%	[64]

(Continues)

TABLE 1 (Continued)

Years	Application	Materials	Type	Mode	Sensitivity	Algorithm	Accuracy	References
2020	Writing recognition	Cu–PDMS	TENG	Vertical contact-separation mode	0.192 V kPa^{-1}	LSTM	84.00%	[65]
2020	Gait recognition	Nitrile–silicone rubber	TENG	Vertical contact-separation mode	0.4 V kPa^{-1}	CNN	96.67%	[66]
2020	Gait recognition	Socks/shoe soles–PET	TENG	Vertical contact-separation mode		CNN	96.00%	[67]
2019	Physiological signal acquisition	ITO–PDMS	TENG	Vertical contact-separation mode				[37]
2019	Artificial neuron	PDMS/Mxene	TENG	Single electrode mode	0.197 kPa^{-1}	SVM		[46]
2019	Data glove	Triboelectric:copper–PDMS piezoelectric:PBPG–PVDF	Hybrid nano-generator	Vertical contact-separation mode		LSTM	82.30%	[9]
2019	Data glove	Silicone rubber/PDMS	TENG	Single electrode mode		CNN/SVM	96.00%	[8]
2019	Writing recognition	Wool–PTFE	TENG	Vertical contact-separation mode and lateral sliding mode		BP neural network	98.00%	[63]
2018	Artificial neuron	Graphene	PENG	`				[48]
2018	Auditory simulation	FEP–Cu	TENG	Vertical contact-separation mode	110 mV dB^{-1}			[59]

Abbrevations: AI, artificial intelligence; CNN, convolutional neural network; CNT, carbon nanotube; LSTM, long short-term memory; NF, nanofiber; PDMS, polydimethylsiloxane; PENG, piezoelectric nanogenerator; PMMA, polymethyl methacrylate; PTFE, polytetrafluoroethylene; PVDF, polyvinylidene difluoride; SLS, skin-like sensor; SVM, support vector machine; TENG, triboelectric nanogenerator; TPE, thermoplastic elastomer.

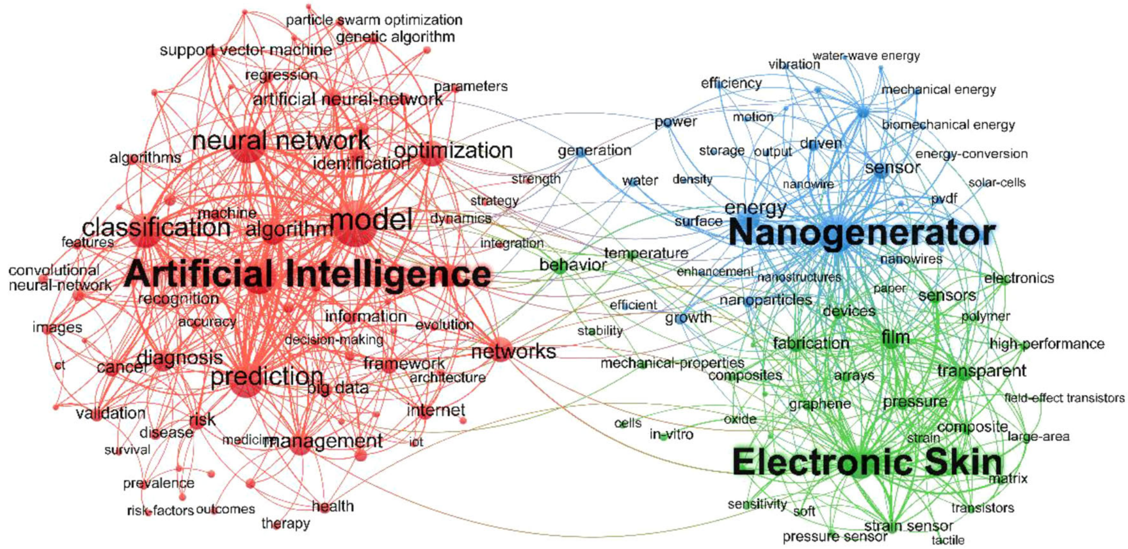

FIGURE 5 Citation and keyword co-occurrence map of artificial intelligence (AI), nanogenerator (NG), and electronic skin

output performance. It is also a good idea to design a TENG that can integrate the two kinds of sensors, which can further expand the scale of data collected. Through mass deployment of sensors, with long-term monitoring for days, weeks, or even months, intelligent algorithms can get enough data for adequate training and optimization. It is foreseeable that AI technology and TENG can support each other in the development process, and there will be a wider combination in the human–machine interaction application.

3 | APPLICATIONS

3.1 | Skin-like sensors for physiological signal acquisition

Physiological signals are a valuable source of data that contribute to the early disease prevention, treatment, and prognosis rehabilitation.[39] For example, cardiovascular disease is one of the leading causes of death in humans, with 18.6 million deaths per year (in 2019),[40] which accounts for 48% of non-communicable diseases deaths.[41] According to statistics, at least 80% of heart disease deaths can be avoided through human intervention,[42] so continuous monitoring of physiological status and timely early warning are very necessary.

NG-based SLSs have the functions of mechanical signal detection and energy harvesting, and can detect physiological signals such as respiration, heart rate, and pulse.[43–46] As implantable electronic devices, NG-based SLSs have great advantages, which are very suitable for early monitoring of disease and continuous monitoring during the recovery phase.[47] Inspired by the light-emitting mechanism of animal skin and spiders, Zhao et al. developed an SLS based on ultrasensitive self-powered mechanoluminescent TENG.[45] The SLS possessed ultra-high sensitivity (gauge factor, GF = 3.92×10^7) with a strain detection limit of 0.001%, response time as low as 5 ms, and cycle stability greater than 45,000. These excellent performances enabled accurate pulse measurements. The SLS could measure the pulse waveforms of the brachial artery, carotid artery, temporal artery, and fingertip artery etc. in detail. In addition, The SLS successfully performed continuous, stable non-invasive pulse monitoring of the radial artery for 400 s. This has important implications for the long-term detection and diagnosis of cardiovascular disease (Figure 6A). Zhang et al. developed an ultrathin stretchable single electrode mode TENG (S-TENG) composed of carbon black/thermoplastic polyurethane with ~646% stretchability, a thickness of ~50 μm and slight mass of ~62 mg.[46] S-TENG acted as an SLS and exhibited high perceptual resolution when recording normal pulses, and it could clearly distinguishing subtle peaks from radial artery pulse waveforms (Figure 6B). Das et al. fabricated a low-cost TENG-based SLS with sensitivity of 7.697kPa^{-1}, detection limit of ~1 Pa, response time below 9.9 ms, and stability over 4,000 compression-release cycles.[44] The designed SLS clearly measured the pulse waveforms from human fingertips (Figure 6C).

Considering the above achievements and related research status, NG can be considered as an effective method for physiological signal monitoring. Among them, the vast majority of SLSs are based on TENG, because TENG has more diverse material choices and device design options compared to PENG. In the future, it is

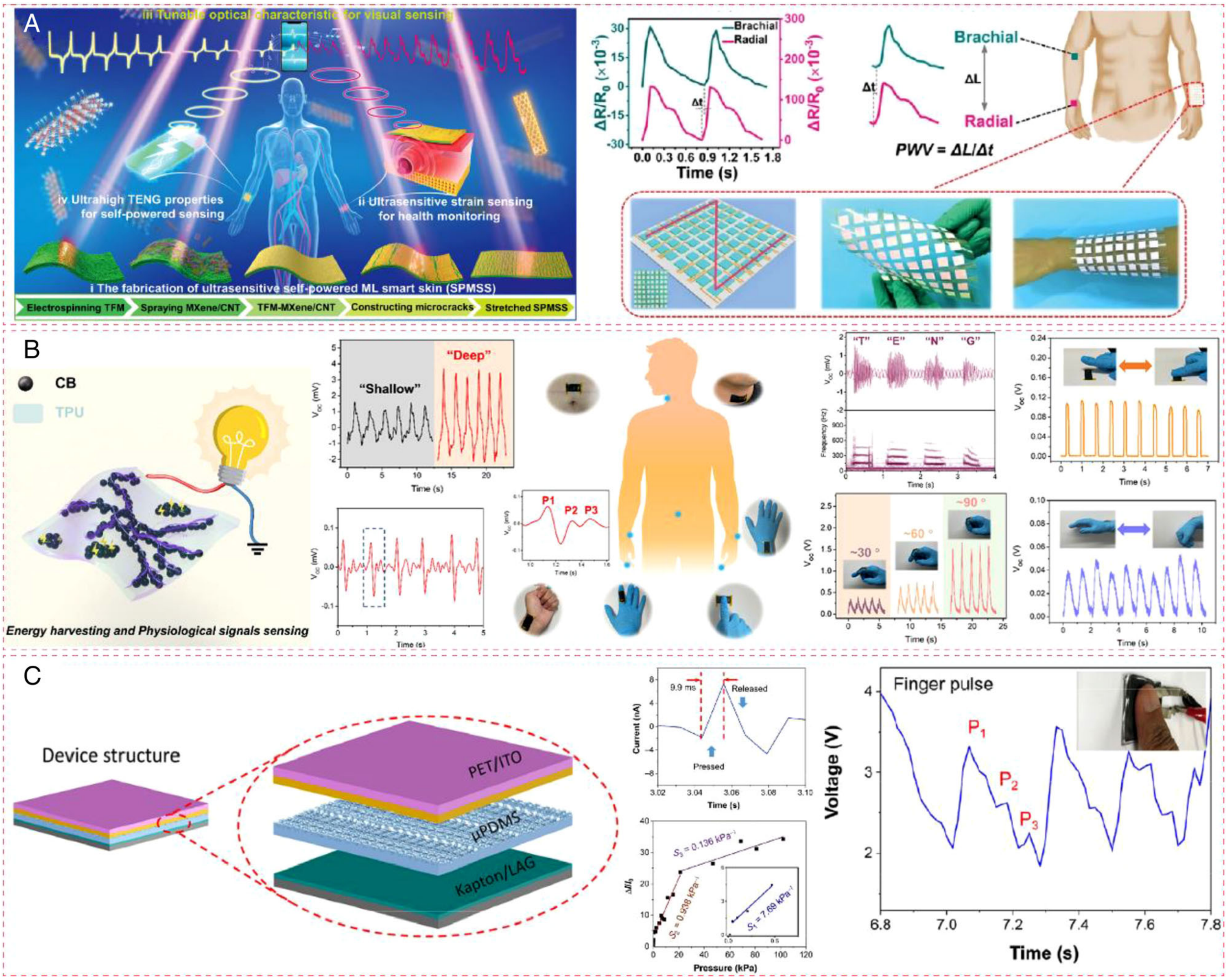

FIGURE 6 Application of for physiological signal acquisition in skin-like sensors (SLSs). (A) Photonic–electronic smart skin with many bio-inspired functions for visual and self-powered sensing and ultrasensitive health monitoring. Reproduced with permission,[45] Copyright 2021, Wiley-VCH GmbH. (B) An ultrathin stretchable triboelectric nanogenerator (TENG) improved by post charging electrode material. Reproduced with permission,[46] Copyright 2021, American Chemical Society. (C) A flexible self-powered pressure sensor for sensing finger pulse and human motions. Reproduced with permission,[44] Copyright 2019 Tsinghua University Press and Springer-Verlag GmbH, Germany, part of Springer Nature

expected to develop more delicate NGs with flexible structures to realize multi-channel detection of complex physiological signals.[47]

3.2 | Skin-like sensors for bioinspired electronics

Bioinspired electronics is a technology that manufactures functional electronic materials and artificial senses by imitating the function and structure of living things.[48–50] SLSs have unique advantages in mimicking biological structures and functions due to their high sensitivity, durability, and low-power consumption.[51] In terms of its specific applications, this section mainly introduces artificial synapses that imitate biological neural structures, and sensory simulations that imitate human perception, such as tactile simulations, olfactory simulations, visual simulations, and auditory simulations.

3.2.1 | Artificial synapses

Artificial synapses mimic the plasticity of the brain and are an important part of future neuromorphic systems. Compared with silicon circuit-based neurons, NG-based artificial synapses has the advantages of simple structure, low manufacturing cost. Compared with the traditional von Neumann calculation method, NG-based artificial synapses has the advantage of lower energy consumption.[48,52] By mimicking the signaling mechanisms and synaptic plasticity of synapses in the brain, precise control of synaptic functions related to learning and memory can be achieved. Shan et al. developed an artificial kinesthetic system consisting of an S-TENG that can be attached to human skin and a field effect synaptic transistor.[53] The friction layers of S-TENG are PDMS and MXene, and the S-TENG has a high sensitivity of $0.197 \mathrm{kPa}^{-1}$ in the low-pressure region of below 6 kPa, and a sensitivity of $0.003 \mathrm{kPa}^{-1}$ in the high-pressure region of $6-30 \mathrm{kPa}$. Field effect synaptic transistor is used to achieve synaptic plasticity and can simulate learning and transition from short-term memory to long-term memory. Therefore, the system has the function of sensing the motion state and direction of the human body. In addition, 15 different simulated sign language gesture signals were collected by the system, and then they were identified by the SVM classification algorithm, and good accuracy was obtained (Figure 7A). Jiang et al. developed a high-resolution pressure piezo-memory system (HPPMS), which is a typical neuromorphic tactile sensor with non-volatile force-resistance switching and force-tunable synaptic functions with a pixel size of only 60 nm.[54] By enhancing processing efficiency and recognition rate, HPPMS enables nanoscale force image sensing and memory action. In principle, the technology offers the opportunity to produce very tiny force dispersion and simplifies the tactile sensor circuit and the development of in-sensor computation (Figure 7B). Chen et al. developed a PENG-based graphene artificial sensory synapse.[55] PENG not only acts as a power source for synaptic devices, but also effectively modulates synaptic weights by changing external strain pulses, and successfully realizes external stimulation/sensing and synaptic transmission. This work achieves modulation of synaptic weights and reduced power consumption by replacing the traditional gate voltage supply with piezoelectric potential, which is highly desirable in low-energy artificial neuromorphic computing systems. This work may be of great help for self-powered AI, neuromorphic sensing systems (Figure 7C).

The current work on artificial synapses is mainly focused on imitating the senses of living things (mainly humans), and in the future it is expected to develop superhuman sensing capabilities, that is, to detect information that cannot be detected by biological sensory organs, such as: ultrasonic or infrasonic waves, infrared or ultraviolet, chemical properties of gases or liquids. In addition, artificial synapses can also provide basic research support for organ chips to some extent.[56] These functions have very broad application prospects for many fields such as robotics, aerospace, or military.

3.2.2 | Tactile simulation

The skin is one of the most sensitive and complicated sensory organs in the human body, transforming environmental inputs into physiological signals that the brain interprets.[35] Typically, mechanoreceptors, as neuronal sensor elements within the skin that receive tactile perception, are buried at varying depths under the skin's surface and react to stresses on varying timescales.[57] There are two kinds of mechanoreceptors, fast adapting (FA) mechanoreceptors and slowly adapting (SA) mechanoreceptors. FA mechanoreceptors primarily perceive force dynamics and generate strong signals during force loading and removal.[58] SA mechanoreceptors are mainly used to feel the continuous effect of static force during long-term stimulation.[57] NG has good mechanical stimulation response ability, and can be used to simulate the mechanoreceptors of skin to realize the function of tactile simulation. Chun et al. presented a self-powered flexible neural tactile sensor (NTS) inspired by human finger skin.[34] The NTS comprises of a 20×20 pixel graphene-based array of ultra-high-density pressure sensors. Importantly, the SA mechanoreceptors and FA mechanoreceptors in NTS devices can detect pressure and vibration as sensitively as real human skin. All signal outputs produced by SA and FA mechanoreceptors, respectively, are very similar to human neural signals. NTS also has the structure and function of simulating human fingerprints, and can classify 12 kinds of fabrics with complex patterns, and the SVM algorithm can achieve a classification accuracy of 99.1% (Figure 8A). Li et al. presented a fiber-structured, highly elastic, and breathable electronic skin.[37] The constructed electronic skin consists of three layers of nanofibers (NFs): polyvinylidene fluoride NFs, carbon NFs, and polyurethane NFs. The electronic skin has a sensitivity of $0.18 \mathrm{VkPa}^{-1}$ and a water vapor permeability of $10.26 \mathrm{kgm}^{-2} \mathrm{d}^{-1}$ in the pressure range of $0-175 \mathrm{kPa}$. Not only does this electronic skin have outstanding tactile sensing capability, but it also has good qualities such as high elasticity, high permeability, self-powered supply, cheap cost, scalability, etc. (Figure 8B). Bu et al. demonstrated a stretchable triboelectric-photonic smart skin (STPS).[35] STPS employs a grating-structured metal sheet to simulate skin stripes, allowing for multidimensional touch and gesture sensing for vertical pressure sensing with a maximum sensitivity of $34 \mathrm{mVPa}^{-1}$. The pressure sensing qualities are stable under various stretching situations, demonstrating synchronous and independent sensing performance in response to external stimuli and a high level of durability. STPS may find use in soft robotics and human–machine interaction (Figure 8C). Li et al. created a PENG-based flexible

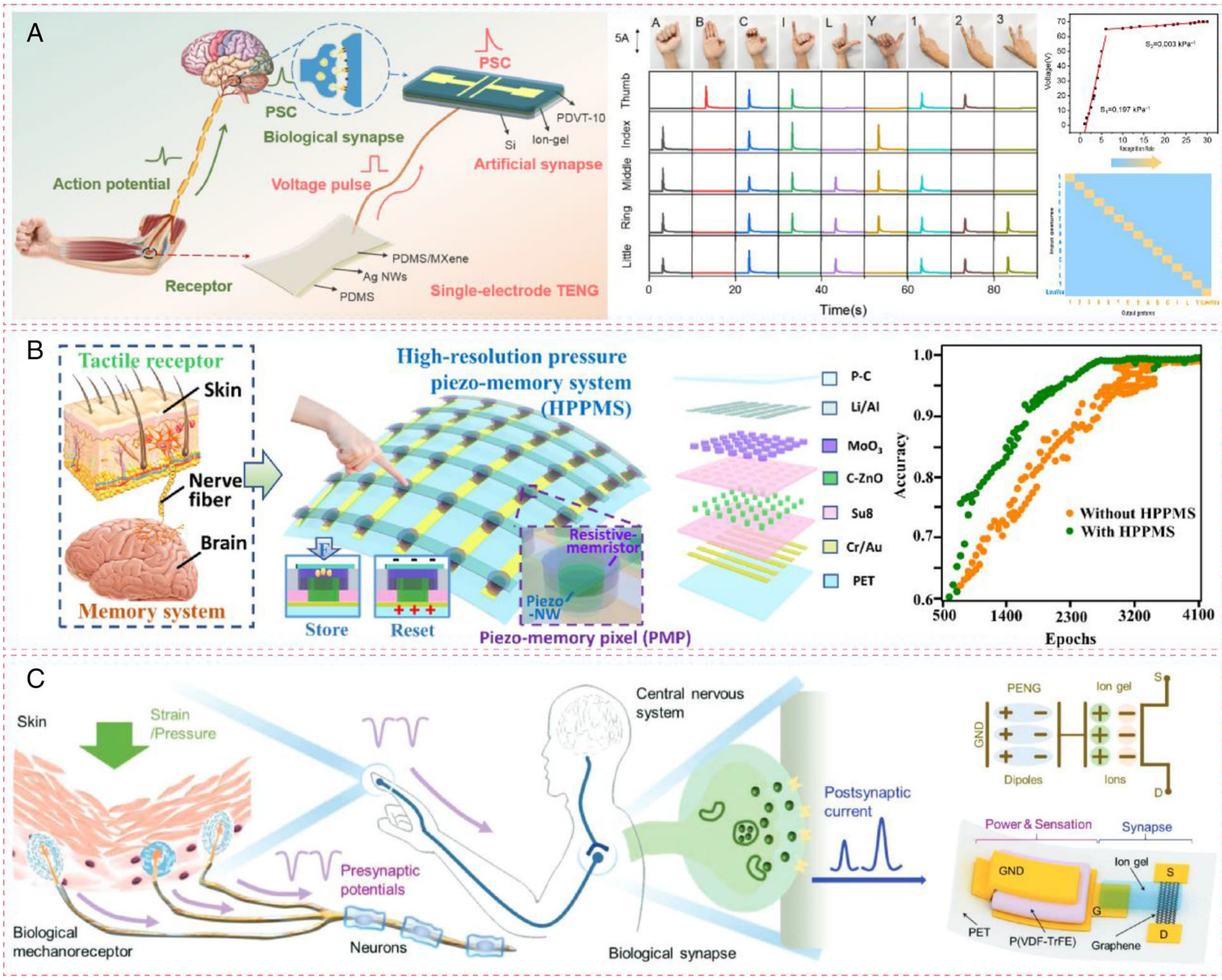

FIGURE 7 Application of artificial synapses in skin-like sensors (SLSs). (A) A triboelectric nanogenerator (TENG) that may be applied to human skin and a field effect synaptic transistor constitute an artificial kinesthetic system, Reproduced with permission,[53] Copyright 2021, Elsevier Ltd. (B) A pressure piezo-memory device with 60 nm pixel size as an ultrahigh-resolution neuromorphic tactile sensor for on-chip computing. Reproduced with permission,[54] Copyright 2021, Elsevier Ltd. (C) By combining piezoelectric nanogenerator (PENG) with an ion gel-gated transistor, a piezotronic graphene artificial sensory synapse was constructed. Reproduced with permission,[55] Copyright 2019, WILEY-VCH Verlag GmbH & Co. KGaA, Weinheim

pressure sensor with a high output voltage by employing a tetrafluoroethylene–hexafluoropropylene–vinylide/cyclic olefin copolymer with outstanding positive/negative charge storage capabilities.[36] By optimizing the compressive properties of piezoelectric electrodes, the sensor exhibits a sensitivity of up to 30 mV kPa^{-1}. At the same time, in the interval of $0-150$kPa, it has a linearity as high as $R^2 = 0.99963$. This work presented a concept for creating PENG with high sensitivity and a broad linear pressure zone, which is beneficial for the development of wearable pressure SLSs. (Figure 8D).

3.2.3 | Olfactory simulation

As one of the most important functions of artificial nose, olfactory simulation can be used to distinguish different kinds of gases. Despite great progress, existing artificial noses still lack sensitivity and selectivity.[59] AI technology plays a very important role in olfactory simulation and can improve the accuracy of gas identification.[60] NG can be used to ionize gases due to its high voltage advantage. Zhu et al. reported a TENG-based sensor for volatile organic compound (VOC) recognition for the simulation of biological olfaction.[61] Using TENG to generate a high output voltage of 600V, the plasma discharge modes of several VOCs with distinct ion transport characteristics were determined. Since the emission patterns of different VOC mixtures are unique and repeatable, the ML algorithm can be used for gas identification. The CNN algorithm is used to automatically extract specific features from the ion mobility spectrometry data to realize the detection of methanol, the four gases, ethanol, acetone, and Isopropyl alcohol (IPA), were classified with an accuracy rate of

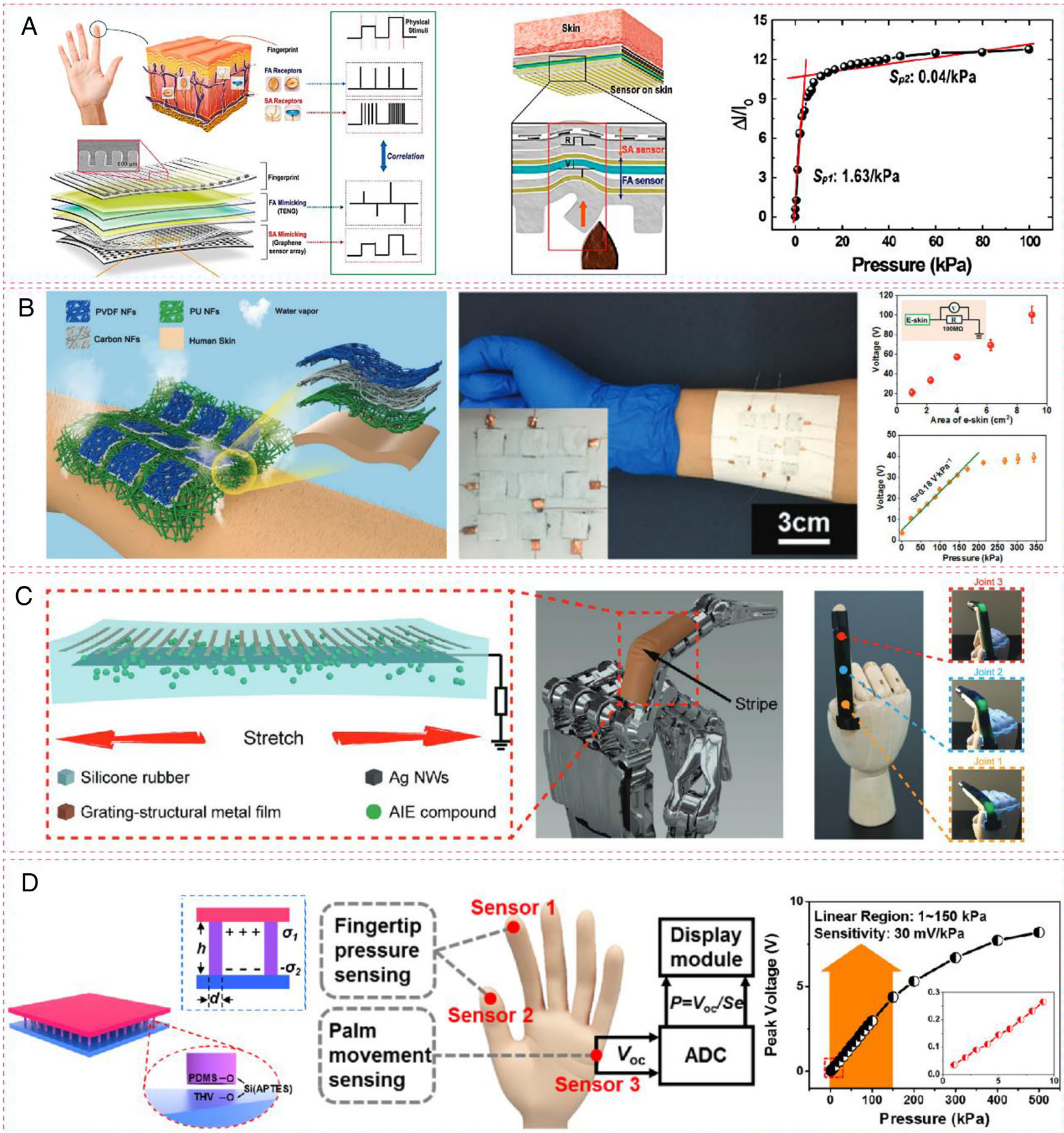

FIGURE 8 Application of tactile simulation in skin-like sensors (SLSs). (A) On the basis of neural finger skin, self-powered pressure, and vibration sensitive tactile sensors. Reproduced with permission,[34] Copyright 2019, American Chemical Society. (B) A scalable electrospinning production method for a fiber-only electronic skin. Reproduced with permission,[37] Copyright 2019, Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim. (C) A triboelectric–photonic flexible smart skin for touch and gesture sensing. Reproduced with permission,[35] Copyright 2018, Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim. (D) A flexible piezoelectric nanogenerator (PENG) that is stable, sensitive, and has a large pressure range that is linear. Reproduced with permission,[36] Copyright 2018, American Chemical Society

48.214%. Although the accuracy is lower than that of traditional ML, it is still within an acceptable range considering the properties of gas molecules (Figure 9).

3.2.4 | Visual simulation

Computer vision has benefited greatly from advances in ML techniques. Computers can recognize a huge number of images with high accuracy using this technique. The challenge of visual simulation can be addressed by merging computer technology with NG image recognition technology.[62] Yu et al. constructed and used a bio-inspired mechanical photonic artificial synapse with a synergistic impact of mechanical and optical plasticity to help mechanical plasticity.[63] A graphene/MoS_2 heterostructure-based phototransistor and an integrated TENG make up the artificial synapse. By controlling the charge transfer in the structure through the friction potential, the photoelectric behavior of synapses such as

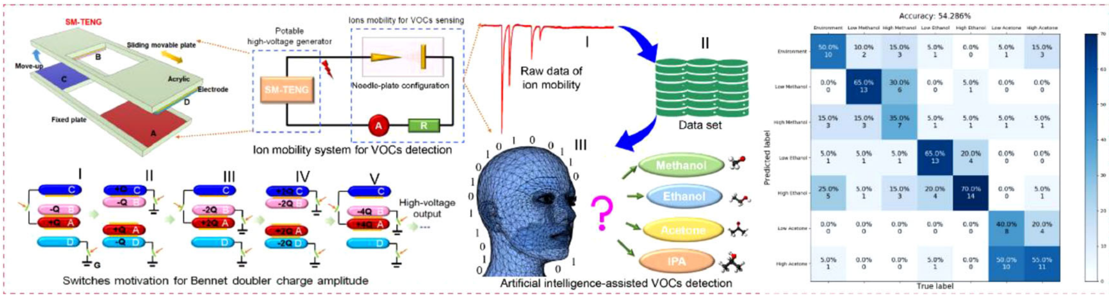

FIGURE 9 Application of olfactory simulation in skin-like sensors (SLSs). Volatile organic compounds sensing based on triboelectric nanogenerator (TENG) and machine learning (ML)-assisted ion mobility analysis. Reproduced with permission,[61] Copyright 2021, Science China Press

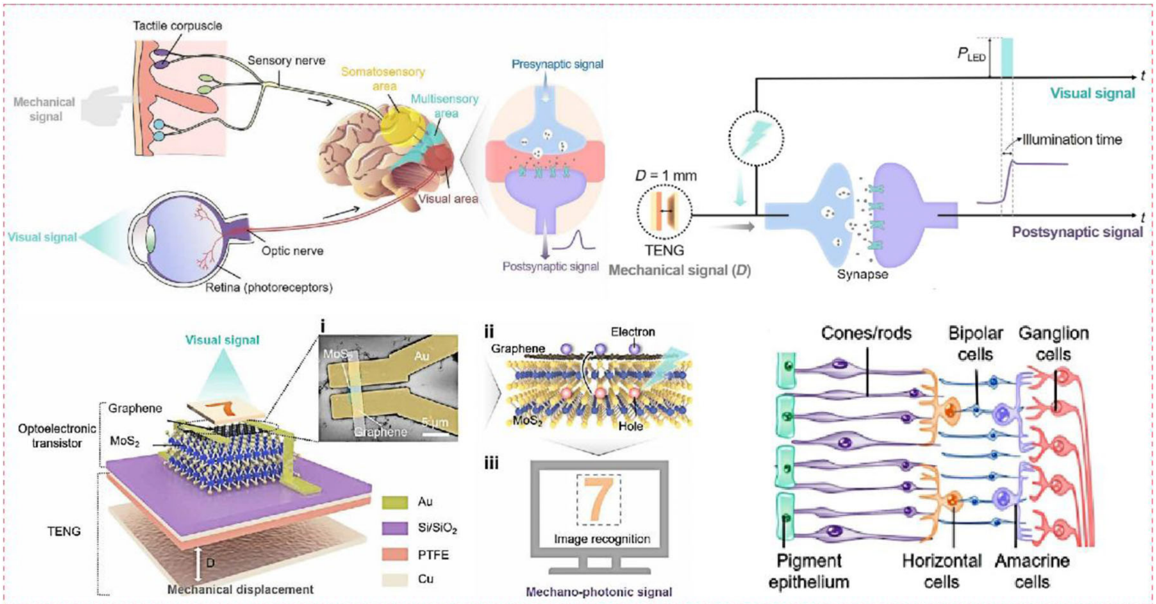

FIGURE 10 Application of visual simulation in skin-like sensors (SLSs). Bio-inspired mechanical photonic artificial synapse with synergistic effect of mechanical and optical plasticity. Reproduced according to the terms of the CC-BY license.[63]

postsynaptic photocurrent, persistent photoconductivity, and photosensitivity can be easily regulated. The error BP technique is utilized to increase the accuracy of image identification to 92% (Figure 10).

3.2.5 | Auditory simulation

More than 10% of the world's population currently suffers from hearing impairment,[64] and external hearing aids can amplify specific damaged sound areas to audible levels.[65] NG is very suitable for auditory simulation due to its good acoustic response performance. Guo et al. designed a self-powered triboelectric auditory sensor for the realization of auditory analog functions.[66] Based on TENG technology, triboelectric auditory sensor shows an ultra-high sensitivity of 110 mV dB^{-1}. By systematically optimizing the design of the boundary structure, the broadband response range can reach 100–5000 Hz. Accurate speech recognition was demonstrated when triboelectric auditory sensor was combined with intelligent robotics (Figure 11).

3.3 | Skin-like sensors for human movement status recognition

The use of NG on SLSs has been shown to detect and monitor human motion and accurately identify different motion states.[67–69] This section reviews the application of existing AI enhanced SLSs in human activity monitoring. The current main application scenarios focus on three aspects: smart gloves,[18–20] handwriting recognition,[70–74] and gait recognition.[10,11]

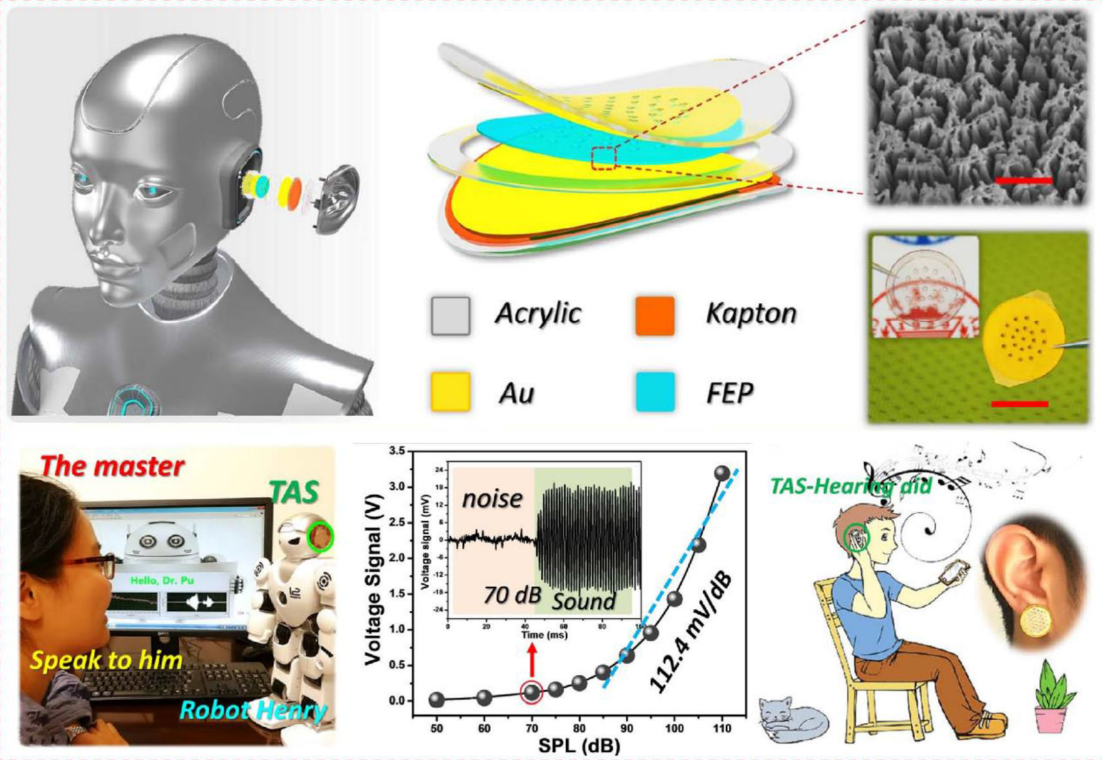

FIGURE 11 Application of auditory simulation in skin-like sensors (SLSs). A triboelectric nanogenerator (TENG) auditory sensor for social robots and hearing aids that is very sensitive and runs on its own power. Reproduced according to the terms of the CC-BY license.[66]

3.3.1 | Smart glove

As a commonly studied human–computer interaction technology, smart gloves based on NG can collect a lot of information from human (mainly hand) movements.[75] Wen et al. investigated a glove with a covering of carbon nanotube/thermoplastic elastomer TENG.[20] By utilizing ML technology to perform different gesture detection tasks in real-time, they can accomplish high-precision virtual reality/augmented reality control, especially in humid circumstances (Figure 12A). Syu et al. developed a bionic and flexible hybrid self-powered sensor by combining copper triboelectric sensors with biomimetic PDMS triboelectric sensors to improve energy harvesting properties.[19] Additionally, smart gloves and force sensors have been validated sequentially using a method based on long- and short-term memory neural network that is capable of distinguishing the movements of five individuals adequately. The developed bionic and flexible hybrid self-powered sensor is a wearable self-power sensor technology with a wide range of application possibilities (Figure 12B). Zhu et al. presented a tactile feedback smart glove that incorporates a triboelectric finger bending sensor, a palm sliding sensor, and a piezoelectric mechanical stimulator.[18] They demonstrate how a self-generated triboelectric signal may be used to identify multi-directional bending and sliding events in a virtual world. The CNN and SVM algorithms are utilized to recognize targets with an accuracy of up to 96% (Figure 12C).

3.3.2 | Writing recognition

Handwritten signature is one of the key biometric qualities, and it is widely employed in scenarios such as reception of products and signing of agreements in everyday life. With the advent of the electronic information age, the storage carrier of handwritten signatures is no longer restricted to paper, but can also be kept through computer hard disks. Therefore, it is vital to design an SLS that can recognize handwritten information. Because NG has the advantages of self-powered and low cost, Zhang et al. used TENG to develop an intelligent self-powered tablet based on the leaf design.[70] The handwriting tablet features a cylindrical surface micro/nano structure, and the recorded handwriting signals have distinct characteristics. Using an SVM decision tree multi-class classifier to recognize six different handwritten English sentences, this classifier has a classification accuracy of 99.66% (Figure 13A). This innovative method for letter recognition of text signals was proposed by a team led by Ji et al. and successfully detected 26 different handwritten letter signals.[71] The PDMS porous

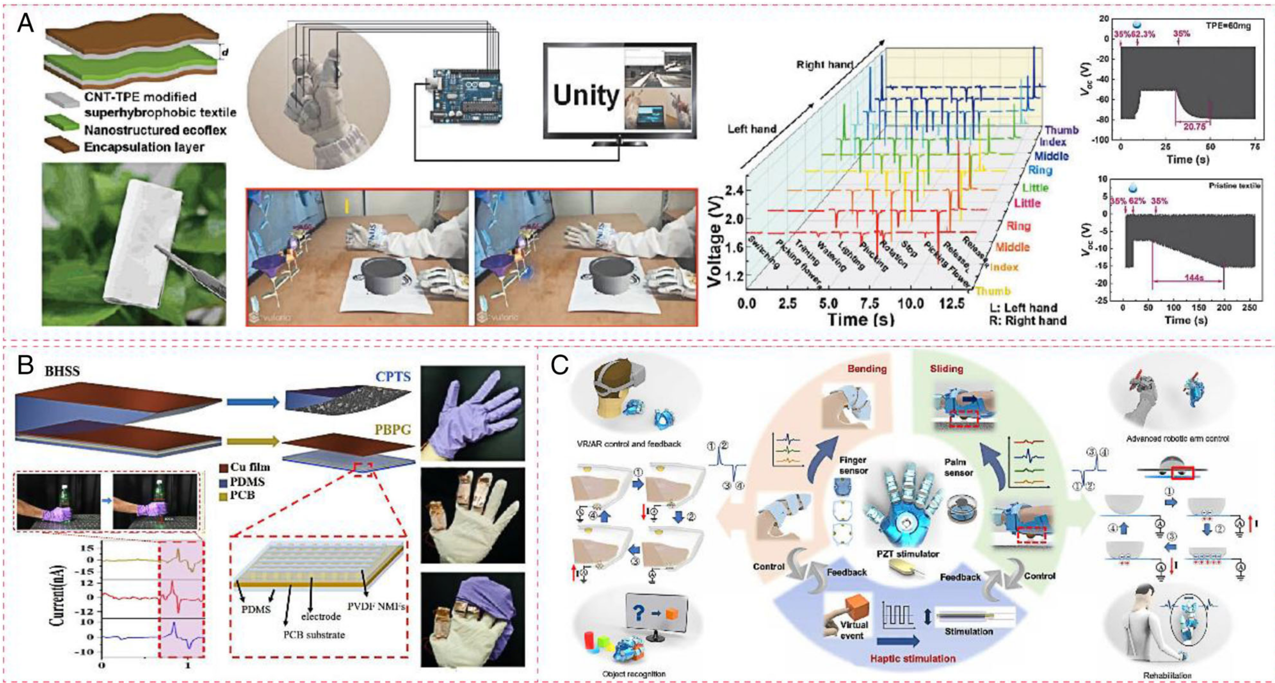

FIGURE 12 Application of smart gloves in skin-like sensors (SLSs). (A) A super-hydrophobic glove based on triboelectric nanogenerator (TENG), which can still maintain a high recognition rate of 96.9% for 11 movements under wet conditions. Reproduced according to the terms of the CC-BY license.[20] (B) Based on long- and short-term memory algorithm biomimetic and flexible hybrid self-powered sensors. Reproduced with permission,[19] Copyright 2020, Published by Elsevier Ltd. (C) A finger bending sensor based on triboelectricity, and the piezoelectric chip performs tactile mechanical stimulation to achieve enhanced human machine learning (ML). Reproduced according to the terms of the CC-BY license.[18]

structure constructed by TENG using sodium chloride can effectively improve the friction area in the application process, and the PDMS and woven copper mesh are fabricated by the water treatment process, which has the advantages of environmental protection and low cost. When employing short-time energy as the letter fingerprint, extracting the letter fingerprint from the short time energy of the original signal, and applying maximum likelihood technology to identify 26 letters, the mid-Gaussian SVM has the highest identification accuracy, reaching 93.5%. A $n*n$ matrix of sensing units is employed when TENG is used to recognize handwritten data. Such a surface design aids in the effective collecting and subsequent processing of handwritten data (Figure 13B). Jeon et al. developed a cloth touchpad that is worn on the wrist based on TENG.[72] The touchpad is composed of low-cost commercial fabric, with seven columns and seven rows (49 pixels), each row or column contains seven-shaped cells, and the friction layer is wool and PTFE. It also uses vertical-contact separation and horizontal sliding blending mode. It is capable of tracking basic movements and creating appropriate output signals. It can classify the numerals 0–9 on the touch panel with 98% accuracy using the pre-trained BP neural network. The technology can be used to connect devices employed in the field of e-textiles, among other things (Figure 13C).

Yun et al. presented a TENG-based touch panel that is self-powered. The touch panel pixel sensor unit is made up of a TENG matrix with seven columns and seven rows (49 pixels).[73] It operates in a hybrid method of vertical-contact separation and horizontal sliding. It detects each pixel that has been touched by comparing the signal peaks generated at the same moment. The number patterns from '0' to '9' are identified with bending angles of 0°, 119°, and 165°, and the classification accuracy is 93.6%, 92.2%, and 91.8%, respectively, using a pre-trained neural network based on the CNN method (Figure 13D). This discovery is likely to be applied in AI-oriented practical internet of things applications such as smart calculators.[75] In addition, Liu et al. proposed a fast-response, high-sensitivity, self-powered artificial sensory memory driven by a triboelectric sensor, and constructed a 28*28 matrix triboelectric sensory receptor with high uniformity and anti-crosstalk to enable real-time vision of handwritten pictures.[74] Specifically, it integrates TENG with field-effect synaptic transistors and enables real-time neuromorphic calculations utilizing the TENG matrix for the first time. The typical aspects of sensory memory, including excitatory postsynaptic current and paired-pulse facilitation, as well as the hierarchical memory process from sensory memory to short-term memory and two long-term memories, have been shown (Figure 13E). It has applications

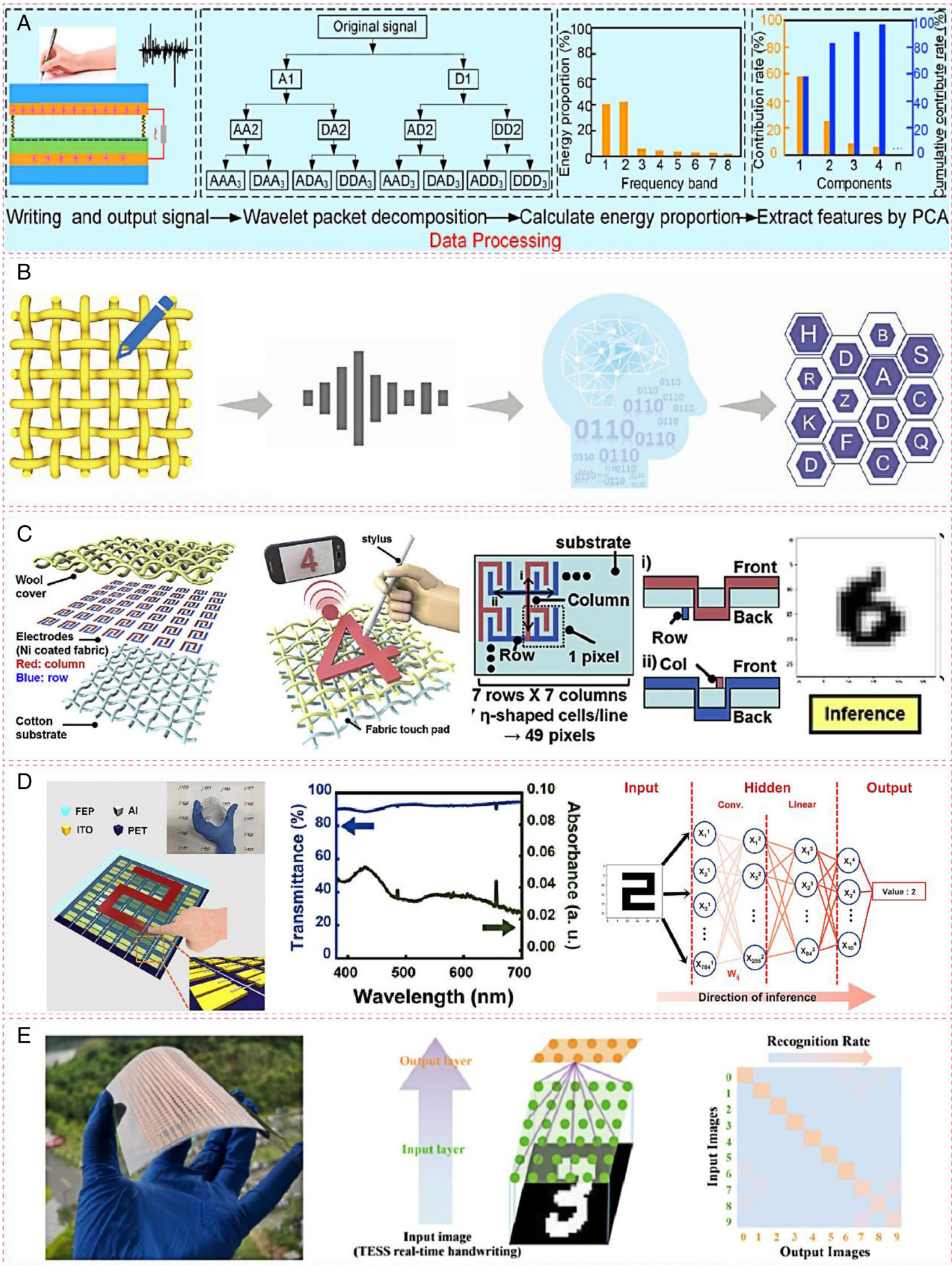

FIGURE 13 Application of writing recognition in skin-like sensors (SLSs). (A) A blade heuristic intelligent self-powered handwriting board based on triboelectric nanogenerator (TENG). Reproduced with permission,[70] Copyright 2020, Elsevier Ltd. (B) A high-sensitivity flexible TENG that adopts a new method for letter recognition of text signals. Reproduced with permission,[71] Copyright 2020, WILEY-VCH Verlag GmbH & Co. KGaA, Weinheim. (C) Self-powered wearable fabric touchpad based on backpropagation algorithm neural network. Reproduced with permission,[72] Copyright 2019, Elsevier Ltd. (D) Flexible self-powered touch panel based on convolutional neural network. Reproduced with permission,[73] Copyright 2020, Elsevier Ltd. (E) A TENG with a 28 × 28 matrix and a high level of uniformity and resistance to crosstalk. Reproduced with permission,[74] Copyright 2020, Elsevier Ltd

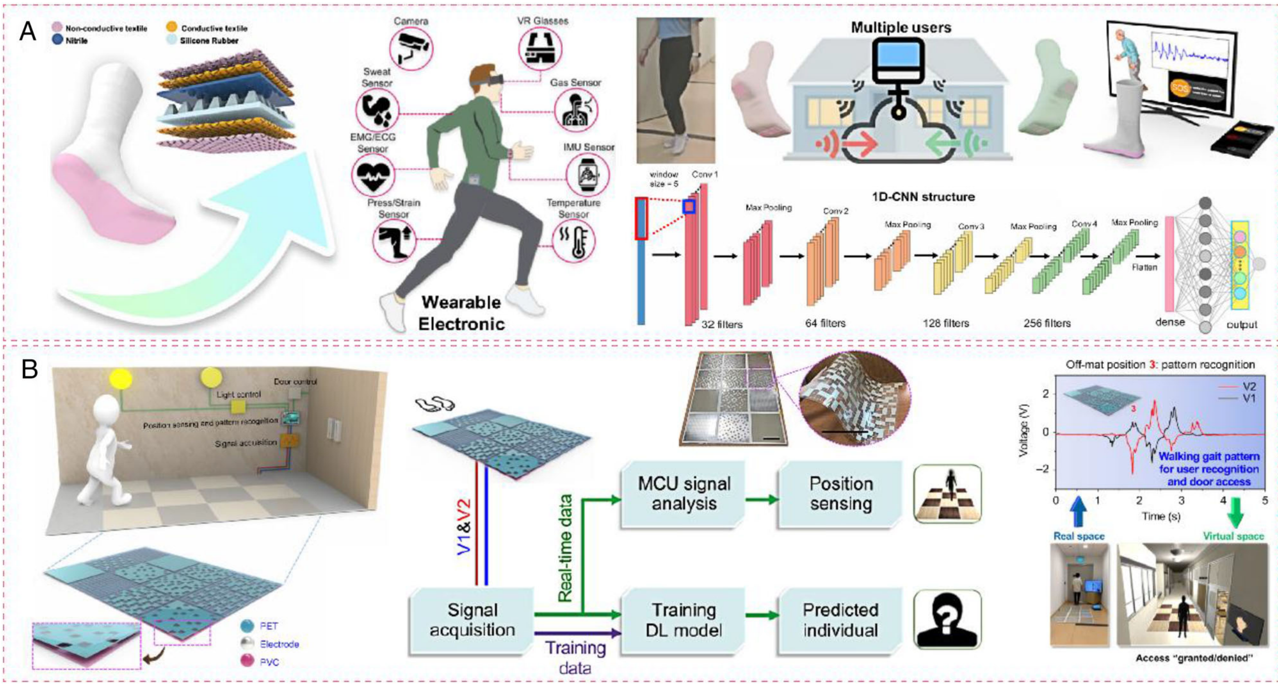

FIGURE 14 Application of gait recognition in skin-like sensors (SLSs). (A) A low-cost smart sock that uses friction to collect extra energy from low-frequency human movement to send sensor data wirelessly. Reproduced according to the terms of the CC-BY license.[10] (B) A smart floor monitoring system that utilizes real-time sensor data processing to determine how many steps have been taken, the number of persons using the floor, and what type of activity is being done. Reproduced according to the terms of the CC-BY license.[11]

in areas such as human–computer interaction and edge computing.[76]

3.3.3 | Gait recognition

NG has the characteristics of flexibility, low cost, strong scalability, etc. It is suitable as a sensor for human motion state detection and has a wide range of applications in smart home monitoring. Zhang et al. created low-cost friction smart socks that collect energy from low-frequency human movement and function as wearable sensors, conveying information about the user's identification, health state, and activities.[10] They achieved a recognition accuracy of 93.54% for 13 people and a detection accuracy of 96.67% for five separate human activities using a DL model with an end-to-end structure on the gait analysis sock signal (Figure 14A). Shi et al. demonstrated a smart floor monitoring system that utilizes self-powered friction electric footpads in conjunction with DL data processing.[11] The floor mat is manufactured with an "identity" electrode design that enables parallel connection, reducing system complexity and DL computation costs. The step position, activity status, and identifying information may be determined by the processing of real-time sensory data. It can be used in intelligent sports and medical monitoring systems (Figure 14B).

4 | CURRENT CHALLENGES AND OUTLOOK

4.1 | Stress adaptation

SLSs tend to work directly on the skin and therefore have performance requirements for flexibility and stretchability. Many reported works have achieved flexibility and stretchability through material selection and structural design. However, there is still a lot of work to be done to truly meet the needs of practical applications and achieve close contact between materials and skin. One of the most important issues to address is stress adaptation. Generally speaking, due to the difference in Young's modulus between two materials, the deformation amount of the two materials is different when subjected to external force, and this difference becomes particularly pronounced at the contact interface. When subjected to periodic external force, the connection interface is prone to mechanical damage, which affects the sealing performance and structural integrity of the material. In the design process of flexible SLSs, two stress adaptation issues need to be considered: one is the stress adaptation between the two flexible materials of the sensor, and the other is the stress adaptation between the sensor material and the human skin adaptation. Future studies urgently require material innovation to simultaneously achieve more accurate sensing functions and better solve stress adaptation issues.

4.2 | Stretchability–conductivity

SLSs usually consist of functional materials, structural materials, and electrode materials.[77] Among them, the circuit part often uses metal electrodes with special patterns or fully flexible polymer conductive materials. However, regardless of the material, as the length and cross-sectional area of the electrodes change due to stretching, so does the electrical conductivity. Changes in the circuit part will generate some false signals, thus misleading the judgment of the sensor. Special circuit design, such as a high-resistance sensor section, can mitigate stretchability–conductivity interference. In addition, designing flexible circuits that are less affected by stretchability–conductivity or have higher conductivity are also a possible solution.

4.3 | Algorithm optimization

Due to differences in materials, architectures, and application situations of TENG-based sensors, they will generate data of varying sizes and types. Therefore, it is critical to choose an appropriate AI optimization method for the characteristics of these data. For instance, supervised learning algorithms are the most commonly used in sensor-related applications (61%) compared to reinforcement learning (27%) and unsupervised learning (12%).[78] In the future, more efficient and targeted algorithms will emerge to adapt to the sensors in the SLS systems, thereby increasing SLSs efficiency and minimizing energy loss. The AI algorithms research based on TENG will contribute to the integration and development of AI and TENG.

4.4 | Function integration

Currently, many TENG-based SLS implementations are still monolithic. In the future, with the increasing demand for multi-function, devices will gradually develop in the direction of miniaturization, integration, and multi-function coupling. For example, SLSs are expected to monitor multiple physical quantities or different sites simultaneously. Therefore, it is very necessary to study the functional integration of AI technology in TENG-based SLSs applications, which will promote the integration and development of AI technology and TENG in SLSs. Additionally, the development of hybrid TENGs to continuously improve the energy harvesting efficiency also has practical significance for its application in SLSs. For example, by combining TENG with electromagnetic generator,[79,80] the frequency range of mechanical energy collection can be greatly increased (from low to high frequency, from small to large amplitude), therefore enabling wider sensing and more efficient energy supply. At present, hybrid TENG systems mainly consist of simple stacks of various energy harvesters. Therefore, it is necessary to improve the interoperability of the hybrid power system by logically organizing various energy units.[81]

In conclusion, the AI-enhanced SLSs based on NG is a systemic effort that incorporates multiple current advanced technology. It is not a simple patchwork of several technologies, but complementary advantages. Each of the included technologies must be synergized with other technologies, with the ultimate goal of achieving higher performance sensor system. It is foreseeable that AI-enhanced SLSs will play a more important role in the field of biomedical diagnosis and treatment with the improvement in stress adaptation, stretchability–conductivity, algorithm optimization, and function integration.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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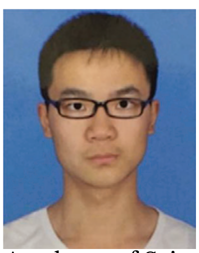

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