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PERSPECTIVE

Machine-Learning-Aided Self-Powered Assistive Physical Therapy Devices

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ABSTRACT: **An expanding elderly population and people with disabilities pose considerable challenges to the current healthcare system. As a practical technology that integrates systems and services, assistive physical therapy devices are essential to maintain or to improve an individual's functioning and independence, thus promoting their well-being. Given technological advancements, core components of self-powered sensors and optimized machine-learning algorithms will play innovative roles in providing assistive services for unmet global needs. In this Perspective, we provide an overview of the latest developments in machine-learning-aided assistive physical therapy devices based on emerging self-powered sensing systems and a discussion of the challenges and opportunities in this field.**

Almost one billion people worldwide suffer from hearing,[1−3] visual,[4−6] verbal,[7−9] or physical[10−12] disabilities. Individuals with disabilities are at high risk of experiencing healthcare and employment barriers,[13−15] depression,[16−18] anxiety,[19,20] distress,[21,22] and even danger from their medical conditions.[23−25] Furthermore, by 2050, approximately 22% of the world's population will be over 60 years old, creating a new global challenge for healthcare systems.[26] As a practical tool for aiding those with disabilities engage in social life, assistive physical therapy (APT) devices play a critical role in their daily lives.[27−29] Assistive physical therapy devices are adaptive and rehabilitative devices that are designed to mitigate the effects of disabilities in performing tasks such as cognition,[30,31] communication,[32,33] literacy,[34,35] and mobility;[36,37] these devices can take different forms, including accessories or implants. Because individuals display unique health profiles by virtue of their varying family medical histories, lifestyles, and genetics, providing assistive services depends on practical, sensor-acquired data analysis.[38−40] Challenges in creating APT devices thus far largely stem from the demand for a diversified application market for more advanced functionality and portability.

As the world marches into the era of the Internet of Things (IoT) and 5G technologies, APT devices have become more interactive and have the potential to provide user-generated data continuously at the Gigabyte level per person per day.[41−43] Culling effective parameters from such large data sets for APT devices has been particularly challenging for practical employment. Machine learning (ML) is a widely used artificial intelligence (AI) technology for big data processing.[44−46] Machine-learning boundaries are a deep-learning domain that can classify and process a large amount of sensor data.[47−49] A deep-learning method is an algorithm that can mimic human cognitive processes.[50−52] It can learn rules from data and automatically improve the learning process without explicit programming. Typically, large-scale, deep-learning systems require 1 million or more data points because AI technology commands a large amount of data to train its model. Machine learning can also optimize sensor networks and monitor dynamic signals that change with time. Moreover, ML based on artificial neural networks (ANNs) can also compress and

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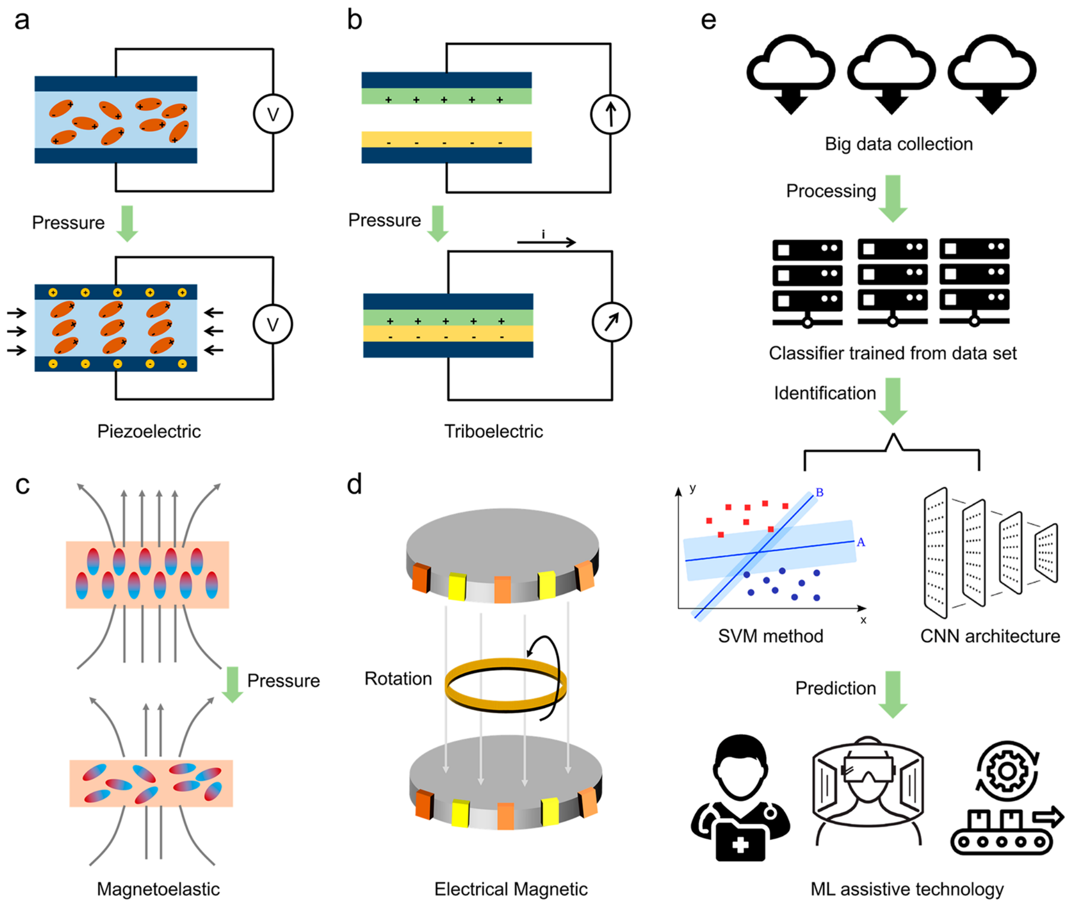

Figure 1. Working mechanism of machine-learning (ML)-aided self-powered assistive physical therapy (APT) devices. Schematics of working mechanism of (a) piezoelectric nanogenerator, (b) triboelectric nanogenerator, (c) magnetoelastic generator, and (d) electrical magnetic generator. (e) Common process of ML-aided APT devices.

restore data for IoT and edge computing systems, thereby improving transmission efficiencies for sensor data collection and processing.[53,54] Significantly, machine learning algorithms can help retrieve the most accurate information for APT devices through incomplete signals.[55−57]

However, most traditional APT devices require battery power to sustain normal operations. Because batteries have low power densities, limited life spans, and high weight, they not only fail to contribute to the miniaturization and portability of APT devices but can increase the wearing burden on people with disabilities.[58,59] In addition, battery-related environmental issues, power costs, charging time, and node maintenance cannot be ignored.[60] For elderly or motion-impaired users, buying and replacing batteries for their APT devices will become a nagging problem.[61] To resolve these issues, it is vitally important to exploit self-powered APT devices.[62−65] By leveraging biomechanical energy conversion, self-powered sensors are able to measure biomechanical motion by the generated electrical signals.[66−75] They can track and record the dynamic changes of biomarkers such as sound,[76−80] pulse wave,[81−85] and biomechanical motion[67,70,86−88] using electrical signal profiles. Self-powered sensors based on piezoelectric,[89−91] triboelectric,[84,92−94] magnetoelastic[95−98], and electromagnetic effect[99,100] have been developed in the community. Moreover, some self-powered sensors can be used in harsh and distributed environments[101] to reduce the maintenance costs of replacing batteries.[102] For these reasons, self-powered sensors are well suited to ML data delivery, providing a new impetus for the development of self-powered APT devices.

In this Perspective, we first illustrate the working principles of different types of self-powered APT devices based on mechanical-to-electrical conversion, including piezoelectric, triboelectric, magnetoelastic, and electromagnetic effect-based devices. We then describe ML algorithms employed in APT devices and highlight each self-powered sensor category for APT devices from the perspective of advanced materials innovation, functional system design, and ML algorithms. Finally, we describe the technical nuisances and potential pathways of future APT devices.

WORKING MECHANISMS

Piezoelectric Effect. First developed in 2006, piezoelectric nanogenerators (PENGs) based on zinc oxide nanowires are commonly built with a sandwiched structure containing a specific piezoelectric material and two vertically aligned electrodes (Figure 1a).[103] Applied forces cause dipoles to diverge in the piezoelectric material, which contributes to charge accumulation at the electrodes. Inorganic piezoelectric materials such as zirconate titanate[104,105] lead zirconate titanate (PZT), barium titanate,[106,107] zinc oxide,[108,109] lead titanate,[110] and aluminum nitride[111] enable ions and anions to move asymmetrically to induce polarization because of their particular crystal structure. Other polymer piezoelectric materials such as poly(vinylidene fluoride trifluoroethylene)[112] and nylon[113,114] enable constant dipole correction in the presence of an applied

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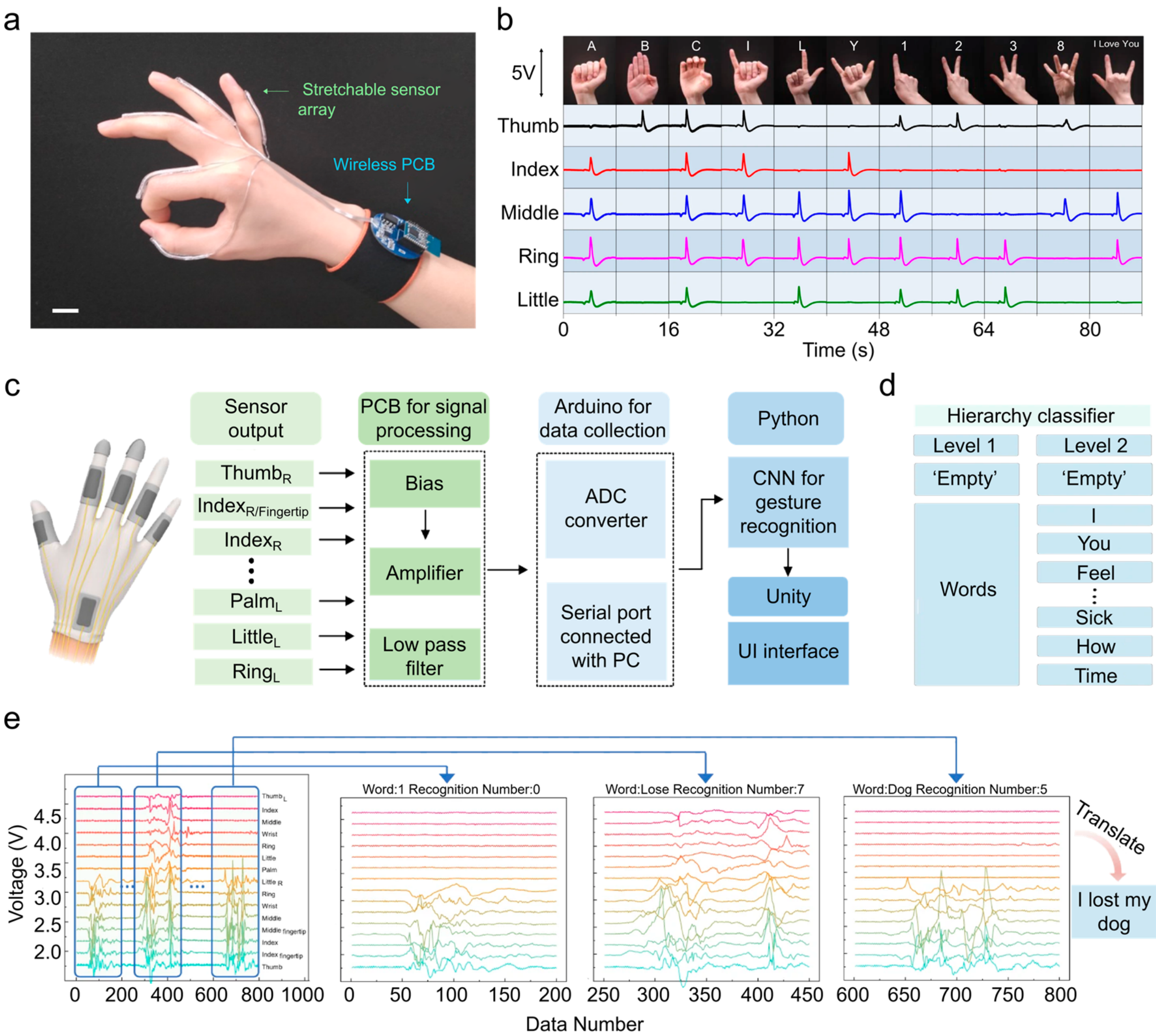

Figure 2. Sign language translation. (a) Photograph of the skin-attached wearable sign-to-speech translation system. Scale bar, 2 cm. (b) Photographic representations of sign language hand gestures as defined by American Sign Language and the corresponding generated voltage profiles as recognition patterns to express letters, numbers, and short phrases. PCB = printed circuit board. Adapted with permission from ref 69. Copyright 2020 Springer-Nature. (c) Flowchart of the sign language recognition and communication system. (d) Schematic diagram of the hierarchy classifier. (e) Recognition process of three new sentences that the convolutional neural network (CNN) model had not previously learned, taking "I lost my dog" as an example. ADC = arduino data collector. UI = User interface. Adapted with permission from ref 153. Copyright 2021 Springer-Nature.

force. Piezoelectricity-based sensing is a widely used transduction method that refers to the electrical potential generated in certain materials in response to applied mechanical power. As a result, piezoelectric sensors have sparked great interest due to their mechanical flexibility, extended lifetime, and chemical stability. However, piezoelectric sensors have been limited in their use due to issues of sensitivity, material selectivity, and preparation.

Triboelectric Effect. Since 2012, triboelectric nanogenerators (TENGs) have been of particular interest as candidates for wearable electronics due to their compelling features,[64,65,94] including diverse material choices, simple configuration, light weight, high output voltage, and good biocompatibility.[115−120] Their mechanical-to-electrical conversion results from the coupling of the triboelectric effect and electrostatic induction.[71,121−126] Take the vertical contact-separation working mode for illustration: mechanical compression contributes to the charge transfer between the surfaces of the two triboelectric materials, generating an electrical signal in the external circuitry (Figure 1b).[73,85,127] Various flexible and stretchable triboelectric materials, such as polytetrafluoroethylene,[128] polydimethylsiloxane,[129] Kapton,[130] polyethylene terephthalate,[131] and nylon,[132] as well as conductive materials,[133] are commonly used for TENG fabrication. The sensitivity of the TENG can be improved through physical, chemical, biological, and hybrid approaches.[134−136] However, the compelling characteristics of TENGs are built upon functional triboelectric materials and unique surface charge effects, which are typically not stable when exposed to the ambient environment without an encapsulation, especially in wet or chemically charged liquid settings.[137,138]

Magnetoelastic Effect. The magnetoelastic effect is the phenomenon in which the magnetism of some magnetic materials changes with mechanical deformation.[139,140] This effect is traditionally observed in some metals and metal

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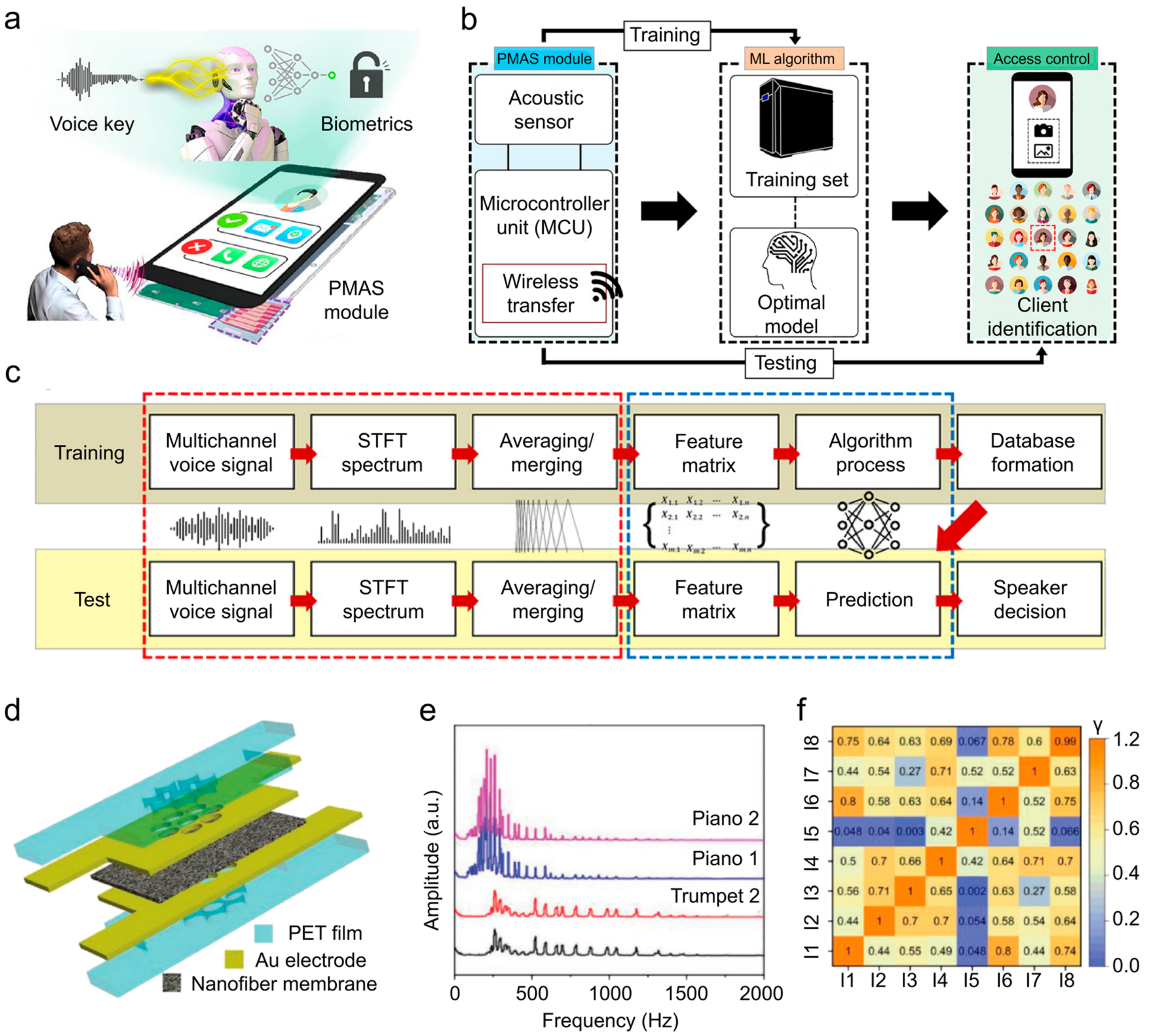

Figure 3. Hearing aid. (a) Biometric authentication for mobile application using integrated acoustic module composed of mini piezoelectric mobile acoustic sensor (PMAS), machine-learning (ML) processor, and wireless transmitter. (b) Schematic diagram of ML-based mobile biometric authentication using PMAS module. (c) Flowchart of Gaussian mixture modeling (GMM) algorithm for speaker training and testing procedures composed of signal averaging, feature extraction, and layer formation. Adapted with permission from ref 105. Copyright 2021 American Association for the Advancement of Science. (d) Schematic structure of the acoustic sensor device. (e) The "db5" wavelet decomposed signals from the sounds generated by piano and trumpet. (f) Pearson correlation coefficients calculated among the "db5" decomposed signals recorded from various musical instruments (I1, I2, I3, I4, I5, I6, I7, I8, representing piano, cello, basslap, organ, flute, guitar, trumpet, and violin, respectively). Adapted with permission from ref 154. Copyright 2021 Wiley-VCH GmbH.

alloys.[141,142] In 2021, the giant magnetoelastic effect was discovered in a soft system without the need of external magnetic fields by the Chen group at the University of California, Los Angeles,[95] enabling the development of high-performance self-powered magnetoelastic sensors (Figure 1c).[95−97] The giant magnetoelastic effect observed in soft matter arises from changes in the micromagnet wavy chain structure under mechanical deformation. This effect differs from the traditional magnetoelastic effect seen in metal alloys, which is caused by stress-induced magnetic domain rearrangement under an externally applied magnetic field. With magnetization, the nanomagnets inside the soft magnetoelastic layer are analytically considered to be single magnetic dipoles and well-aligned in a wavy chain structure to maintain a stable system. When compressed, the pressure provides constant energy for the movement and rotation of these magnetic nanoparticles, thus changing the surface magnetic flux density. The recovery of the wavy chain structure after the uniaxial pressure release brings the magnetic flux density back to its original level. With their compelling features of being soft, stretchable, and intrinsically waterproof, magnetoelastic sensors are ideal for providing high-quality biomechanical sensing.

Electromagnetic Effect. Electromagnetic sensors are based on Faraday's law of electromagnetic induction (Figure 1d). The mechanical force induced relatively movement between magnet and coils, resulting in a magnetic flux change within the coils and thus converting the mechanical force into electrical signals induced by the conductor into a change in the output signal.[143−145] Because electromagnetic sensors have a high output signal, good anti-interference performance, and do not require an external power supply, they can be used in various harsh enviroments with smoke,[146] oil,[147,148] water, and gas.[149]

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Their output amplitude is related to the velocity of the gear rotation caused by the magnetic gap change in the probe coil. Made of magnet and metal coils, the electromagnetic sensors are usually not flexible and could be integrated into wearable platforms such as watches, bracelets, and accessories on bags and clothes.

MACHINE LEARNING

Machine learning uses algorithms and statistical models to enable a computer to perform a given task without explicit guidance, usually dividing data into training, validation, and test data. Given a training set consisting of a sample X and its label Y, an ML algorithm can learn a function that produces an output vector Y from an input X. After formulating the model in the training phase, the learned model can predict the labels of new data. Validation data are used to select the model, and its parameters are estimated from the training data. Validation losses are obtained by applying a trained model to the validation data. Finally, the performance of the algorithm is evaluated using the test data. Core ML methodology for APT devices includes standard methods (Gaussian mixture modeling, GMM; support vector machine; hidden Markov model) and deep-learning methods (deep neural network; convolutional neural network, CNN; recurrent neural network) (Figure 1e). As AI technology evolves, more and more devices are integrated with ML to support fast processing and real-time big data analysis for intelligent decision making, state recognition, and automatic control. To understand and interpret the signal flow generated by gestures and actions, we need to use automated algorithmic models for long-term, efficient, and reliable data processing. By training neural networks on an end-to-end basis, computers can learn more representative features of raw signal data, enabling advanced capabilities.

APPLICATION SCENARIOS

The provisioning of APT devices is an individual and collective service of the welfare state. Overarching goals include reducing social exclusion and marginalization and, most importantly, making everyday life easier for people. In light of burgeoning assistive technology trends, we discuss the latest ML-aided APT devices based on emerging self-powered sensing systems for sign language translation, hearing aids, gait analysis,[150−152] human−machine interfaces (HMIs), and mobility aid.

Sign Language Translation. One promising ML-aided technology is a wearable sign language recognition device that establishes communication between signers and nonsigners. An estimated 466 million people worldwide suffer from disabling hearing impairment, and many face communication challenges due to a lack of tools to communicate effectively with others who do not know sign language. Recently, Zhou *et al.* developed a wireless, wearable, sign-to-speech translation system that is worn as a glove (Figure 2a).[69] Central to this achievement is a TENG-based stretchable sensor, including a stretchable microfiber as the inner core, a conductive yarn based on twisted microfibers of stainless steel and polyester, and a polydimethylsiloxane sleeve to cover the entire structure. The conductive yarn forms a coil structure around the rubber microfiber to afford uniaxial stretchability of up to 90%. With ML algorithm support and a mobile application interface, it can independently translate sign language into voice at an accuracy of greater than 98% in real time (Figure 2b). This cost-effective wearable technology was developed to break down barriers between signers and non-signers for communication.

Additionally, a smart glove integrated with a triboelectric sensor system and ML-assisted intelligence has successfully achieved recognition of 50 words and 20 sentences in sign language recognition.[153] By integrating functions of hand motion capturing (by TENG-based gloves), signal preprocessing (by circuit boards), data collection, and signal recognition (by deep-learning-based analytics), Wen *et al.* developed a system of recognition and communication, as shown in the flowchart in Figure 2c. They also developed a classifier with a hierarchical structure to improve sentence recognition and to pave the way for the identification of new sentences (Figure 2d). Segmented into first- and second-level classifiers, the disturbance of capricious empty signals on common sorters was reduced significantly, raising the recognition accuracy for word pieces to 83%. In addition, the system also successfully identified never-before-seen New1−New3 sentences, which were formed by new-order word recombination with an order that differed from that of the sentences in the data set. The process shown in Figure 2e demonstrates the accurate recognition of the new/never-before-seen sentence with the stage of segmentation and real-time sequential fragment identification. This system provides a universal and practical platform to improve sign language translation toward practical communication.

Hearing Aids. Recently, Lee and colleagues reported a highly sensitive and flexible piezoelectric mobile acoustic sensor (PMAS) *via* biomimetic frequency band control.[105] By gathering acoustic data from PZT film on an ultrathin polymer membrane, they applied ML-based biometric authentication as an algorithm processor and signal transmitter (Figure 3a). Thereby, multichannel data from a PMAS inserted into a smartphone was wirelessly transmitted to an ML processor and a customized biometric app. Eventually, control to access permission and prohibition to the mobile smartphone was done through a GMM algorithm that compared the PMAS module multichannel signal with the pretrained database. The process of AI-based biometric authentication is shown in detail in Figure 3b. The integrated PMAS module consisted of a mini PMAS, a signal transmitter, and an ML processor, and the multichannel PMAS was connected to a microcontroller unit (Raspberry Pi 3 Model B+) for the wireless transfer of input voice information. The GMM-based training and testing procedures for the multichannel PMAS module are presented in the Figure 3c flowchart. The input voice signal of the PMAS module is used for feature extraction and layer formation, and the voice information on an individual speaker is recorded into the database with the training procedure.

Another investigation of voice recognition with ML assistance is based on a PENG fabricated from electrospun polyacryonitrile (PAN) nanofibers. The structure of the nanofiber sensor consists of a piece of electrospun PAN nanofiber membrane sandwiched between two Au-coated polyethylene terephthalate (PET) films as piezoelectric electrodes (Figure 3d).[154] By processing the voltage output from the sound played by the piano and trumpet, the Daubechies wavelet of order 5 ("db5") decomposed signals from the sounds generated by the piano and the trumpet (Figure 3e). All of the Pearson correlation coefficients from the same instrument were above 0.99, indicating excellent signal repeatability, whereas those between different musical instruments were below 0.80 (Figure 3f), indicating excellent capability to distinguish sound with high reliability.

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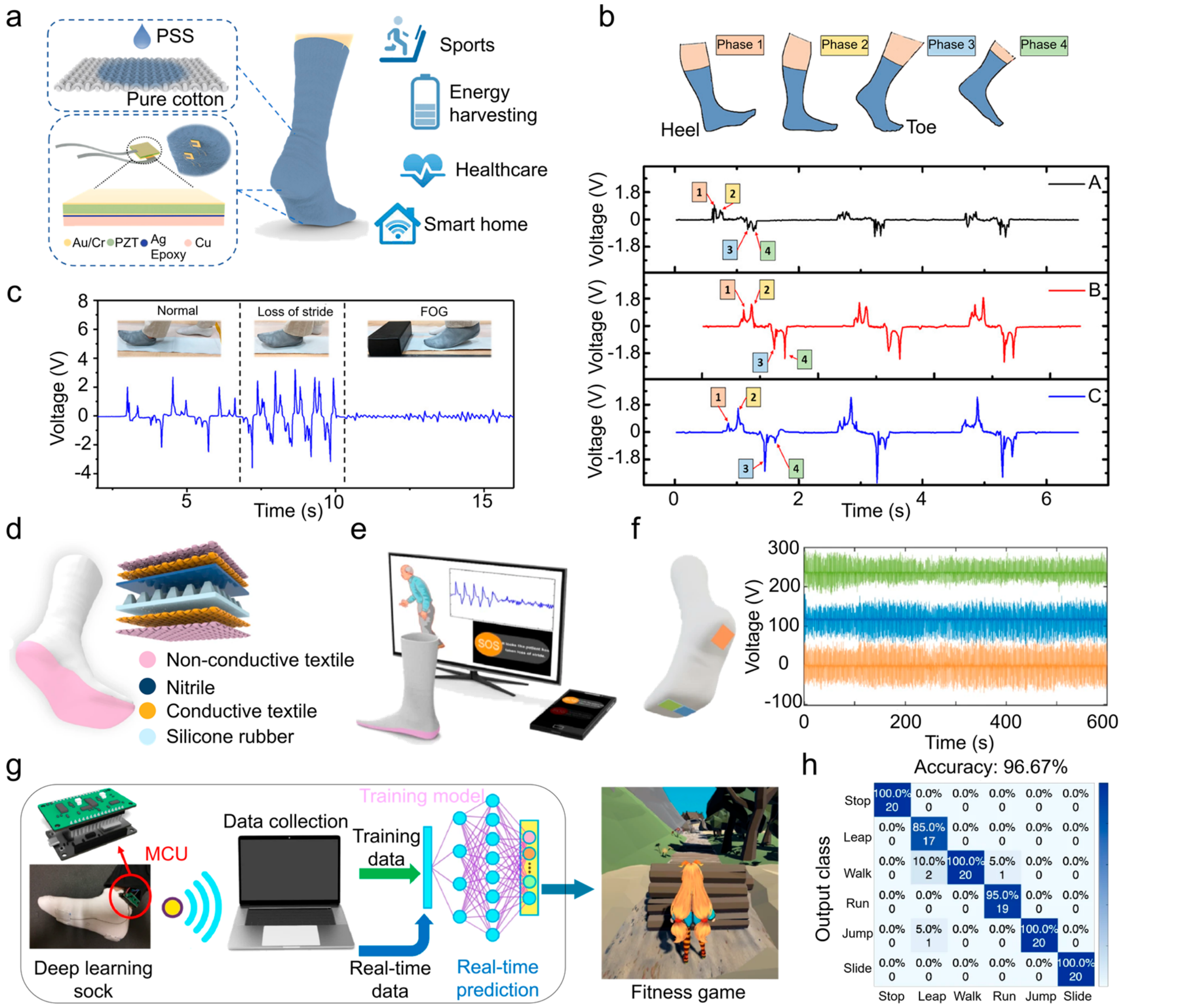

Figure 4. Biomonitoring systems. (a) Schematic of PEDOT:PSS-coated triboelectric S^2-sock integrated with lead zirconate titanate (PZT) force sensors for diversified applications, with the left side showing enlarged views of the triboelectric nanogenerator (TENG) textile and embedded PZT sensor. (b) Schematics of four phases of the typical contact cycle and corresponding signals: (1) heel contact, (2) forefoot/toe contact, (3) heel leave, and (4) forefoot/toe leave. (c) Mimetic walking patterns of a Parkinson's disease patient under three conditions: normal, loss of stride, and freezing of gait (FOG). Adapted from ref 155. Copyright 2019 American Chemistry Society. (d) Detailed structure of intelligent socks to assist wearable electronics. (e) Maximum output power of a single sock on the right foot. (f) Schematic of triple-sensor sock and its three-channel output characteristics within 600 s. (g) Process flow from sensory information collection to real-time prediction in virtual reality fitness games. MCU = microcontroller. (h) Confusion map for deep-learning outcome. Adapted with permission from ref 156. Copyright 2020 Springer-Nature.

Gait Analysis. The ML-aided APT devices could also be applied for gait analysis. Zhu *et al.* reported a self-powered and self-functional sock (S2-sock) based on a poly(3,4-ethylenedioxythiophene):polystyrenesulfonate (PEDOT:PSS)-coated TENG textile with the integration of a PZT piezoelectric sensor, as illustrated in Figure 4a.[155] Typically, a complete foot–ground contact sequence for walking can be decomposed into four phases: heel contact, toe contact, heel leave, and toe leave (Figure 4b). Based on the data from the regular walking of the three participants, the authors observed distinguishable signal patterns corresponding to each participant, as well contact forces and contact angles of the heel and forefoot. Based on these results, the S2-socks show promise for use in Parkinson's disease monitoring. Using ML processing, this sock can be a useful technique for accurate pattern recognition and biomechanical activity monitoring, particularly in the detection of "freezing of gait" as a measurable physiological signal (Figure 4c).

In another smart sock application, Zhang *et al.* designed a sock for harvesting energy from the body to transmit sensory information wirelessly for foot-activity monitoring.[156] Based on a structural engineered triboelectric sensor (Figure 4d), the smart sock measured the walking gaits of Parkinson's patients and incorporated the preprocessing circuit and microcontroller unit (Figure 4e) to obtain an analog signal (Figure 4f). The signal was then wirelessly transmitted to a computer for identification by a one-dimensional CNN and was divided into specific types for further investigation. As shown in Figure 4g, the deep-learning-enabled sock could create an immersive experience for virtual reality (VR) fitness games. It could achieve a classification accuracy of over 96% for the five gait types (Figure 4h).

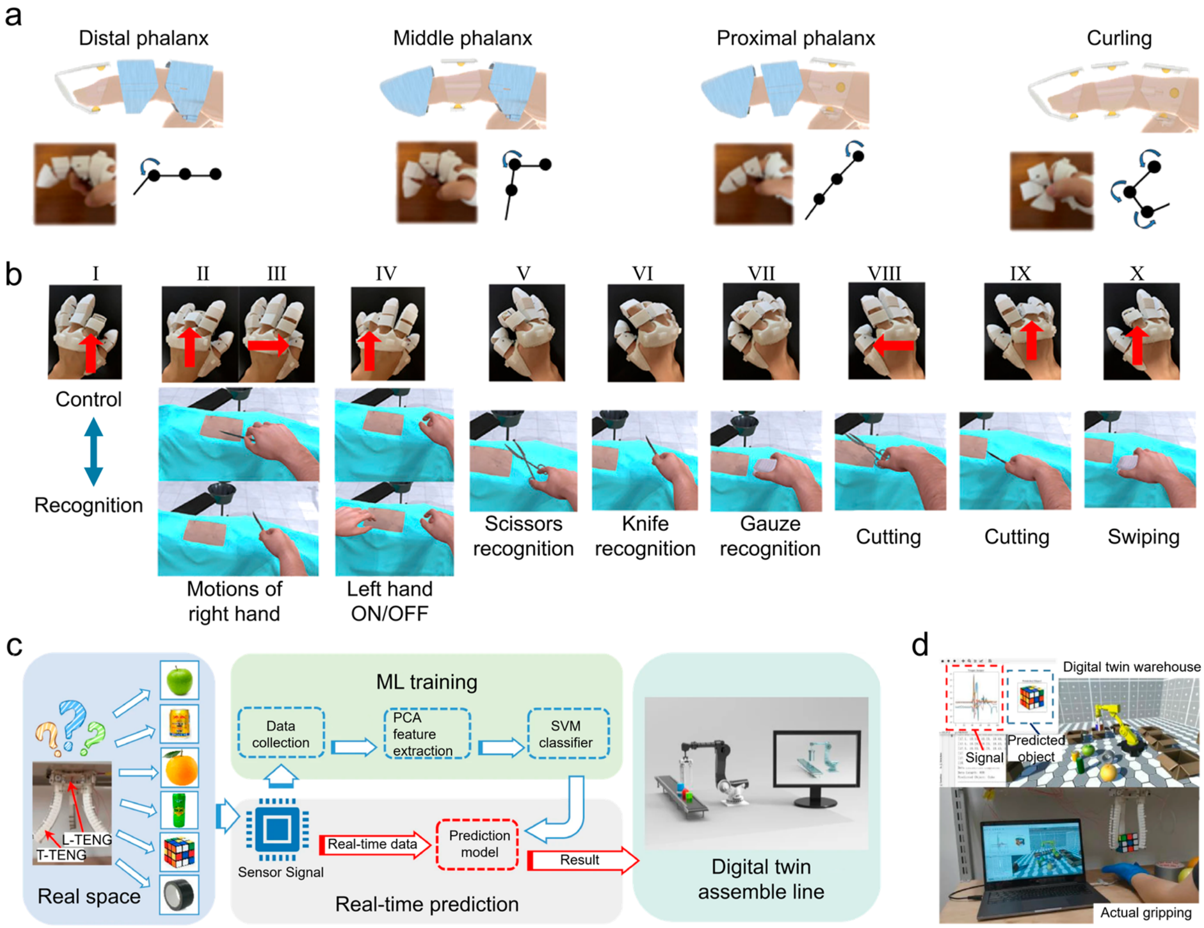

Figure 5. Human−machine interfaces. (a) Bending mechanism of (i) distal phalanx, (ii) middle phalanx, (iii) proximal phalanx, and (iv) all three phalanges (curling). (b) Photographs and screenshots of the finger motions for realizing (I) mode switching, (II,III) motions of right-hand, (IV) display of left-hand, (V) recognition of scissors, (VI) recognition of a knife, (VII) recognition of gauze, (VIII) operation of scissors (cutting), (IX) operation of knife (cutting), and (X) operation of gauze (swiping). Adapted with permission from ref 159. Copyright 2020 American Association for the Advancement of Science. (c) Process flow from sensory information collection to machine-learning (ML) training and real-time prediction in digital twin system. L-TENG = length triboelectric nanogenerator; T-TENG = tactile triboelectric nanogenerator; PCA = principal component analysis; SVM = support vector machine. (d) System interface integrated with object recognition and its digital twin warehouse application. Adapted with permission from ref 160. Copyright 2020 Springer-Nature.

Human−Machine Interfaces. As AI and the IoT rapidly evolve, wearable sensors have become increasingly important as a medium for HMIs.[157,158] In addition to advances in foot-gait monitoring, hybrid nanogenerators also show extraordinary adaptability in the field of glove-based HMIs, where well-designed haptic feedback is essential to achieve precise control *via* immersion experience and comprehensive sensation.[159] A smart glove consisting of an elastomer-based triboelectric tactile sensor and a PZT piezoelectric haptic mechanical stimulator was a cost-effective approach for intuitive HMI applications. They fitted the index finger with six sensors to measure upward and downward bending (Figure 5a). Moreover, left−right bending sensors were added to the proximal phalanx. Finger movements could be detected and recognized with ML-aided APT and able to satisfy the requirements of various operations. The authors tested applications for VR surgical training programs and augmented reality (AR)-based human−humanoid interactions. The authors assigned the left glove to control the movement of the entire arm and hand and the switching of the operation modes, whereas the right glove enabled object recognition and surgical operation (Figure 5b). Beyond VR training programs, more intuitive interactions involving virtual space communication could be harnessed by AR technologies with smart gloves. Thus, HMIs have applications in VR training, entertainment, social networking, and robotic control.

Due to the strong support of robotic manipulators in various industries, increasingly novel robotic wrist designs have been developed to enable these robots to accomplish specific tasks. A recently developed triboelectric sensor system with patterned-electrode and gear-structured length sensors has been proposed for enhancing the intelligence of the soft manipulator.[160] Manipulators assisted by ML technology can understand automatic sorting and real-time monitoring in a noncamera environment, which is conceptualized as a digital twin-based unmanned storage system for the real-time projection of the real space to a virtual one. The current process of establishing and using the digital twin-based unmanned warehouse system is depicted in Figure 5c. The digital twin virtual projection successfully creates a virtual space where the objects are randomly arranged to be gripped by a soft gripper (Figure 5d). Gripped objects are identified by trained support vector machine models based on input signals collected by triboelectric sensors, aided by ML technology. Based on the improved intelligence of the soft gripper, the digital twin model simulates

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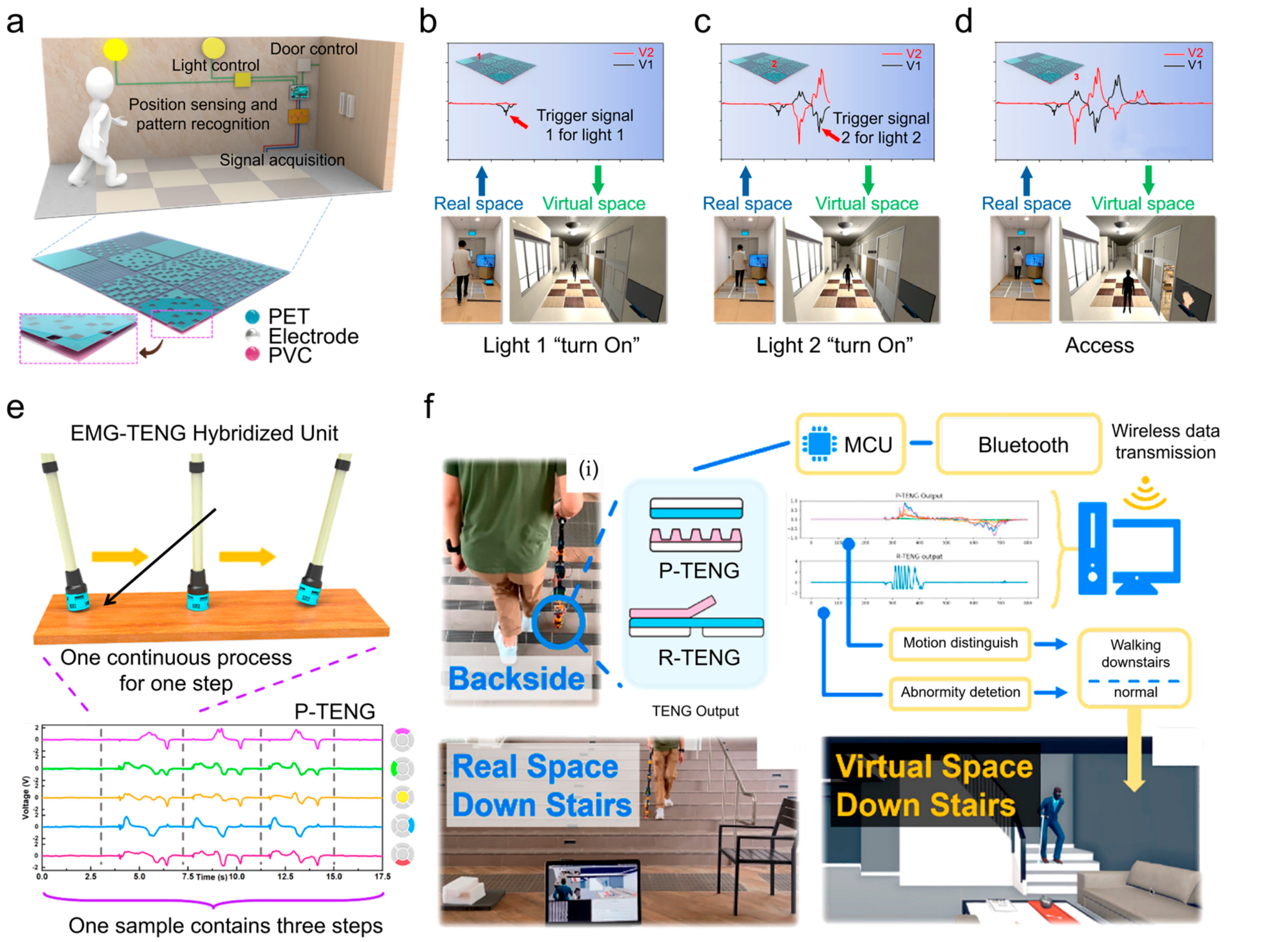

Figure 6. Physical aid. (a) Conceptual diagram of smart floor-monitoring system and its potential applications of position sensing, activity monitoring, and individual recognition in smart building/home scenarios. (b−d) Demonstration of the different stages in real-time position sensing and individual recognition. Adapted with permission from ref 163. Copyright 2020 Springer-Nature. (e) Schematic of one contact and leaving process of the walking stick for one step and the corresponding output curve generated from three steps of a user. (f) Demonstration to implement indoor monitoring with a caregiving walking stick: (i) a backside view showing a person walking downstairs, (ii) a photo taken from real space, (iii) a whole setup showing the signals generated from a top press triboelectric nanogenerator (P-TENG) and a rotational triboelectric nanogenerator (R-TENG), wirelessly transmitted to the computer through Bluetooth, and then analyzed to obtain the real-time motion status of a user. MCU = microcontroller; EMG = electrical magnetic generator. Adapted from ref 166. Copyright 2021 American Chemical Society.

robotic manipulation and real-time object recognition in a duplicate virtual environment. It can be further applied to an assembly line for production control management in next-generation smart floor management at unmanned warehouses.[161,162]

Mobility Aids. Triboelectric sensors offer a significant competitive edge in converting mechanical energy into electricity, both for electrical output and signal flow. Combined with the intrinsic advantages of triboelectric sensors, ML-assisted APT devices are a rising trend in building the future of the IoT and high-intelligence life. To replace conventional high-cost, intervention-prone, camera-based surveillance systems, Shi *et al.* developed a TENG-based smart mat supported by ML-assisted technology to realize an intelligent, low-cost, and highly scalable floor monitoring system.[163] As shown in Figure 6a, a typical application scenario involves walking and personal recognition in a smart home corridor, which can be implemented in an automatic manner by opening the door for recognized valid users.[163] Under smart floor monitoring systems, deep-learning-enabled smart mats (DLES-mats) are prepared with different electrode coverage rates and fabricated through screen printing of the designated electrode patterns on a PET film and further packaging with another polyvinyl chloride (PVC) film. The three stacking device layers—the PET friction layer, the Ag electrode layer, and the PVC substrate layer—provide a difference in electron affinity, resulting in a minor current flux in the external circuit. As the stepping position on the patterned DLES-mat changes, the output current/voltage varies accordingly, which provides substantial data sets for training ML models. In a practical use scenario in a hallway environment, the floor monitoring system realized the on and off of different bulbs and executed the door opening command in response to the movement of the person on the mat (Figure 6b−d).

With the advent of multipurpose wearable devices, the main concerns of wearable sensors have shifted to the continuous and convenient monitoring of diversified physiological signals. Self-powered wearable devices with hybrid mechanisms that combine an individual element with specific properties are garnering increased interest.[120,164,165] Hybrid sensing techniques also produce complex analytical problems, particularly for unifying data sets and modeling training for signal flows from

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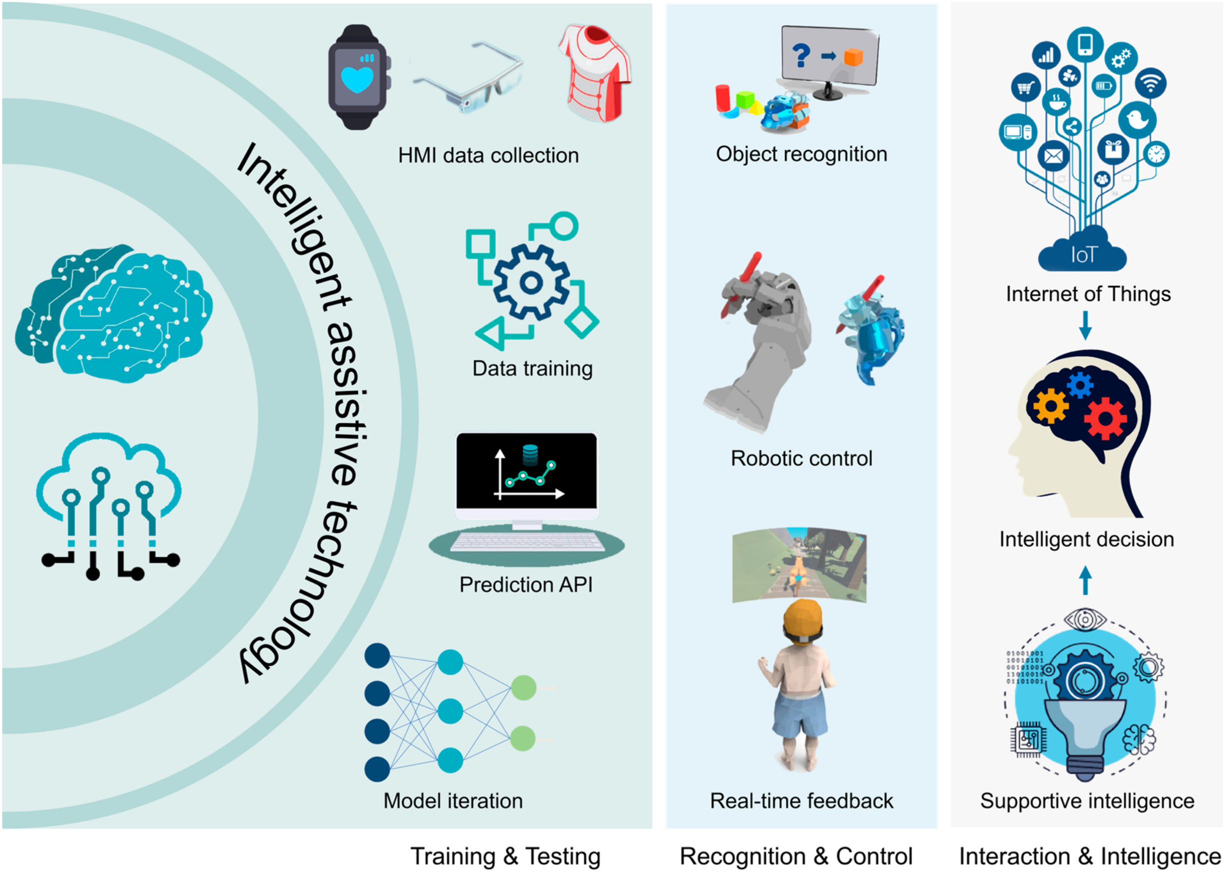

Figure 7. Perspective toward future development of machine-learning-aided assistive physical therapy devices. HMI = human−machine interface; API = application programming interface.

different sources. The latest advanced ML technology provides strong support for multifunctional wearable smart systems, which have made remarkable progress in the blueprint of the IoT society.

As reported in this issue of *ACS Nano*, Guo *et al.* used ML technology to develop a smart walking stick, powered by ultra-low-frequency human motion, to assist elderly and motion-impaired users. A prepared walking stick gathered real-time motion data from each hybridized unit containing a top press TENG (P-TENG), a rotational electromagnetic generator, and a rotational TENG (R-TENG).[166] To achieve a caregiving walking stick with intelligent monitoring functions, the researchers implemented a deep-learning assistive method to analyze and to extract all features of the five-channel P-TENG output from varying contact points, contact sequences, and contact forces (Figure 6e). To illustrate the practical uses of the system, a virtual environment that mimics real life was built to reflect the real-time motion status of a person using a caregiving walking stick (Figure 6f). Output voltage signals from the R-TENG and P-TENG were first collected by the Arduino mega 2560, then sent to the computer through a Bluetooth module for data processing and analysis. The exact motion was detected through the trained deep-learning model mentioned above, and the stable R-TENG output also reflected the normal motion status.

As reported in this issue of *ACS Nano*, Guo *et al.* used ML technology to develop a smart walking stick, powered by ultra-low-frequency human motion, to assist elderly and motion-impaired users.

CONCLUSIONS AND OUTLOOK

In this Perspective, we have summarized the research progress of ML-aided self-powered APT devices. Existing self-powered sensors include piezoelectric, triboelectric, magnetoelastic, and electromagnetic types. Machine learning could be widely adopted in APT devices. Classifying algorithms are able to solve analysis challenges, regression algorithms could be utilized for design and fabrication challenges, and probability algorithms could help for application challenges (Figure 7).

Despite significant research progress, a number of challenges must be addressed before widespread adoption of ML-aided self-powered APT devices for daily usage. For data training and testing, researchers should endeavor (1) to collect significant volumes of real-time efficient raw data, (2) to realize the rapid transmission and processing of data, and (3) to ensure user data security. For subject recognition and control, researchers could aim (1) to design highly sensitive sensors, (2) to develop efficient control algorithms, and (3) to deploy high-speed data transmission modes. For real-time interactions and intelligence, researchers could put efforts into (1) introducing distributed IoT systems, (2) designing intelligent interactive algorithms, and (3) developing practical assistive technology for the general population. Continued technological progress from a combined

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interdisciplinary and global effort from material science, physics, chemistry, biology, engineering, ergonomics, AI, and IoT will offer a promising future for APT devices.

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[†]J.C. initialized and supervised the whole project. X.X., Y.F., X.X. contributed equally to this work. All authors have given approval to the final version of the manuscript.

Notes

The authors declare no competing financial interest.

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