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Topical Review

Integration of AI with artificial sensory systems for multidimensional intelligent augmentation

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Abstract

Artificial sensory systems mimic the five human senses to facilitate data interaction between the real and virtual worlds. Accurate data analysis is crucial for converting external stimuli from each artificial sense into user-relevant information, yet conventional signal processing methods struggle with the massive scale, noise, and artificial sensory systems characteristics of data generated by artificial sensory devices. Integrating artificial intelligence (AI) is essential for addressing these challenges and enhancing the performance of artificial sensory systems, making it a rapidly growing area of research in recent years. However, no studies have systematically categorized the output functions of these systems or analyzed the associated AI algorithms and data processing methods. In this review, we present a systematic overview of the latest AI techniques aimed at enhancing the cognitive capabilities of artificial sensory systems replicating the five human senses: touch, taste, vision, smell, and hearing. We categorize the AI-enabled capabilities of artificial sensory systems into four key areas: cognitive simulation, perceptual enhancement, adaptive adjustment, and early warning. We introduce specialized AI algorithms and raw data processing methods for each function, designed to enhance and optimize sensing performance. Finally, we offer a perspective on the future of AI-integrated artificial sensory systems, highlighting technical challenges and potential real-world application scenarios for further innovation. Integration of AI with artificial sensory systems will enable advanced multimodal perception, real-time learning, and predictive capabilities. This will drive precise environmental adaptation and personalized feedback, ultimately positioning these systems as foundational technologies in smart healthcare, agriculture, and automation.

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Keywords: artificial sensory system, artificial intelligence, sensor, deep learning, signal processing

1. Introduction

Artificial sensory technology imitates the five human senses such as vision, smell, taste, hearing, and touch to enable data interaction between virtual and real worlds, providing intelligent feedback to external stimuli[1–6]. The core of the technology involves using perceptual interfaces to gather versatile environmental information and enhance understanding and interaction with the external world through digital processing[7–12]. To achieve this, the field integrates multiple disciplines including nanomaterials synthesis, sensor device fabrications, signal processing, and AI algorithms[13–19]. Based on these multidisciplinary collaborations, the artificial sensory systems continuously expand human sensory capabilities, enabling various applications in digital healthcare, smart robotics, and smart agriculture[20–24].

These devices typically convert external stimuli into electrical signals, which are then analyzed by AI systems in the backend[25–29]. They often integrate components such as electrical, electrochemical, optical, or mechanical sensing devices[30–32]. The signals generated by these devices include variations in voltage, impedance, current, or resistance responses[33,34]. These electrical signals are digitized, forming the basis for further analysis and interpretation by AI systems, allowing for more advanced classification and recognition of the sensory inputs[35,36]. Through the integration of these various materials and technologies, artificial five-senses are achieving significant multifunctionalities such as simultaneous temperature, pressure, and tactile sensing, while their sensitivity has improved to the level of detecting even minute changes (e.g., approximately 10 micrometers for touch, 100 pascals for pressure, 120 decibels for vision, and about 20 kilohertz for hearing)[37–45].

Each type of sensor for the five senses generates different forms of raw data[46]. To enhance the functionality of artificial perception systems, these signals must be properly processed to obtain meaningful data, making data processing particularly important[47,48]. Traditionally, statistical methods such as Kalman Filtering, Z-score, and Fourier Transform have typically been used for the signal processing of artificial sensory system[49–51]. However, due to the wide and dynamic range of stimuli that humans encounter, the resulting sensory data exhibits nonlinear, massive, and multidimensional characteristics, such as spiking patterns in neural recordings from tactile sensors that represent touch intensity and texture across tens of thousands of data points[52]. These features lead to a high noise level in the raw data, which complicates signal extraction[53–55]. They also slow down processing speeds, hindering the real-time analysis capabilities of artificial sensory systems as they take several minutes to process a single image frame[56]. Additionally, conventional methods struggle to effectively capture the complex relationships and patterns within the data[57,58].

AI has shown the potential to address these challenges. The integration of AI with artificial sensory systems can be traced back to the 1990s, with examples such as using artificial neural networks (ANN) to identify similar beer aromas or employing AI for human-computer interaction[59–61]. Today, AI has been fully integrated into artificial sensory systems at both the device and system levels[12,62–64]. For instance, in visual sensing, neural network can automatically extract features from vast amounts of images, enabling high-precision object recognition and classification[65,66]. In olfactory sensing, machine learning models can handle large, complex datasets of odor molecules, achieving higher sensitivity and accuracy in odor recognition[67,68]. Similarly, in taste, auditory, and tactile sensing, AI algorithms can extract key information from massive raw data and perform multidimensional signal analysis, enhancing the detection speed and accuracy of the artificial sensory systems[35,69,70]. The fusion of AI with artificial sensory devices has not only enhanced sensor performance such as sensitivity, selectivity, and stability, but also equipped them with real-time learning and adaptive capabilities enabling better adaptation to dynamic environments[71–73]. This integration significantly enhances the interaction between devices and users, enabling them to experience more realistic and immersive sensations[74,75]. By collecting user behavior and environmental changes, the system can automatically adjust sensing modes and feedback mechanisms, making the user experience more personalized and intuitive[76–79]. Furthermore, AI can predict user needs and optimize the interaction process, transforming devices from passive tools into intelligent assistants capable of proactively understanding and responding to user demands[80–83]. Therefore, the integration of AI in artificial sensory systems has become a key factor in elevating their level of intelligence, opening up broad prospects for fields[84].

Although the integration of AI into artificial sensory systems has shown the most critical technological components, there has been no systematic research that categorizes the target output functions of various artificial sensory systems and comprehensively analyzes the raw data processing methods and AI algorithms required to achieve these functions. Most current research focuses on individual artificial sensory devices or specific signal processing techniques, without providing AI insights for the overall artificial sensory system or addressing the technical challenges from a user interaction perspective. This gap leaves researchers without clear guidelines for handling complex sensory signals. Organizing AI-based enhancement methods can provide a framework for developing artificial sensory devices, maximizing their performance and efficiency.

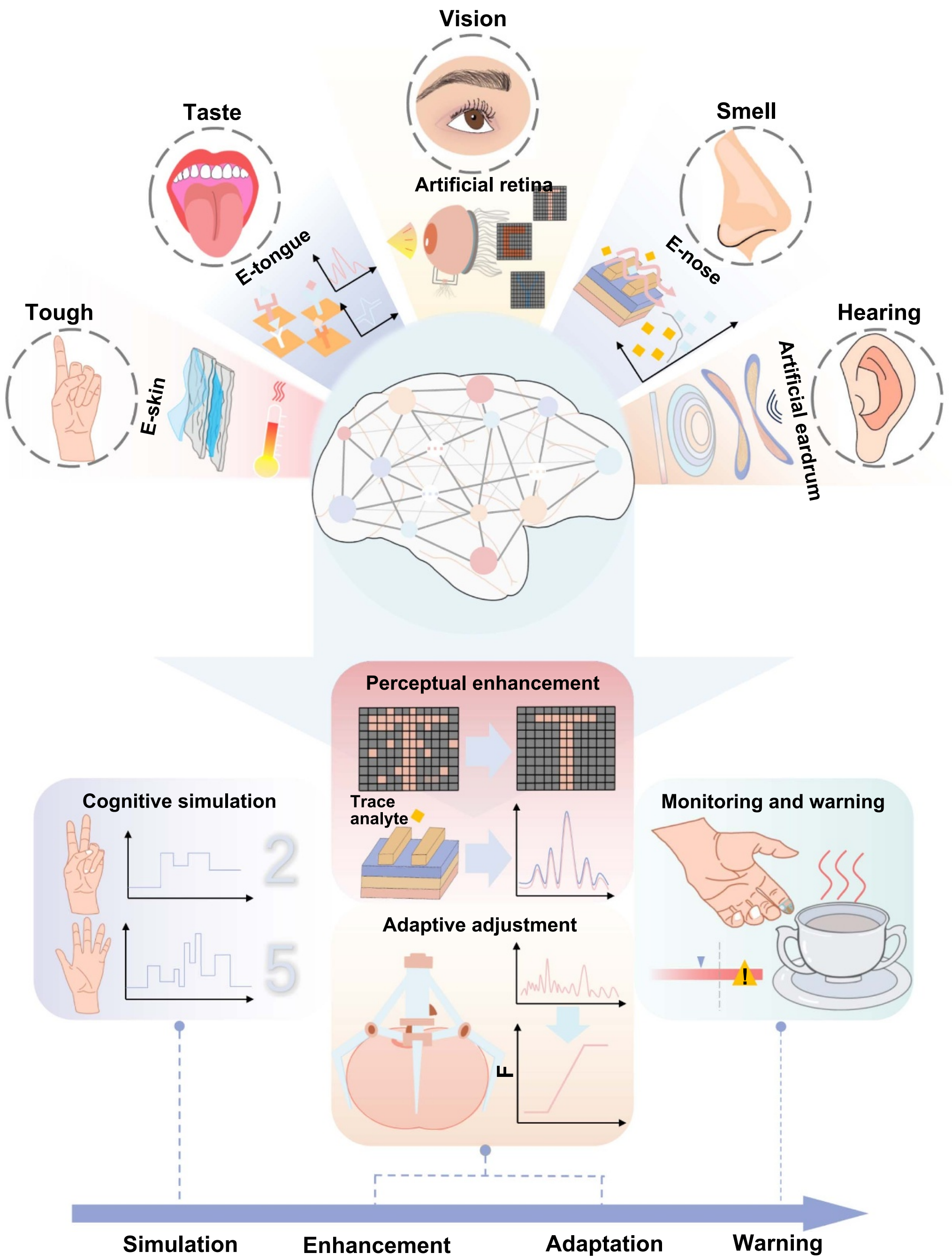

Figure 1. Schematic illustration of AI integration with artificial sensory systems for multidimensional intelligent augmentation. Five types of artificial sensory devices (touch, taste, vision, smell, and hearing) are integrated with AI to enhance cognitive simulation, perceptual enhancement, adaptive human-machine interaction, and early warning.

In this review, we outline recent AI techniques aimed at enhancing the cognitive performance of artificial sensory systems that mimic the five human senses. We categorize the enhanced performances of artificial sensory systems into four key functions: cognitive simulation, that mimics human perception; perceptual enhancement, improving sensitivity beyond human limits; adaptive adjustment, allowing dynamic responses to environmental changes; and early warning, providing anticipation of potential risks (Figure 1). For each function, we introduce specific AI algorithms and raw data processing methods tailored to optimize their sensing performance. First, under cognitive simulation, traditional physical and chemical sensors can only detect basic signals such as temperature, touch, and odor concentration, but they lack the ability to deeply understand and respond to complex, multidimensional signals and dynamic environments. For example, in artificial olfactory systems, sensors face difficulties in identifying mixed odors or locating odor sources. By incorporating deep learning and recurrent neural networks (RNNs), these systems can learn patterns from multimodal data to simulate human cognitive abilities. In terms of perceptual enhancement, we focus on how AI enables sensor systems to overcome physical limitations, improve their ability to detect subtle signals, and minimize the impact of noise on perception. We will also explore how AI can improve the robustness and stability of perception across various application scenarios, particularly in visual image recognition. For the adaptive adjustment function, we will analyze how artificial sensory systems can develop adaptive capabilities, automatically adjusting sensing modes and feedback mechanisms based on environmental and user behavior changes. The focus will be on applying adaptive and reinforcement learning in AI to optimize real-time feedback and self-regulation, enhancing both user experience and system efficiency. The early warning section will cover AI's predictive algorithms and data analysis capabilities to identify potential risks and anomalies in advance, enhancing system safety and reliability. We will analyze how real-time monitoring and data prediction can prevent failures or hazardous events in areas such as harmful gas detection, early diagnosis, and industrial safety control. Finally, we will also suggest directions for the future technological development of AI-integrated artificial sensory system for real-world applications.

2. AI integration with artificial sensory systems for enhanced functionalities

2.1. Cognitive simulation of artificial sensory systems using AI

Cognitive simulation involves using AI to mimic human perceptual abilities for processing complex sensory tasks[85–87]. Enhancing cognitive simulation improves the understanding of multidimensional external signals and responsiveness in dynamic environments. For example, Wu et al. utilized convolutional neural networks (CNNs) to simulate the excitatory-inhibitory balance, a critical feature of the human olfactory system, which is essential for brain data processing in humans (Figure 2(a))[88]. The researchers adjusted gas pulse parameters such as pulse intensity and duration to long-term potentiation (LTP) and long-term depression (LTD), generating complex signals (Figure 2(a-i)). Traditional methods typically rely on manually extracted features such as using Fourier transform to analyze frequency-domain information or statistical methods to identify distribution characteristics. These approaches require extensive domain knowledge and are limited in handling high-dimensional, nonlinear data[89]. In contrast, CNN performs weighted summation on local regions of time and current signal data using sliding convolutional kernels, which not only extracts key features while preserving spatial information but also integrates signals at the neuronal level through multi-channel parallel processing (Figure 2(a-ii)). It increased the classification accuracy of the eight gases including butyl acetate, dimethyl sulfoxide, hydrogen sulfide, methylene blue, ammonia, nitrogen dioxide, trichloromethane, and tetrahydrofuran to 97%, and also enhanced its sensitivity and precision in responding to changes in gas concentration (Figure 2(a-iii)). Furthermore, the integration of AI significantly improved processing speed and response efficiency, covering both the recognition of gases and the dynamic simulation of interactions between gas molecules and bionic synaptic devices[15,90]. AI-based perception simulation also enables artificial tasting based on the identification of complex food components[91,92].

Jung et al. recently developed an electronic tongue (e-tongue) that simulates the human taste perception process using the soft voting mechanism (Figure 2(b))[93]. The sensory device consists of multi-channel chemical sensors integrated into a polydimethylsiloxane (PDMS) substrate, using a lipid membrane solution and polyimide encapsulation (Figure 2(b-i)). The system employs four different lipid membranes (for saltiness, sourness, astringency, and sweetness) to mimic the functions of taste receptor cells. The chemical signals obtained through the electrochemical reactions of the receptors are converted into electrical signals, which are then processed using the soft voting ensemble learning method. This involves weighted averaging or voting to combine the outputs of multiple classifiers to derive the most probable classification result. They also implemented a prototype-based classifier to address uncertainties in taste recognition. This approach improved the accuracy of taste analysis for beverages such as wine, beer, and coffee (Figure 2(b-ii)). Even when handling large or faulty data, the e-tongue system achieved 95% accuracy in analyzing six types of wine, and maintained over 90% accuracy even when one-third of the data was incorrect (Figure 2(b-iii)).

Niu et al. integrated multi-layer perceptron (MLP) technology into full-surface bionic electronic skin (FSB e-skin), enabling it to effectively learn and simulate the sensory processing mechanisms of human skin (Figure 2(c))[94]. It allows for the decoding and responsive handling of complex signals such as real-time pressure and stretching. This AI-enhanced FSB e-skin exhibits high sensitivity and rapid response capabilities, constructed with a single-sided low microstructure (LMS) Au/PDMS bottom layer, a double-sided LMS ionic gel middle layer, and a double-sided heterogeneous structure (VHS/LMS) PDMS/Au top layer through a stacked assembly (Figures 2(c-i)). The system uses an MLP neural network with five-layer and six-layer structures to process capacitance and voltage signals collected by the supercapacitor ion electronic skin and the triboelectric effect. As a feedforward neural network, the MLP consists of an input layer, hidden layers, and an output layer, with each neuron processing input data through weighted summation and activation functions, enabling the automatic extraction of complex data features. This mechanism allows the system to efficiently decode and respond to dynamic signals such as real-time pressure and stretching. The device collected datasets from 12 different American Sign Language gestures and materials for training and testing, achieving an average recognition accuracy of 90.83%, which increased for common gestures like "A," "B," and "C." The average accuracy for material recognition was 98.34%, with over 99% accuracy for eight of the materials and 85% accuracy for the remaining (Figure 2(c-ii)).

Jiang et al. recently showed that an ultra-thin eardrum-like self-powered acoustic sensor (ETAS) can be achieved through the use of the DenseNet deep convolutional network algorithm (Figure 2(d))[95]. The sensor is composed of

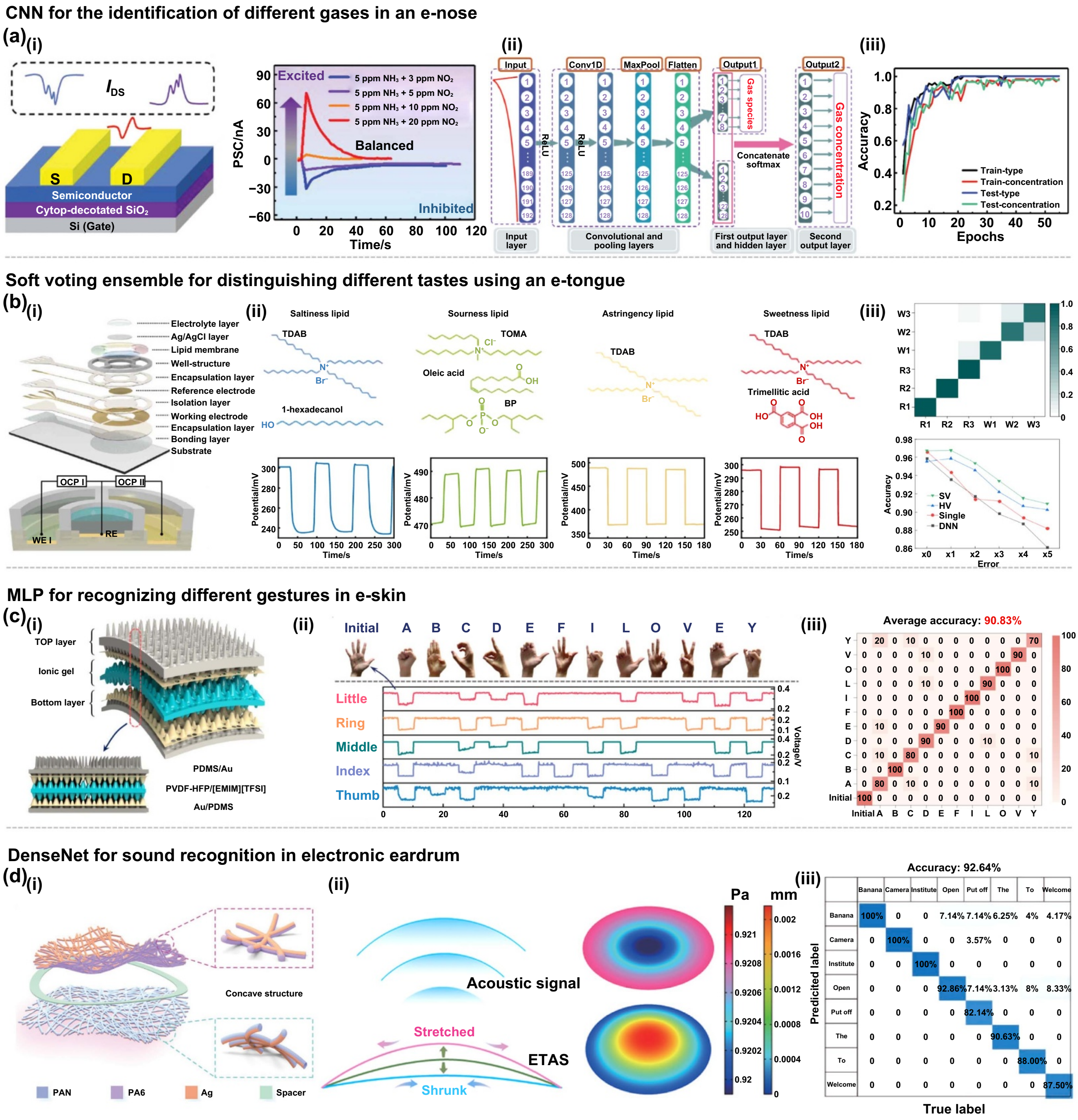

Figure 2. Cognitive simulation of artificial sensory systems using AI. (a) CNN for the identification of different gases in an e-nose. (i) Diagram of an artificial synapse using a bottom-gate top-contact transistor structure, and a signal diagram showing the adjustment of balance characteristics using excitatory input. (ii) CNN structure for gas recognition. (a-iii) Accuracy for gas recognition using CNN. (a-i)–(iii)[88] John Wiley & Sons. © 2024 Wiley-VCH GmbH. (b) Soft voting ensemble for distinguishing different tastes using an e-tongue. (i) Schematics of the e-tongue system. (ii) Chemical structures of four lipids and their signals, from left to right: TDAB and hexadecanol (salty), TOMA (sour), oleic acid and PB (astringent), TDAB and trimellitic acid (sweet). (iii) Confusion matrix for six types of wine, along with the accuracy comparison between four models with different numbers of errors. (b-i)–(iii) Reprinted (adapted) with permission from[93]. Copyright (2023) American Chemical Society. (c) MLP for recognizing different gestures in e-skin. (i) Schematics of the FSB e-skin configuration. (ii) AI-recorded waveform for twelve gestures collected by the GMCGS. (iii) Accuracy of different gesture validations. (c-i)–(iii)[94] John Wiley & Sons. © 2022 Wiley-VCH GmbH. (d) DenseNet for sound recognition in electronic eardrum. (i) Schematic illustration of the three-dimensional network structure of the ETAS, enlarged image shows the nanofiber coated with Ag. (ii) Schematic illustration of the vibration of the film. (iii) The confusion matrix for word recognition in ETAS analyzed with DenseNet. (d-i)–(iii)[95] John Wiley & Sons. © 2022 Wiley-VCH GmbH.

polyacrylonitrile and polyamide 6 nanofibers coated with silver, fabricated through electrospinning and magnetron sputtering (Figure 2(d-i)). By adjusting the geometric parameters of the sensor, the frequency response range can be tuned from 20 Hz to 5 000 Hz. The deformation displacement and pressure distribution of the film at various frequencies are simulated using COMSOL multiphysics (Figure 2(d-ii)). By converting the sound signals into Mel spectrograms and training the system using DenseNet, which consists of multiple convolutional layers, each layer not only receives input from the previous layer's features but also from all preceding layers' features, forming a densely connected network. In each convolutional layer, DenseNet performs sliding extraction of features from the Mel spectrogram (such as frequency, waveform, etc.). This structure allows each layer in the dense block to share features, improving the efficiency of information flow across the network. Through this approach, the sensor has achieved a sound recognition accuracy of up to 92.64% (Figure 2(d-iii)). Overall, AI significantly enhances the cognitive simulation of artificial sensory systems which results in more accurate recognition and response to diverse sensory inputs.

2.2. Perceptual enhancement of artificial sensory systems using AI

Building on these perception simulations, the performance of the artificial sensory systems can be further enhanced using AI[96,97]. The aim is not just to mimic human perception, but to surpass its natural limits, offering more advanced perceptual capabilities[12,98]. Achieving this requires integrating diverse data sources, analyzing latent features in high-resolution, and pushing AI for greater precision and broader feature extraction[99,100]. For example, Cho et al. combined a GRU based on autoencoders with an electronic nose (e-nose) composed of a multi-array metallic channel system, significantly enhancing its detection performance for ultra-low hydrogen (H_2) concentrations below the limit-of-detection (LOD) obtained using a signal-to-noise ratio (SNR) method (Figure 3(a))[57]. Researchers selected six different metals (gold, copper, molybdenum, nickel, platinum, and palladium) for H_2 adsorption as the sensitive channel materials of the chemiresistor devices (Figure 3(a-i)). The sensors collected resistance change data at various H_2 concentrations and under normal conditions (only nitrogen, with H_2 concentrations of 0.205 $mg \cdot m^{-3}$ and 0.82 $mg \cdot m^{-3}$, both below the limit of detection (Figure 3(a-ii)). When the resistance changes of six metals over time are input into the GRU (the gated recurrent unit)-based autoencoder, as a computational model simulating biological neural networks, it receives this resistance change signals through the input layer and converts them into a format that can be processed by the neural network. The signals then pass through multiple hidden layers, where each GRU unit computes the weighted sum of the input resistance change features and processes the nonlinear characteristics of the signals using activation functions. Each GRU unit not only receives input from the previous layer but also integrates information from other layers through gating mechanisms, enhancing the precision of feature extraction. Finally, the signals pass through the output layer for classification or regression processing, yielding predictions such as gas concentration. This process allows the autoencoder to effectively learn and identify the key features in the resistance changes. In the autoencoder network, the average detection accuracy for 0.205 $mg \cdot m^{-3}$ H_2 was 70.0%, while for 0.82 $mg \cdot m^{-3}$ H_2, it was 66.2% (Figure 3(a-iii)). Kernel density estimation plots and receiver operating characteristic (ROC-AUC) scores were used to evaluate the model's ability to detect hidden signals, achieving ROC-AUC values of 0.817 and 0.874 for 0.205 $mg \cdot m^{-3}$ and 0.82 $mg \cdot m^{-3}$ H_2, respectively. This indicates that the e-nose system can detect the presence of H_2 even below its LOD region. This capability is primarily due to the autoencoder's ability to identify weak yet critical signal features that are nearly invisible in the raw data, demonstrating the immense potential of deep learning in enhancing chemical sensor performance.

Leong et al. developed a surface-enhanced Raman scattering (SERS) platform for the artificial tongue, called the "SERS taster", for multiplex flavor analysis, utilizing machine learning to achieve high-precision flavor detection and quantification in wine (Figure 3(b))[101]. They selected four surface receptors to introduce a range of receptor-flavor chemical interactions, focusing on five representative wine flavor molecules, including alcohols (menthol), terpenes (pinene, limonene), and sulfur compounds (Figure 3(b-i)). Subsequently, support vector machine (SVM) discriminant analysis was employed, achieving 100% accuracy in flavor classification. Principal component analysis (PCA) was used for the complete identification of the flavor molecules, even distinguishing alcohols with different degrees of substitution. Building on this, the researchers applied the partial least squares regression (PLSR) algorithm to analyze the concentration of flavor molecules. The concentration gradient ranged from 10 μM to 100 mM, and SERS spectra from these standard samples were collected and input into the PLSR model. The model adjusted its parameters by learning the relationship between the SERS spectra and concentration. The accuracy of the model was evaluated by calculating the correlation coefficient (R^2) and root mean square error (RMSE) between the predicted and actual concentrations. By learning a large number of patterns, the model can effectively identify and correct concentration deviations caused by various factors, demonstrating strong robustness. The results showed that the PLSR model achieved a correlation coefficient of up to 0.98 and a low RMSE in predicting the concentration of wine flavor molecules, demonstrating high accuracy and reliability (Figure 3(b-ii)).

Niu et al. demonstrated that all-fabric bionic electronic skin (AFB e-skin), which combines dual-modality sensing for intuition and touch with AI algorithms, can achieve high-precision material perception, even for materials with similar tactile sensations (Figure 3(c))[102]. AFB e-skin was made

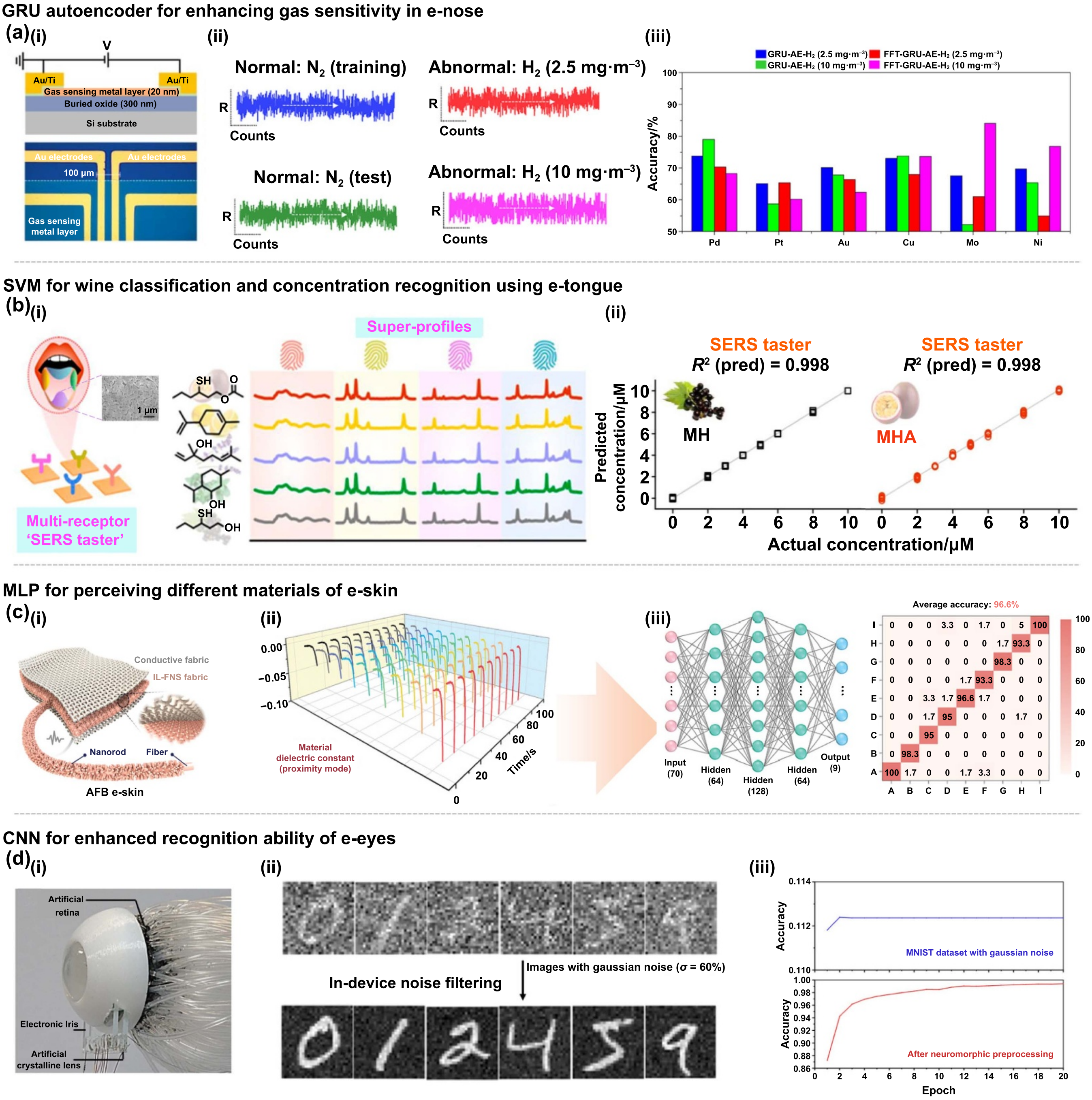

Figure 3. Perceptual enhancement in artificial sensory systems using AI. (a) GRU autoencoder for enhancing gas sensitivity in e-nose. (i) Schematic and optical microscope image of the sensing devices. (ii) Signal characteristic graphs under N_2, 10 mg·m^{-3} H_2, and 2.5 mg·m^{-3} H_2 conditions. (iii) Detection accuracy of the encoder under different metal sensors for N_2, 10 mg·m^{-3} H_2, and 2.5 mg·m^{-3} H_2. (a-i)–(iii) Reprinted (adapted) with permission from[57]. Copyright (2020) American Chemical Society. (b) SVM for wine classification and concentration recognition using e-tongue. (i) Schematic diagram of the multi-receptor SERS taster substrate structure. (ii) PCA score plot of the relative flavor data clustering in the SERS taster, along with a schematic diagram for concentration identification. (iii) PCA score plot of the relative flavor data clustering in the SERS taster, along with a schematic diagram for concentration identification. (b-i)–(iii) Reprinted (adapted) with permission from[101]. Copyright (2021) American Chemical Society. (c) MLP for perceiving different materials of e-skin. (i) Dual interlocking structure of the e-skin. (ii) Waveform signals generated by nine materials in proximity and pressure modes. (iii) MLP structure and the confusion matrix for nine materials. (c-i)–(iii)[102] John Wiley & Sons. © 2023 Wiley-VCH GmbH. (d) CNN for enhanced recognition ability of e-eyes. (i) Diagram of the bionic eye structure. (ii) The reconstructed images after in-device noise filtering. (iii) Accuracy curves of CNN-based pattern recognition for the MNIST dataset with and without neuromorphic preprocessing under Gaussian noise conditions. (d-i)–(iii) Reproduced from[26]. CC BY 4.0.

from conductive fabric electrodes and a polyvinylidene fluoride composite infused with ionic liquid, effectively capturing capacitance changes caused by variations in material hardness and texture (Figure 3(c-i)). They collected 2 700 sets of proximity and pressure signals from nine materials, using 2 160 sets for training and 540 sets for testing (Figure 3(c-ii)). Subsequently, a five-layer MLP neural network was used to learn and train the capacitance changes of different materials, successfully distinguishing nine materials with similar tactile sensations (e.g. ceramics and glass), achieving an average recognition accuracy of 96.6% (Figure 3(c-iii)). Through extensive learning of tactile data patterns, the AFB e-skin effectively detects and adjusts for perception deviations resulting from differences in material hardness and texture, showcasing high resilience. Even when these materials feel very similar, it can maintain high-precision recognition ability.

When artificial vision systems receive light signals, they must translate them into brain-interpretable images, and AI enhances this process by minimizing noise and boosting image clarity and precision[103,104]. A representative example is the development of a hemispherical perovskite nanowire array-based bionic retina by Long et al., which integrates advanced color vision and image preprocessing functions (Figure 3(d))[26]. The bionic eye uses $CsPbI_3$ perovskite nanowires, a material that responds to the entire visible spectrum due to its narrow bandgap ($\sim$1.8 eV). The nanowires are arranged in a high-density array, with SnO_2 and NiO double-layer oxides coated on top to form electron and hole transport layers (Figure 3(d-i)). The bionic eye also integrates an artificial lens and electronic iris to adjust focal length and light intake, further enhancing image quality (Figure 3(d-ii)). CNN-based ResNet-18 model was used to analyze and classify the image data collected by the bionic eye. These data, consisting of photocurrents generated by the perovskite nanowires under various light intensities and color temperatures, were then used to reconstruct the captured color images. After the CNN learns the color features of different regions in the image, the system automatically detects and corrects color distortion, adjusting color temperature, saturation, and contrast to achieve optimal color balance. This dynamic adjustment process can adapt to varying lighting conditions in real time, optimizing the response of each pixel, thereby achieving 99.4% accuracy in color balance and contrast, significantly enhancing the overall stability of the visual effect (Figure 3(d-iii)). However, relying on a single index such as accuracy does not fully capture the system's true performance. In practical applications, additional factors including the algorithm's adaptability to varying lighting conditions, processing speed, and false alarm rate, should be considered to more comprehensively evaluate the stability and resilience of AI in enhancing perception across diverse environments[105]. CNN, autoencoders, SVM, and MLPs have significantly enhanced the precise detection of low-concentration substances, differentiation of similar materials, and advanced recognition of flavors and colors[106]. This allows sensory systems to surpass human perception limits, improving sensitivity, accuracy, and adaptability in areas such as chemical detection, tactile recognition, taste analysis, and visual processing.

2.3. Interaction and adaptive regulation of artificial sensory systems using AI

In addition to utilizing AI for simulation and enhancing the performance of artificial sensory systems, human-machine interaction can also be significantly improved by optimizing user interfaces and feedback mechanisms for more natural and efficient communication between users and systems[107–109]. Adaptive regulation allows the system to dynamically adjust its responses based on environmental changes and user behaviors, thereby enhancing overall performance and user experience[110–112]. The integration of these technologies boosts device interactivity while increasing their responsiveness to environmental changes, enabling versatile applications across real-world scenarios[113,114]. For example, Lu et al. developed a multi-sensory neural network system (MSeNN) that connects vision, touch, hearing, smell, and taste by simulating human sensory processing (Figure 4(a))[115]. Silicon-based photodetectors, MXene-based pressure sensors, MEMS microphones, and metal oxide semiconductor gas sensors were used to simulate signals from the five senses, which are then encoded using analog-to-digital converters and converted into optical pulses via optical modulators. (Figure 4(a-i)). They used a hierarchical dilated recurrent neural network (DRNN) with gradient descent to achieve cross-modal learning (Figure 4(a-ii)). The structure of DRNN introduces an expansion factor that allows nodes in each recurrent layer to skip over several time steps. Instead of simply connecting to the previous time step, the network "expands" to link to earlier or later time steps, increasing the receptive field and enabling the network to capture long-term dependencies while maintaining computational efficiency. This approach enabled the fusion of input from different senses, such as visual images, sound clips, pressure data, and simulated smell and taste data, for the recognition and understanding of multimodal information. The performance and recognition capability of the model were evaluated based on recognition accuracy and mean square error (MSE) loss functions. When combining visual and auditory data, the system exhibited high performance, with recognition accuracy reaching 97% (Figure 4(a-iii)). When tactile data were introduced, the overall system accuracy remained stable above 95%, and the MSE was around 0.06. MSeNN can assist individuals with visual or auditory impairments by developing devices that interact with the nervous system to restore or enhance sensory functions.

Guo et al. demonstrated an AI-assisted caregiving walking cane based on tactile sensors (Figure 4(b))[116]. This device integrates a piezoelectric triboelectric nanogenerator (P-TENG), an electromagnetic generator (EMG), and a rotary triboelectric nanogenerator (R-TENG), effectively capturing voltage changes when the cane contacts the ground (Figure 4(b-i)). These changes are closely related to the user's gait, walking speed, and contact force, providing a rich source

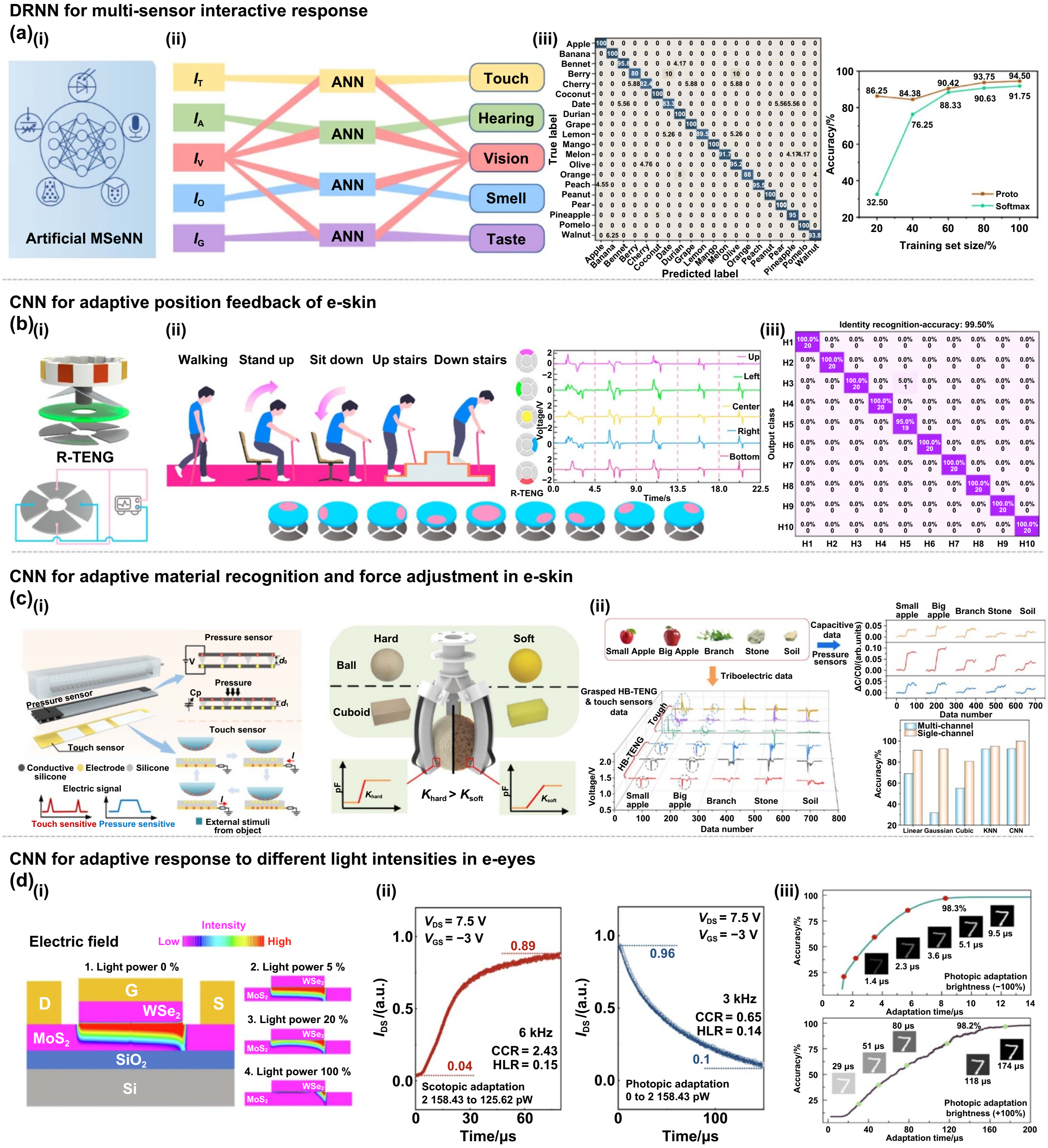

Figure 4. Adaptive human-machine interaction of artificial sensor systems using AI. (a) DRNN for multi-sensor interactive response. (i) MSeNN five-sense sensor schematic diagram. (ii) Schematics of the operation flow of MSeNN. (iii) MSeNN interactive confusion matrix and accuracy. (a-i)–(iii) Reproduced from[115]. CC BY 4.0. (b) CNN for adaptive position feedback of e-skin. (i) Schematics of the R-TENG based artificial tactiles. (ii) Output curves of the five-channel P-TENG and a depiction of the nine typical contact points between the P-TENG and the ground across five different movement states. (iii) Confusion matrix of 10 users. (b-i)–(iii) Reprinted (adapted) with permission from[116]. Copyright (2021) American Chemical Society. (c) CNN for adaptive material recognition and force adjustment in e-skin. (i) Schematics of the skin-inspired tactile sensor consist of pressure and touch sensors, operating on the principle that touch drives the flow of free electrons, while subsequent pressure deformation alters the capacitance value. (ii) Common operational tasks in fruit sorting, showing the reflection capacitance data obtained from pressure sensors, triboelectric data from HB-TENG and touch sensors, as well as the accuracy results of multi-channel concatenation, single-channel concatenation, linear, Gaussian, cubic KNN, and CNN for five grasped objects. (c-i)–(ii) Reprinted (adapted) with permission from[117]. Copyright (2024) American Chemical Society. (d) CNN for adaptive response to different light intensities in e-eyes. (i) Schematic diagram of simulated electrical characteristics. (ii) Correlated current signals under light and dark adaptation conditions. (iii) Visual adaptation results under dark and light adaptation conditions. (d-i)–(iii) Reproduced from[118]. CC BY 4.0.

of dynamic data (Figure 4(b-ii)). The cane employs a one-dimensional CNN to extract high-level features from the signals, identifying user activity states such as standing, sitting, walking, and climbing stairs, achieving an accuracy of 99.5% (Figure 4(b-iii)). For specific tasks such as identity verification and mobility impairment classification, the accuracy reached 100%. Additionally, the system includes GPS tracking and environmental sensing capabilities, enabling it to automatically send emergency signals using wireless networks to preset contacts or healthcare providers when abnormal movements, such as falls, are detected. This functionality ensures a quick response in emergencies, highlighting AI's critical role in adaptive regulation.

Wang et al. combined tactile sensors with a CNN model to achieve real-time feedback on grasped objects (Figure 4(c))[117]. The highly bendable triboelectric nanogenerator (HB-TENG) sensor is made from silicone and conductive fabrics. The upper-pressure sensor features a pyramid structure to mimic slowly adapting receptors, while the lower touch sensor consists of Ni fabric and silicone in varying sizes, operating in a single-electrode mode for flexibility. When an object approaches, it generates current by driving free electrons. Increased pressure deforms the sensor and raises capacitance, while removing pressure restores the original state and decreases capacitance. When the object separates, electrons return to the ground, producing an opposite triboelectric current (Figures 4(c-i)). The system captures detailed tactile and pressure information, which is then analyzed by the CNN to identify patterns in the tactile and pressure data. For example, when the system grips an apple, it automatically determines its material and, based on its shape, deduces the appropriate pressure range for grasping. This information is then fed back into the system, enhancing the AI adaptability of the robotic system. The system can accurately identify the size, shape, and material of various objects, adjusting its gripping strategies accordingly for example, by modulating grip strength to match the object's properties and reducing the risk of damage. Additionally, by analyzing multimodal data in real time, the robot can respond quickly in dynamic environments, improving operational efficiency and safety. The CNN model achieves up to 95% accuracy in identifying complex and irregularly shaped objects, demonstrating learning and adaptation capabilities (figure 4(c-ii)).

Li et al. combined bio-inspired transistors with CNN to develop a system that surpasses the human retina, achieving ultra-fast and high-frequency visual adaptation (Figure 4(d))[118]. The device is based on a junction field-effect transistor consisting of an ultrathin molybdenum disulfide (MoS_2) channel and a tungsten diselenide gate electrode on top (Figure 4(d-i)). By adjusting the gate voltage, the device can quickly adapt to changes in light intensity by altering the photo response of the MoS_2 layer. Under strong light, the device enters avalanche mode, with a sharp increase in current; as the light decreases, it switches to photoconductive mode, maintaining stable operation (Figure 4(d-ii)). The system learned the variation patterns of 60 000 MNIST images with different brightness levels, analyzed the relationship between brightness and voltage, and performed reverse correction on the generated images. After 30 training cycles, under dark adaptation conditions, the system achieved an accuracy of 98.3% within 9.5 microseconds, while under light adaptation conditions, it reached an accuracy of 98.2% within 174 microseconds (Figure 4(d-iii)). With CNN integration, the system can rapidly adapt to different brightness environments within microsecond timescales, significantly improving image recognition accuracy and speed, which is highly valuable for applications such as facial recognition and autonomous driving. In general, through deep learning and neural network models, the artificial sensory systems can integrate multiple perceptual information and respond quickly to environmental changes, laying the groundwork for future applications such as autonomous driving.

2.4. Prediction monitoring and early warning of artificial sensory systems using AI

With enhanced perception and machine adjustments by artificial sensory devices as the foundation, we can ultimately use the systems for event prediction and early warning[98,119,120]. For example, AI-integrated portable breathalyzer, known as GeNose C19, analyzes exhaled breath components to assess the likelihood of COVID-19 infection and issue alerts (Figure 5(a))[121]. The system uses a metal oxide semiconductor-based gas sensor array to detect volatile organic compounds (VOCs) in exhaled air, which exhibit specific patterns in individuals infected with coronavirus disease 2019 (COVID-19) (Figure 5(a-i)). The study included 615 exhaled breath samples, 43 positives and 40 negatives, verified through the reverse transcription-quantitative polymerase chain reaction (Figure 5(a-ii)). The researchers used four machine learning models—Linear Discriminant Analysis (LDA), SVM, Stacked Multilayer Perceptrons (SMP), and DNN—to train and test the data. These models each employed different data processing strategies and feature extraction methods, enabling the system to achieve high accuracy under laboratory conditions while maintaining robustness and stability in the face of variations in different populations, environments, and samples, thus meeting the diverse requirements of practical applications. In the experiment, the highest detection accuracy reached 95%, with a sensitivity of 94% and a specificity of 95% (Figure 5(a-iii)). Through real-time data processing and intelligent algorithms, GeNose C19 can analyze and identify virus infection risks within a few minutes, significantly improving rapid response to pandemics. Its non-invasive and easy-to-use nature makes it ideal for wide deployment in resource-limited areas, providing timely warnings and isolating potential carriers to prevent the spread of infections. The warning technology is critical for early detection of infection hotspots, implementing preliminary control measures, and optimizing the allocation of emergency medical resources, especially in the face of rapidly mutating viruses and widespread outbreaks[122].

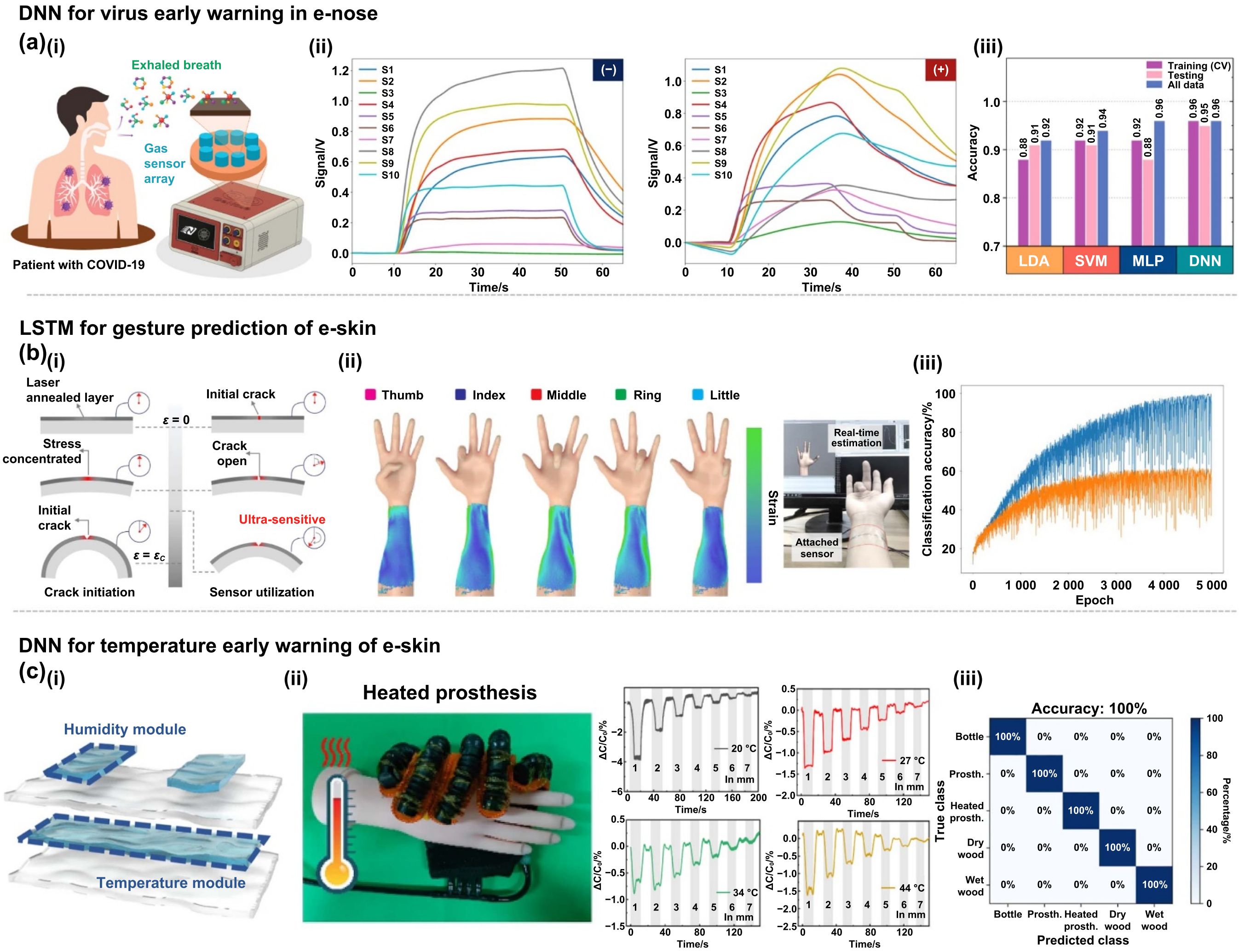

Figure 5. Prediction and early warning functions of artificial sensor systems enabled by AI. (a) DNN for virus early warning in e-nose. (i) Schematics of VOCs detection mechanism in exhaled breath using a metal oxide gas sensor array. (ii) Response signals of the gas sensor array in GeNose C19 for the breath of COVID-19 negative and positive patients. (iii) Accuracy of virus detection using four machine learning algorithms: LDA, SVM, MLP, and DNN. (a-i)–(iii) Reproduced from[121]. CC BY 4.0. (b) LSTM for gesture prediction of e-skin. (i) Photograph of the e-skin (left), and its electrical response mechanism during deformation (right). (ii) The bending of the fingers under different skin deformations and the real-time prediction of these changes. (iii) Accuracy of gesture prediction. (b-i)–(iii) Reproduced from[123]. CC BY 4.0. (c) DNN for temperature early warning of e-skin. (i) Schematics of the multilayer stacked structure of the e-skin. (ii) CNN structure to identify signals obtained from grasped objects. (iii) Accuracy of temperature early warning using multimodal electronic skin. (c-i)–(iii) Reproduced from[124]. CC BY 4.0.

In addition to detecting airborne viruses, this technology can also detect harmful gases, provide early warnings for high-temperature contact, or identify abnormal frequencies in sound waves as potential threats[125]. For example, Kim et al. combined an e-skin with AI to predict finger movements by detecting subtle changes in the wrist's skin (Figure 5(b))[123]. The sensor is fabricated by coating a CPI film onto a glass substrate, spin-coating AgNP ink, and employing laser processing to create a crack-sensing layer. Combined with PDMS film for skin attachment, the crack-induced resistance changes under mechanical strain enable signal transmission. The sensors were placed on the surface of the wrist, and when the fingers bent, the wrist sensors experienced stretching or compression of the cracks, causing changes in resistance and current (Figure 5(b-i)). The deep learning network utilized consisted of two parts: an encoder that used LSTM layers to process the temporal patterns of the sensor signals, generating latent vectors representing hand dynamics; and a decoder that mapped these vectors to a predefined hand motion measurement space (Figure 5(b-ii)). The system achieved 96.2% accuracy in predicting finger bending and effectively distinguished deformations caused by non-finger movements, such as wrist twisting (Figure 5(b-iii)). Additionally, the researchers applied this technology to predict finger key presses on a digital keyboard, achieving similarly impressive results.

Researchers have optimized existing systems, maintaining their original predictive capabilities while expanding their functions to enable real-time risk alerts. For instance, Li et al. combined DNN with multimodal e-skin, achieving precise identification of environmental objects and rapid detection of harmful gases (Figure 5(c))[124]. The humidity and temperature detection is based on the hydrogen bonding interaction between the abundant O-H groups in PVA-CNF organic hydrogels and water molecules. As humidity increases, the hydrogel absorbs more water, leading to enhanced ion migration and increased conductivity, thereby reducing the sensor's resistance. An increase in temperature accelerates ion diffusion and interfacial charge transfer, further enhancing conductivity and enabling temperature and humidity detection (Figure 5(c-i)). The experiments used 100 data samples, including plastic bottles, rubber prosthetic hands, heated rubber prosthetic hands, dry wood, and wet wood, with 20 samples per object. The sensors on the robot's hand collected signals related to temperature, humidity, pressure, and proximity, which were standardized using Z-scores and then input into the DNN model (Figure 5(c-ii)). DNN is composed of multiple layers of neurons including an input layer, one or more hidden layers, and an output layer. Each neuron is connected to neurons in adjacent layers via weighted connections. Activation functions such as ReLU or Sigmoid are used to introduce non-linearity, allowing the model to learn complex patterns from signals such as temperature, humidity, and pressure. The network adjusts the weights by minimizing the error between predicted and actual outputs, typically using backpropagation and gradient descent methods. After 200 training cycles, the model could distinguish these objects with 100% accuracy (Figure 5(c-iii)). Additionally, the system features real-time NO_2 concentration monitoring. When the concentration exceeds the safety threshold, the system immediately triggers an alert. The sensor demonstrated high sensitivity to NO_2, with a detection limit of 11.1 parts per billion (ppb) and a sensitivity of 254% ppb^{-1}. By integrating a microprocessor and wireless circuitry, the system transmits data to mobile devices via Bluetooth, enabling remote monitoring and instant response. This system shows great potential in improving rescue efficiency and safety, particularly in complex disaster response scenarios. By integrating multimodal sensors with deep learning, AI can efficiently analyze complex signals and detect potential risks in real time, such as harmful gases, environmental threats, or health abnormalities[126,127]. This technology provides more accurate risk warnings and is widely applicable in areas such as disaster response and urgent health monitoring, significantly enhancing the system's intelligence and adaptability[128,129].

2.5. Comparative analysis of AI algorithms in different artificial sensory systems

Artificial sensory systems face varying demands across stages such as cognitive simulation, perceptual enhancement, interaction, and adaptive regulation, as well as prediction monitoring and early warning, which determine the type and complexity of the algorithms employed (Table 1)[130,131]. In the cognitive simulation stage, the primary goal is to identify stable environmental patterns. High-dimensional and complex olfactory data often utilize CNNs for odor recognition, which excel in feature extraction but involve complex structures and high training costs[89,132]. Auditory data can benefit from DenseNet, which maintains network depth while controlling the parameter count, though parameter tuning is challenging and resource-intensive[95,133]. For simpler tactile data, MLPs are effective due to their ease of implementation and low resource requirements, but they struggle with capturing more complex features[94,134]. Gustatory signals favor DNNs for extracting refined features, but they require large-scale datasets and are prone to overfitting[135].

In the perceptual enhancement stage, the focus is on improving signal quality in complex or noisy environments[136]. For olfactory data containing anomalies or sparsely distributed samples, variational autoencoders or GRU-based autoencoders capture distributions and temporal features in latent spaces, enabling effective denoising and anomaly detection[57,137]. However, their training is complex and requires large amounts of high-quality data[138]. For tactile data, multi-layer MLPs enhance features and are easy to train, though they are less effective in extreme noise conditions[102]. Gustatory data can use Gaussian kernel SVM-R for precise feature differentiation, suitable for small-scale datasets, but it is sensitive to parameters and difficult to scale to high-dimensional or large-scale data[139,140]. Visual signals frequently employ CNNs for image feature extraction and denoising, but this comes with high computational costs and data requirements[105].

In interaction and adaptive regulation scenarios, multimodal and dynamic data require algorithms that can quickly adapt to environmental changes[141,142]. For multimodal sequential data, expanded RNNs extend the temporal receptive field, while prototype learning networks quickly adjust to category shifts[143,144]. However, these models have complex structures, are challenging to tune, and demand significant computational and storage resources[145]. When processing tactile data in constrained environments, simple interpolation or KNN methods remain efficient and cost-effective but lack advanced feature extraction and generalization capabilities[146,147]. For more complex tactile textures, CNNs are advantageous but require higher computational power and data resources[148,149].

In the prediction monitoring and early warning stage, algorithms infer future states based on historical time-series data[150,151]. LSTMs and DNNs effectively capture long-term dependencies and high-dimensional features in tactile signals, significantly improving prediction accuracy and robustness, though they are time-consuming to train and prone to overfitting[123,124]. For small-scale olfactory data, LD, SVM, or MLP offer fast convergence and are well-suited for data-limited scenarios, but they fall short for high-dimensional complex problems[121]. As data complexity increases, DNNs showcase strong deep representation capabilities but require more training data and computational resources[123]. In multi-class recognition tasks, accuracy is commonly used to measure overall classification rates[10,152]. For anomaly detection and denoising in olfactory data, reconstruction errors and

Table 1. Algorithms for different functional stages and sensory modalities in artificial sensing systems.

	Types of artificial sensory systems	Algorithms	Evaluation metrics
Cognitive simulation	Smell	CNN	Accuracy
	Taste	DNN, Single, HV, SVV	Accuracy
	Touch	MLP	Accuracy
	Hearing	DenseNet	Accuracy
Perceptual enhancement	Smell	Fully-connected autoencoder, LSTM-based autoencoder, CNN1D-based autoencoder, Variational autoencoder, GRU, AnoGAN	Accuracy, ROC-AUC
	Taste	SVM-R	Accuracy RMSE
	Touch	Five-layer MLP	Accuracy
	Vision	CNN	Accuracy
Interaction and adaptive regulation	Touch+ Hearing	DRNN, Softmax-classification layer neural network, Prototype learning neural network	Accuracy MSE
	Touch	Linear, Gaussian, Cubic, KNN, CNN	Accuracy
	Vision	CNN	Accuracy
Prediction monitoring and early warning	Smell	LD, SVM, MLP, DNN	Accuracy
	Touch	LSTM, DNN	Accuracy, sensitivity, specificity

ROC-AUC are key metrics, while sensitivity and specificity are better suited for evaluating detection precision and false positive rates in multi-layered auditory features[153,154].

The selection of algorithms for artificial sensory systems should not be confined to single-dimensional comparisons but should instead consider model capabilities, data characteristics, sensor types, task objectives, and resource constraints comprehensively[155,156]. Deep learning models excel in feature extraction and representation but demand larger datasets and higher computational resources[157,158]. Traditional methods are easier to implement and suitable for small-scale, low-dimensional scenarios but struggle with complex and multimodal data. Generative and sequential models perform well in noise and anomaly detection but increase training and deployment costs[154,159]. Multimodal and adaptive capabilities are crucial in dynamic environments, requiring a balance between flexibility and interpretability[10,64]. By weighing accuracy, speed, scalability, and interpretability, robust algorithms for the artificial sensory system can be developed[1].

3. Summary and outlook

In summary, we reviewed recent advancements in the integration of AI with artificial sensory systems, focusing on replicating and augmenting sensory functions across vision, hearing, smell, taste, and touch. Most of the studies introduced in this review began in the late 2010s and have been actively applied to artificial sensory systems since 2020 (Figure 6). Early research primarily focused on single-function integration. Since 2020, there has been a significant increase in studies, transitioning from single-function applications to multifunctional integration and optimization. For now, the combination of AI and sensors is increasingly applied to complex real-world scenarios, emphasizing interactive, application-oriented functionalities and efficient adaptation to real environments. Leveraging advanced signal processing and AI models, these systems convert diverse environmental inputs into signals akin to human perception, effectively simulating sensory and cognitive processes. These developments significantly improve the accuracy of cognitive simulation, enabling artificial sensory systems to surpass natural human senses. They can adapt to dynamic environments in real time based on past experiences, offering proactive responses. Furthermore, these systems continuously optimize their perceptual mechanisms and provide early predictions or warnings for potential hazards.

Despite these advancements in this field, the integration of AI with artificial sensory systems still has technological challenges for real-world applications (Figure 7). First, the adaptability of AI algorithms to environmental factors such as temperature and humidity fluctuations, or chemical pollution should be solved. In addition to the target perception of the sensors, it is necessary to develop denoising and calibration algorithms to effectively filter out extrinsic noise while ensuring that the sensors provide accurate perception data in complex environments (Figure 7(a)). For example, in medical rehabilitation applications utilizing e-skin, pressure sensors must consistently perform denoising to account for real-life noise variations and external temperature changes unique to each user. Similarly, in industrial leak alarming applications employing e-nose, gas sensors must distinguish noise caused by fluctuations in temperature and humidity, as they are highly sensitive to these environmental changes. These targeted examples highlight both the potential of AI-sensor integration and the necessity for adaptive solutions across different fields. The stability of the algorithms is crucial for the long-term operation and commercial potential of

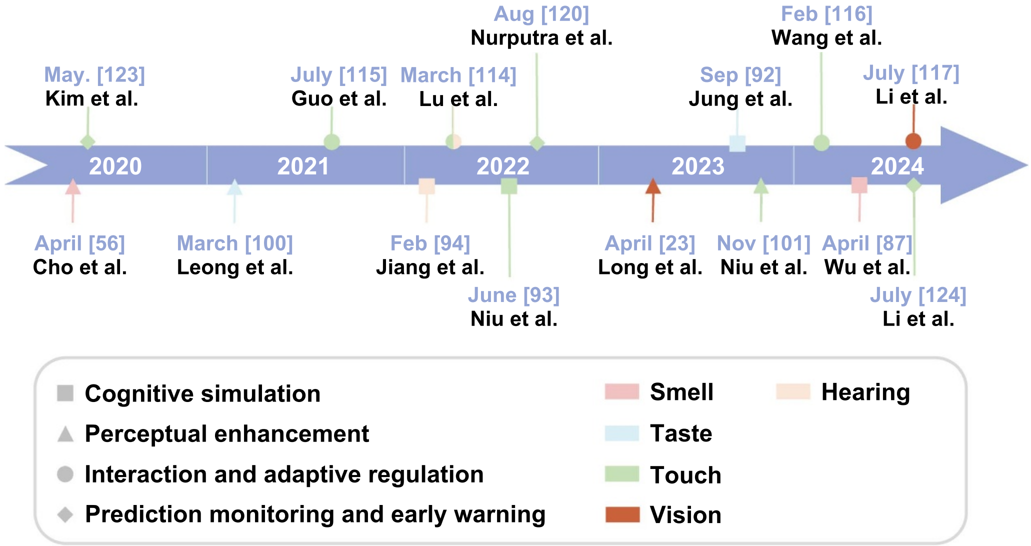

Figure 6. The development timeline of AI integration with artificial sensory systems. The number next to the author's name corresponds to the reference number for the respective study.

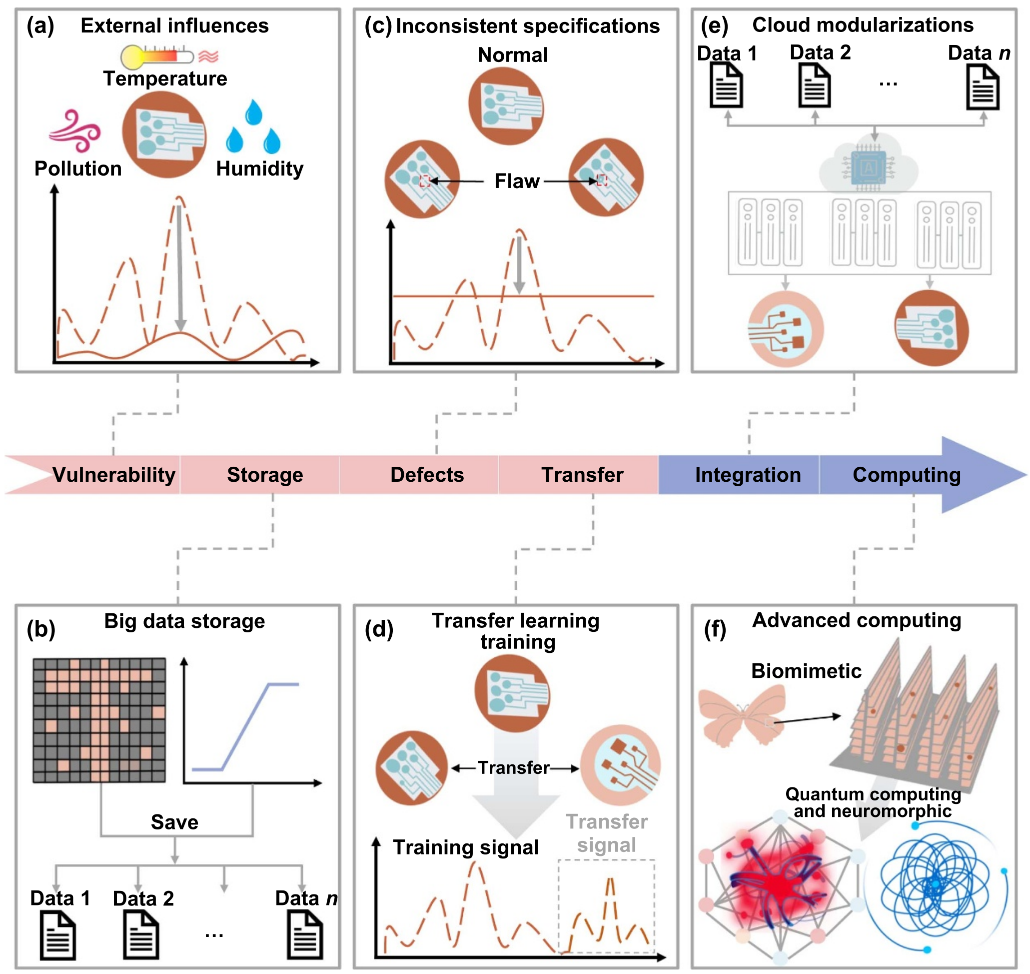

Figure 7. Technical challenges and opportunities for further innovation. (a) The adaptability of AI algorithms to environmental factors. (b) Consistency in sensor device production. (c) Specification compatibility and environmental adaptability. (d) Multi-signal transfer and algorithm adaptability. (e) Cloud integration and module robustness. (f) Biomimetic expansion and quantum-neuromorphic integration.

the systems. Additionally, as the number of integrated sensors in the artificial sensory system increases, the complexity of data management and protection rises significantly. Thus, it is essential to systematically organize raw data into accurately labeled datasets, apply appropriate preprocessing techniques, and implement efficient storage and retrieval strategies for effective data management (Figure 7(b)). Typically, such systems require several gigabytes of data or thousands of labeled samples to effectively conduct training and real-time processing. The exponential growth in data volume not only places higher demands on storage solutions but also raises additional challenges. Consistency in device production is a significant issue, as variations in materials and device configurations can impact sensor data quality, leading to instability in AI performance. Ensuring the consistency of material performance and manufacturing processes through strict quality control standards, automated production lines, and online monitoring systems can effectively enhance the stability of sensor data quality and AI performance (Figure 7(c)). Furthermore, the cost of implementing and maintaining these systems is a key consideration, as it may restrict widespread adoption. Costs related to hardware production, system maintenance, and upgrading existing infrastructure could present financial barriers to large-scale deployment. If there are significant differences in the sensor outputs, it may introduce biases when the models process the data, thereby affecting the overall sensory capability and adaptability. Furthermore, artificial sensory systems require a large amount of consistent and high-quality data for training, and insufficient production consistency can make data acquisition challenging, limiting the performance of AI algorithms. Therefore, ensuring production consistency not only enhances sensor performance but also supports the application and adaptability of AI systems in dynamic environments. Another crucial factor is the compatibility of these new systems with existing technologies. Legacy systems may require substantial modifications or upgrades to accommodate AI-driven artificial sensory systems, which can increase the complexity and cost of implementation (Figure 7(d)). Lastly, the rapid development of AI and new sensor engineering presents significant challenges for whole system design. The focus needs to be on modularity and scalability to ensure flexibility in adapting to fast technological changes. By integrating a hybrid architecture of cloud and edge computing, real-time data processing can be achieved while reducing the burden on central servers and enhancing data processing flexibility (Figure 7(e)). In sensor design, machine learning can accelerate the reverse design process, automatically optimizing parameters to improve performance, ensuring that the system remains adaptable to changing conditions. To handle complex data processing needs, adaptive algorithms can dynamically allocate resources and improve efficiency. Through technological integration, modular design, and algorithmic optimization, systems can maintain flexible and easily upgrade as technology evolves, ensuring sustainability. In addition, future exploration could focus on the integration of emerging technologies such as quantum sensing, neuromorphic computing architectures, and bioinspired sensory devices (Figure 7(f)). These approaches are expected to significantly enhance the resolution and adaptability of artificial perception systems, providing overall performance improvements and the expansion of application domains. If these remaining challenges are further researched and improved, we can truly enter an era of digital transformation with artificial sensory systems, fundamentally changing human interaction with technology and contributing to a safer, more convenient living environment.

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