



Raccoon-paw-inspired porous hydrogel electronic skin for self-powered fused perception

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ABSTRACT

Wearable gel electronics require soft material platforms capable of supporting autonomous tactile sensing and physiological monitoring within a compact system. Here, we report a raccoon-paw-inspired porous hydrogel electronic skin for self-powered slip perception and artificial sweat fingerprint recognition. A sacrificial sucrose-template strategy was used to construct an interconnected porous hydrogel network with low volume density, high compressibility, rapid liquid uptake, and continuous ionic transport. After loading with the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ redox couple, the hydrogel generates a thermogalvanic output under a temperature difference. Benefiting from the active piezoresistive effect based on thermoelectricity, the electronic skin enables self-powered pressure sensing with a sensitivity of 161.3 kPa^{-1} , a detection limit of 2.5 Pa , and response and recovery times of 65 and 75 ms, respectively. It is further coupled with a honeycomb-structured contact layer to capture sliding-induced current signals for surface texture perception, achieving 95.23% accuracy in recognizing nine surface textures. In addition, the hydrogel network converts ion-dependent diffusion dynamics of mixed sweat electrolytes into time-resolved sweat fingerprints, allowing eight artificial sweat compositions to be identified with 95.0% accuracy. The recognized compositions are further mapped to three electrolyte-status levels for electrochromic visual feedback. This porous hydrogel platform provides a simple strategy for integrating self-powered tactile perception with artificial sweat classification in wearable electronics.

1. Introduction

The rapid development of flexible electronics, soft robotics, personalized healthcare, and intelligent human-machine interfaces is driving wearable systems toward autonomous and multifunctional perception (Liang et al., 2026; Liu et al., 2025; Wang et al., 2025). Soft electronic materials are expected to bridge the mechanical and physiological gap between biological tissues and conventional electronics while maintaining stable operation under motion and deformation (Bai et al., 2026; Kim et al., 2021; Zhi et al., 2024). Meanwhile, the demand for low-power and untethered devices has promoted self-powered sensing platforms that harvest ambient energy and convert external stimuli into readable signals (Li et al., 2025; Wang et al., 2024; Xu et al., 2024; Yang

et al., 2026; Zou et al., 2026).

Hydrogels, as water-rich polymer networks, offer tissue-like softness, tunable mechanical properties, and high ionic transport capability, making them promising materials for conformal wearable gel electronics (Bariya et al., 2018; Chang et al., 2026; Sung et al., 2025). Compared with dense hydrogels, porous hydrogels possess lower volumetric density, higher compressibility, improved liquid uptake, and enlarged internal interfaces, which are beneficial for constructing soft sensing materials with enhanced deformability and mass-transport capability (He et al., 2022; Li et al., 2023; Liu et al., 2024, Liu et al., 2026). Recent progress has demonstrated that gradient foam-shaped hydrogels with stop-hole structures can simultaneously improve softness, deformability, and pressure sensitivity for conformal

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human-machine interfaces (Hui et al., 2024). When redox couples are introduced into porous hydrogels, the resulting thermogalvanic hydrogels can convert a temperature difference into electrical output, providing an internal energy source for self-powered sensing (Fu et al., 2025; Jiang et al., 2024; Sang et al., 2024; Wei et al., 2025).

Although considerable progress has been achieved in hydrogel-based wearable sensors, the wearable applications of porous hydrogels have not been fully explored (Griffanti and Nazhat, 2020). Most porous hydrogel sensors focus on pressure, strain, or human motion monitoring, whereas dynamic slip perception and surface texture recognition require the efficient conversion of sliding-induced contact fluctuations into distinguishable electrical signals (Alsaied et al., 2021; Li et al., 2024; Lloyd et al., 2025). Meanwhile, sweat sensing is commonly realized by ion-selective membranes, enzymes, or other specific recognition layers, which may introduce additional interfacial modification and cross-interference in mixed electrolyte environments (Wang et al., 2023; Liu et al., 2026; Zou et al., 2026; Xiao et al., 2025; Yin et al., 2022). The water absorption and ion diffusion characteristics of porous hydrogels offer a simple route to record sweat-related transport dynamics, while this strategy has received limited attention (Singh et al., 2024; Xu et al., 2026; H. Zhang et al., 2026). Therefore, it is still desirable to develop a porous hydrogel platform that can be programmed into different sensing units for self-powered tactile perception and sweat status-monitoring.

Here, we report a raccoon-paw-inspired porous hydrogel electronic skin (PHES) for self-powered slip perception and sweat monitoring. The PHES exhibits lightweight characteristics, mechanical compliance,

strong water uptake, and continuous ion transport pathways. For tactile sensing, the PHES loaded with the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ redox couple generates a thermoelectric output under a temperature difference, while pressure and sliding trigger an active piezoresistive effect by modulating the internal resistance and thus regulate the thermoelectric current output. By integrating a honeycomb-structured contact layer, the PHES captures sliding-induced current fluctuations and enables surface texture recognition. For sweat sensing, the porous hydrogel is used without additional ion-selective layers, allowing the diffusion dynamics of mixed electrolytes to be converted into time-resolved electrical fingerprints. The identified artificial sweat compositions are further mapped to electrochromic visual feedback. This integrated strategy enables mechanical perception and ionic information analysis within a common porous hydrogel platform, offering distinct advantages over previously reported hydrogel-based sensing systems (Table S1).

2. Results and discussion

2.1. Design concept of raccoon-paw-inspired porous hydrogel electronic skin

Biological skin integrates softness, hydration, and environmental perception within a compliant interface (Hu et al., 2023; Kumar et al., 2020; N. Li et al., 2025). Raccoon paws exhibit sensitive tactile perception through the palmar skin, where hydration enhances tissue deformability and mechanical coupling with contacted surfaces. As

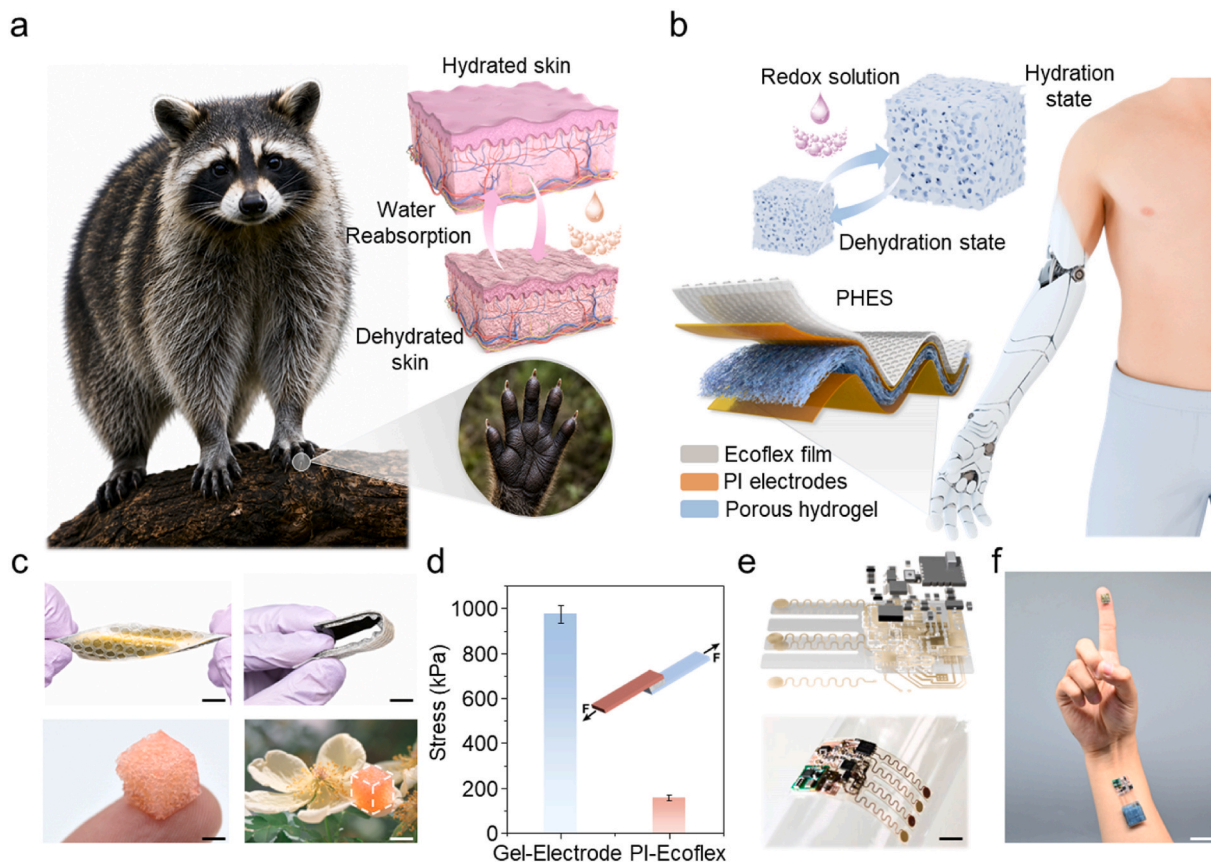


Fig. 1. Design concept and fabrication of raccoon-paw-inspired PHES. (a) Schematic illustration of raccoon palmar skin with hydration-dependent tactile perception, where the dry state shows reduced sensitivity and the hydrated state enables enhanced tactile perception. (b) Schematic illustration of the PHES integrated on a robotic hand for tactile, slip, and surface-roughness perception. (c) Demonstration of the flexibility, conformability, and lightweight feature of the PHES. Scale bar 1 mm. (d) Comparison of interfacial adhesive strength between the gel-electrode interface and the PI-Ecoflex interface. Data are presented as mean $\pm$ standard deviation (SD, $n = 3$). The relative standard deviation (RSD) values of the Gel-Electrode and PI-Ecoflex interfacial stress measurements were 3.5% and 6.1%, respectively. (e) Flexible circuit board for collecting dynamic current changes and driving the electrochromic module. Scale bar 1 cm. (f) Schematic diagram of application for the PHES-based slip and sweat-ion sensor. Scale bar 3 cm.

illustrated in Fig. 1a, dehydration stiffens the palmar surface and weakens the perception of subtle surface features, whereas water uptake restores compliance and conformal contact with surface asperities. Inspired by this hydration-regulated behavior, a raccoon-paw-inspired PHES was developed to integrate a hydration-responsive soft matrix with wearable mechanical and ionic sensing functions.

The PHES was fabricated from a poly(vinyl alcohol) (PVA) hydrogel using a sacrificial sucrose-template strategy. Sucrose particles were dispersed in a PVA/dimethyl sulfoxide (DMSO) solution, followed by freeze-thaw treatment and water exchange to remove the sucrose template and form an interconnected porous network (Fig. S1). The resulting hydrogel could be processed into different shapes and colors (Fig. S2). Its pore architecture was regulated by varying the sucrose content. The characteristic pore size increased from approximately 0.1–0.4 mm at 50% sucrose to 0.3–0.8 mm at 66% sucrose and 0.5–1.2 mm at 75% sucrose, consistent with the quantitative pore-size distributions (Figs. S3 and S4). These results confirm that sucrose proportion provides a direct means of regulating the porous architecture.

For tactile sensing, the porous hydrogel was loaded with the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ redox couple to form the thermogalvanic module (Fig. 1b). The internal cavities reduce the apparent density and mechanical stiffness, while the deformable pore walls accommodate compression,

bending, and shear deformation. Consequently, the PHES can be bent, twisted, and attached to curved surfaces while maintaining structural integrity (Fig. 1c). Its foam-like architecture also provides an ultralight characteristic, allowing the hydrogel to be supported on delicate flowers without visible deformation (Fig. S5).

The interconnected porous network further enables reversible dehydration and rehydration. At 50 °C and 5% relative humidity, the hydrogel mass decreased from approximately 0.36 g to 0.05–0.06 g and recovered to approximately 0.35 g after rehydration, corresponding to a recovery ratio above 95% (Fig. S6a and b). The rehydrated PHES maintained stable thermoelectric current over 50 cycles, with thermopower and ionic conductivity of approximately 2.2 mV K⁻¹ and 1.9 S m⁻¹, respectively (Fig. S6c and d). The gel–electrode interface exhibited an interfacial stress of approximately 0.97 MPa, markedly higher than that of the polyimide (PI)–Ecoflex interface (approximately 0.16 MPa), and remained stable over 500 stretching cycles (Fig. 1d and Fig. S7). Together, the porous architecture and stable interface provide the structural and functional basis for mechanical sensing and sweat analysis.

A customized flexible circuit was developed for signal acquisition, processing, and wireless transmission (Fig. 1e). As demonstrated in Fig. 1f, the tactile sensing unit can be mounted on the fingertip for

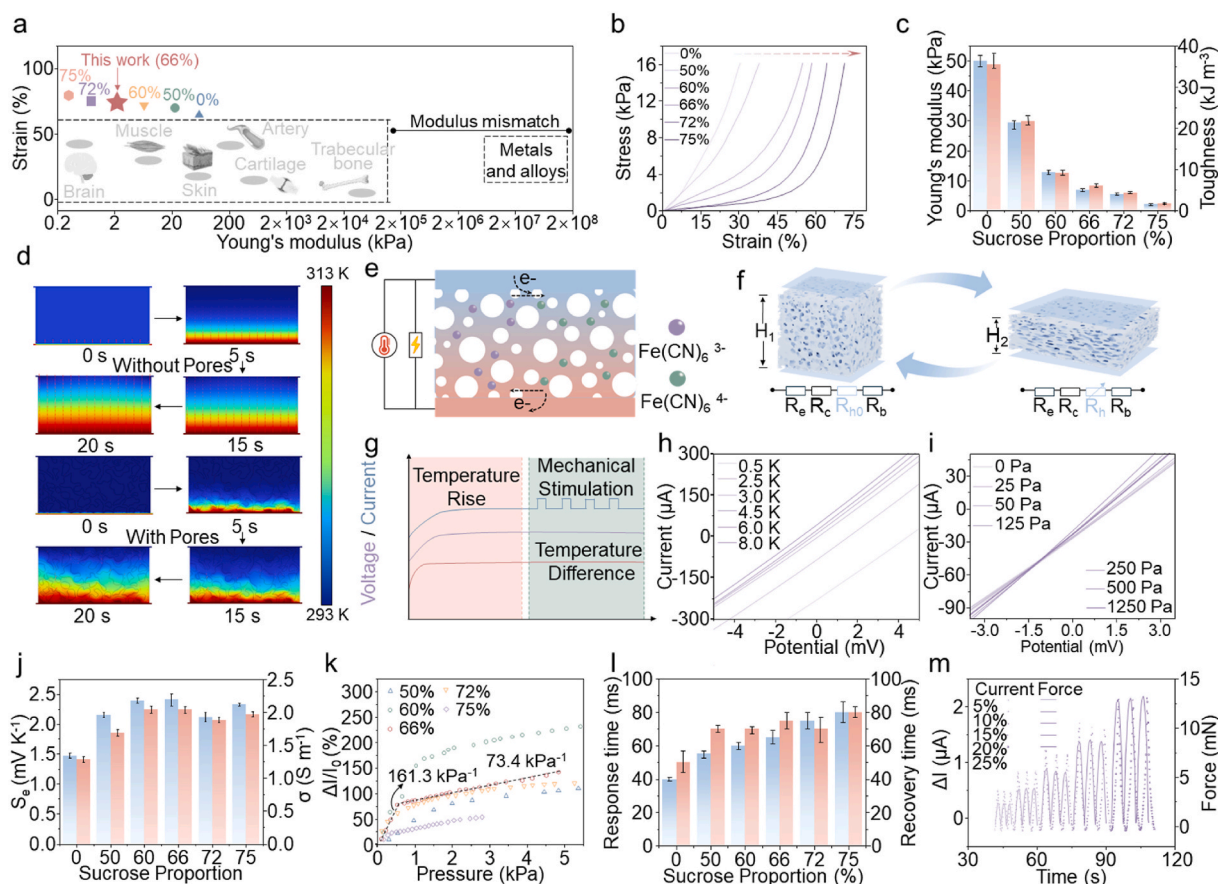


Fig. 2. Optimization of porous hydrogel and its self-powered pressure sensing based on the active piezoresistive effect. (a) Young's modulus-strain comparison of PHES with different sucrose proportions relative to biological tissues and rigid engineering materials. (b,c) Representative stress-strain curves, Young's modulus, and toughness of PHESs with different porous structures. Data are presented as mean $\pm$ SD ($n = 3$), and the corresponding RSD values were below 8%. (d) Comparison of heat-transfer behavior between nonporous and porous hydrogels. (e) Schematic illustration of the thermogalvanic output generated by the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ -containing hydrogel under a temperature difference. (f) Pressure-induced deformation mechanism of the porous hydrogel, where pore compaction shortens ion-transport pathways, increases effective conductive channels, and decreases the hydrogel internal resistance. (g) Schematic illustration of the active piezoresistive effect for self-powered pressure sensing, where the thermogalvanic voltage remains relatively stable while the output current is modulated by pressure-dependent resistance variation. (h,i) Current-potential curves under different temperature differences and applied pressures. (j) Sucrose-proportion-dependent thermoelectric properties of the PHES. Data are presented as mean $\pm$ SD ($n = 3$), with RSD values below 4.2%. (k) Pressure sensitivity comparison of PHESs with different sucrose proportions. (l, m) Response/recovery behavior and hysteresis characteristics of the optimized PHES under mechanical stimulation. Data are presented as mean $\pm$ SD ($n = 3$). The RSD values for the response and recovery times were below 9% and 12%, respectively.

contact and slip perception, while the sweat-sensing unit and flexible circuit can be worn on the forearm. This configuration enables wearable tactile perception and sweat-status analysis within a compact system.

2.2. Optimization of the porous hydrogel and self-powered pressure sensing based on the active piezoresistive effect

To achieve a soft, lightweight, and pressure-sensitive thermogalvanic hydrogel, the porous structure of the PHES was regulated by varying the sucrose proportion. As summarized in Fig. 2a, introducing the porous structure reduced the modulus and increased deformability, thereby decreasing the mechanical mismatch with biological tissues. The Young's modulus decreased from approximately 50 kPa for the nonporous hydrogel to approximately 7 kPa for the hydrogel with 66% sucrose, while the strain increased to approximately 70–75% (Fig. 2b and c). The 66% sucrose hydrogel also retained a toughness of approximately 6 kJ m^{-3} . Hydrogels with higher sucrose proportions were softer but exhibited reduced structural strength, whereas those with lower proportions showed increased stiffness. As summarized in the radar plot (Fig. S8), the 66% sucrose hydrogel provides the most balanced combination of Young's modulus, toughness, thermopower, ionic conductivity, and dynamic response.

The foam-like porous architecture simultaneously regulates thermal and ionic transport within the PHES. Compared with the nonporous hydrogel, the porous structure suppresses cross-plane heat transfer and therefore preserves a larger temperature difference across the device (Fig. 2d). This temperature gradient drives the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ thermogalvanic reaction and provides a relatively stable thermovoltage that serves as the internal electrical bias of the sensor (Fig. 2e). Meanwhile, the interconnected pores provide continuous pathways for electrolyte penetration and ion migration (Fig. S9). Under mechanical compression, pore compaction reduces the hydrogel thickness and transport distance while increasing the effective conductive area, leading to a decrease in the internal ionic resistance (Fig. 2f). Because the thermogalvanic voltage remains nearly unchanged, the pressure-dependent resistance variation is directly translated into a reversible modulation of the output current. Upon release, the porous network recovers its original geometry and resistance, thereby enabling self-powered pressure sensing through the active piezoresistive effect (Fig. 2g and Supplementary Note S1).

The electrochemical measurements further validated this pressure-modulated transport mechanism. In the linear sweep voltammetry measurements, increasing the temperature difference primarily increases the thermogalvanic driving voltage, whereas increasing pressure produces a steeper current-potential response with only a minor change in the thermovoltage (Fig. 2h and i). This behavior is consistent with a pressure-induced decrease in the internal resistance rather than a substantial variation in the thermogalvanic potential. Pressure-dependent cyclic voltammetry (CV) measurements showed that the characteristic redox potentials of the $[\text{Fe}(\text{CN})_6]^{3-/4-}$ couple remained nearly unchanged from 0 to 1250 Pa, while the current response increased moderately with compression (Fig. S10a). The preserved redox potentials indicate that mechanical loading does not markedly alter the redox thermodynamics, whereas the enhanced current is consistent with reduced ionic-transport and ohmic limitations in the compressed porous network. This interpretation is further supported by electrochemical impedance spectroscopy (EIS), where the impedance response shifted progressively toward lower impedance with increasing pressure (Fig. S10b). The results establish that pressure predominantly regulates the transport resistance of the PHES while preserving the thermogalvanic redox characteristics, thereby providing the electrochemical basis for the active piezoresistive sensing mechanism.

The sucrose proportion was further optimized by considering the thermogalvanic and pressure-sensing properties of the hydrogel. Thermopower and ionic conductivity first increased and then decreased with increasing sucrose proportion, reaching approximately 2.4 mV K^{-1} and 2.1 S m^{-1} , respectively, for the 66% sucrose hydrogel (Fig. 2j). This

composition exhibited two pressure-sensitivity regions of 161.3 and 73.4 kPa^{-1} (Fig. 2k). The higher sensitivity at low pressure originates from rapid pore compression, whereas progressive densification restricts further deformation at higher pressure. Response and recovery times of approximately 65 and 75 ms were obtained for the 66% sucrose hydrogel (Fig. 2l). Under cyclic loading with strains ranging from 5% to 25%, the current signals closely followed the applied force and exhibited low hysteresis (Fig. 2m and S11). The rapid and repeatable electrical response can be attributed to the reversible compression and recovery of the porous skeleton. A pressure as low as approximately 2.5 Pa could be distinguished from an obvious stepwise increase in current signals (Fig. S12). When the porous hydrogel was attached above the radial artery, periodic pulse waveforms with identifiable percussion, tidal, and diastolic features were recorded, illustrating its capability for weak physiological signal detection (Fig. S13). Repeatable mechanical responses were also obtained at different applied strains and loading frequencies (Fig. S14). During 500 loading-unloading cycles at 10% strain, no apparent attenuation of the current amplitude was observed, indicating good reversibility and operational stability of the porous hydrogel (Fig. S15). Comparison with recently reported hydrogel-based pressure sensors further confirms its competitive overall sensing performance (Fig. S16). Therefore, the 66% sucrose hydrogel was selected for the subsequent sensing demonstrations because of its balanced mechanical, thermogalvanic, ionic-transport, and dynamic sensing properties.

2.3. Surface texture and slip perception enabled by the honeycomb-structured PHES

Tactile pressure alone provides limited information about the relative motion between a sensor and a contacted object (Bai et al., 2023; Guo et al., 2024; Linghu et al., 2025). During sliding, surface asperities generate coupled normal and tangential forces that carry information about surface texture and slip state. To capture these dynamic cues, a honeycomb-patterned Ecoflex layer was integrated with the porous thermogalvanic hydrogel and flexible electrodes to construct the PHES (Fig. 3a). Under normal loading, the porous hydrogel undergoes predominantly out-of-plane compression, which reduces its thickness and produces a relatively smooth change in internal resistance (Fig. S17). In contrast, sliding introduces tangential shear and spatially nonuniform deformation, causing the pore walls and internal cavities to continuously rearrange along the sliding direction. This dynamic deformation perturbs the ion-transport pathways and gives rise to characteristic current fluctuations (Fig. S18 and Supplementary Note S2). Consistent with this mechanism, Fig. 3b shows a comparatively steady current response under static contact, whereas sliding generates pronounced temporal fluctuations associated with repeated shear deformation of the porous network.

The geometry of the contact layer strongly influences the transmission of texture-induced mechanical fluctuations. PHESs with non-patterned, flat, linear, and honeycomb contact structures were therefore evaluated using five periodic textures (T1–T5) with different feature intervals (Fig. 3c and d and Table S2). The nonpatterned and flat structures generated comparatively weak responses, whereas the linear pattern produced stronger fluctuations but remained sensitive to the relative orientation between the ridges and the sliding direction (Fig. S19a and b). By contrast, the honeycomb structure provides contact edges along multiple in-plane directions, allowing repeated interactions with surface asperities during sliding. Eight-direction tests further confirmed clear current fluctuations and distinguishable time–frequency features across different sliding orientations, indicating favorable directional robustness (Fig. S19c and d).

To resolve texture-dependent differences beyond the time-domain waveforms, continuous wavelet transform was used to analyze the corresponding time–frequency characteristics. As shown in Fig. 3e and Fig. S20, the nonpatterned and flat structures exhibited limited time–frequency responses, while the linear structure produced more distinct

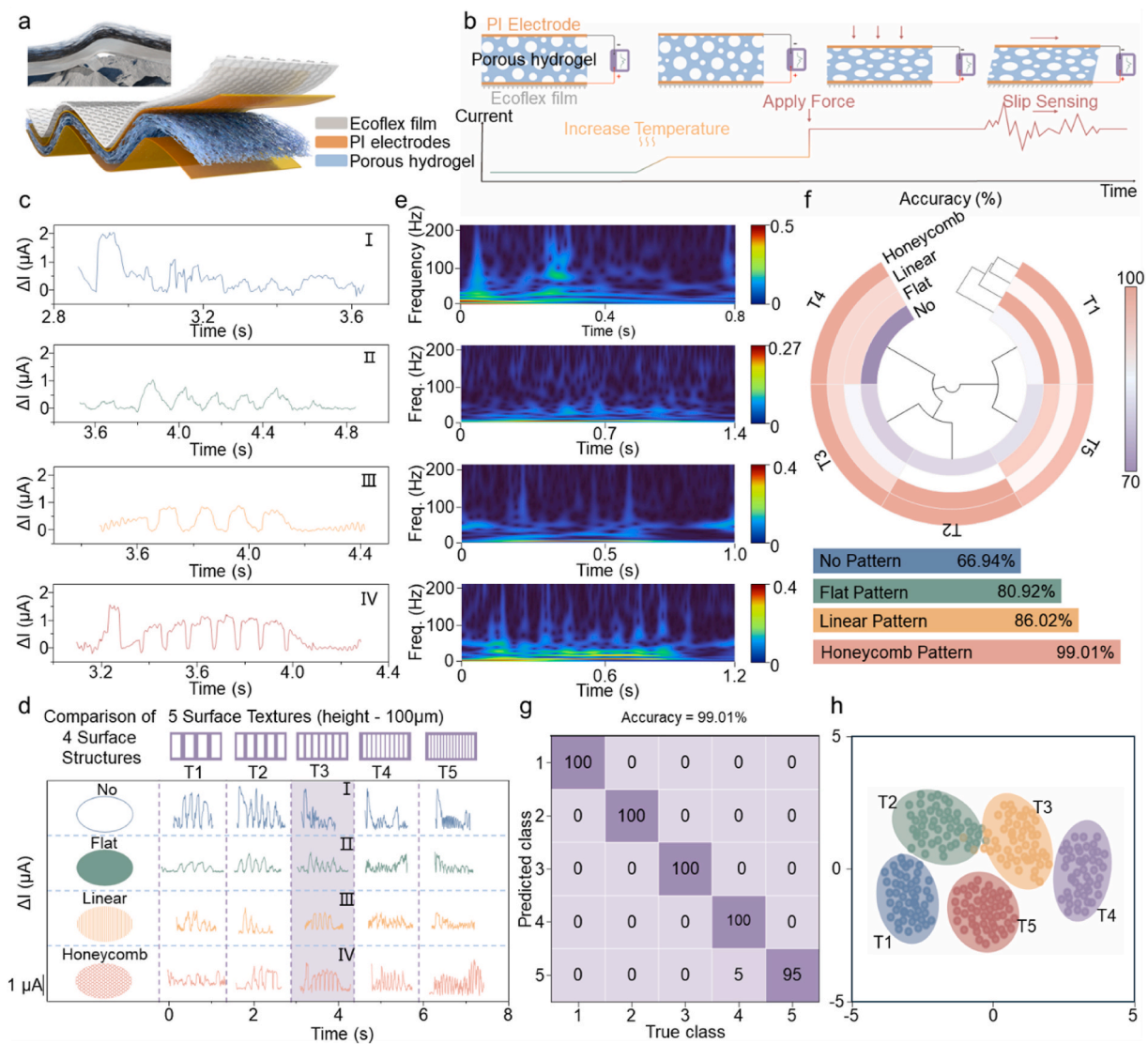


Fig. 3. Design and optimization of the honeycomb-structured PHES slip sensor for surface texture perception. (a) Schematic illustration and photograph of the flexible PHES-based slip-sensing device. The device consists of a honeycomb-structured Ecoflex contact layer, PI-based flexible electrodes, and the porous hydrogel active layer. (b) Schematic illustration of the sensing mechanism under thermal, normal pressure, and sliding stimuli. Under a constant temperature difference, the PHES generates an initial thermogalvanic output, whereas applied force and sliding-induced deformation modulate the hydrogel internal resistance through the active piezoresistive effect. (c,d) Current responses of devices with different surface structures and representative current signals when sliding across five surface textures. (e) Representative current-response-based wavelet time-frequency diagrams illustrate the dynamic features extracted from devices with diverse surface patterns. (f) Comparison of surface texture recognition capability for different surface structures. (g,h) Confusion matrix and t-SNE visualization for classification of five surface textures.

features that varied with sliding orientation. In comparison, the honeycomb-structured PHES generated richer and more widely distributed time-frequency features, which are attributed to repeated mechanical interactions at its multidirectional edges and junctions.

The surface-texture recognition capability of the four structures is compared in Fig. 3f. The honeycomb-structured PHES achieved the highest recognition accuracy of 99.01%. The confusion matrix and t-distributed stochastic neighbor embedding (t-SNE) map further show predominantly diagonal classification and clear separation among the five textures (Fig. 3g,h and Fig. S21), confirming that the honeycomb contact layer provides distinctive slip-induced features for texture recognition.

The optimized PHES was subsequently evaluated using nine practical surfaces with different roughness and surface structures. Sliding across these surfaces generated characteristic current waveforms with differences in amplitude, fluctuation density, and temporal distribution

(Fig. 4a and b). These variations originate from differences in local contact, friction-induced vibration, and shear deformation of the porous hydrogel. The corresponding time-frequency characteristics are shown in Fig. S22. Manual sliding introduces variations in applied pressure and sliding speed, which can affect signal amplitude and temporal spacing. A machine-learning framework was therefore used to extract texture-related features and reduce the influence of these operational variations (Fig. 4c). After feature extraction, the nine surfaces formed distinguishable clusters in the t-SNE space, while the confusion matrix showed a predominantly diagonal distribution (Fig. 4d and e). The model achieved a recognition accuracy of 95.23% for the nine practical surfaces.

As a proof of concept, the honeycomb-structured PHES and flexible circuit were integrated on a human hand for wearable surface-texture recognition (Fig. 4f). The sensing unit was mounted on the fingertip to interact directly with rough surfaces during natural sliding (Fig. 4g and

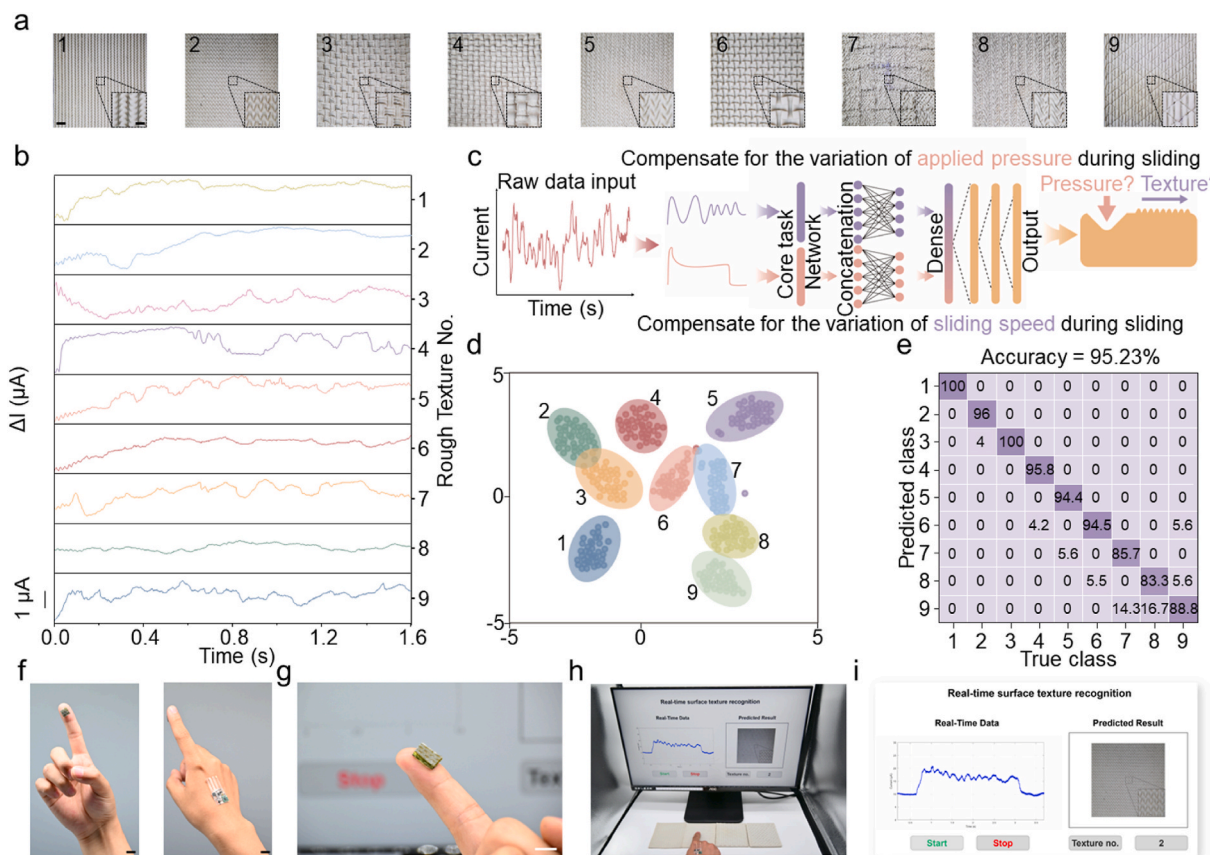


Fig. 4. Wearable slip sensing and machine-learning-assisted recognition of nine surface textures. (a,b) Current responses generated by the PHES-based slip sensor when sliding across nine rough surfaces. (c) Machine-learning framework for surface texture recognition, including raw signal input, feature extraction, compensation for sliding-speed and applied-pressure variations, classification, and output prediction. (d,e) t-SNE visualization and confusion matrix of the extracted features from the nine surface textures. (f) Schematic illustration of the PHES and flexible circuit integrated onto a human hand. Scale bar 1 cm. (g) Detailed view of the honeycomb-structured PHES. Scale bar 1 cm. (h) Demonstration of successful identification of rough surfaces by the PHES via the deep-learning model. Scale bar 10 cm. (i) Interface display of real-time surface texture recognition.

Fig. S23). The generated signals were transmitted to the trained deep-learning model for surface identification, and the predicted category together with the real-time current waveform was displayed on the user interface (Fig. 4h and i and Video S1).

2.4. Ion-diffusion dynamics-based sweat fingerprint identification and visual feedback

Sweat contains abundant ionic information associated with electrolyte balance and exercise-induced physiological changes. Conventional sweat analysis commonly relies on ion-selective membranes, enzymes, or other recognition layers to isolate individual components (Bai et al., 2023; Childs et al., 2024; Davis et al., 2024; Guo et al., 2024; Linghu et al., 2025). Such selective interfaces increase fabrication complexity and may introduce signal drift or cross-interference in mixed electrolytes. The PHES exploited the ion-dependent diffusion dynamics of mixed sweat electrolytes to generate characteristic transient current responses, which were encoded as sweat fingerprints for composition recognition. As depicted in Fig. 5a, the sweat-sensing PHES consisted of a perforated bottom carbon electrode, a porous hydrogel without the redox couple, and a top carbon electrode, with an electrochromic layer integrated above the sensing unit. Sweat entered through the bottom opening and rapidly infiltrated the interconnected porous network owing to its strong water-absorbing capability (Fig. 5b and Fig. S24). Hydrated ions then migrated through the pore channels under concentration gradients, generating dynamic electrical responses governed by ion transport within the hydrogel.

Simulated concentration evolution further verified the ion-dependent transport behavior in the porous hydrogel (Fig. 5c). Under the same porous structure, Na^+ , K^+ , and Ca^{2+} showed distinct diffusion kinetics and spatial concentration evolution. The Na^+ concentration profile gradually evolved from 0 to 0.2 s, while K^+ and Ca^{2+} exhibited distinguishable diffusion behavior within shorter time windows. These differences arose from their distinct hydration characteristics, effective hydrated sizes, and ion-water interactions (Fig. 5d). Single-ion measurements further showed reproducible concentration-dependent current responses for Na^+ , K^+ , Ca^{2+} , and Mg^{2+} (Fig. S25), with sensitivities of $0.048 \mu\text{A dec}^{-1}$ for Na^+ and K^+ , $-0.040 \mu\text{A dec}^{-1}$ for Ca^{2+} , and $-0.061 \mu\text{A dec}^{-1}$ for Mg^{2+} (Fig. 5e). Sequence-dependent measurements also produced distinct temporal profiles, indicating that the PHES preserves information from preceding ion-diffusion events (Fig. S26).

Based on these responses, eight artificial sweat samples were prepared by varying the concentrations of Na^+ , K^+ , and Ca^{2+} to yield eight compositions labeled M1–M8 (Table S3). The eight artificial sweat samples were constructed as a $2 \times 2 \times 2$ composition library using lower and higher concentration levels of Na^+ , K^+ , and Ca^{2+} within the broad ranges reported for exercise-induced human sweat (Baker et al., 2019; Ji et al., 2023). For electrolyte-status classification, M1–M2, M3–M6, and M7–M8 were assigned to lower-, intermediate-, and higher-electrolyte groups according to the combined Na^+/K^+ concentration states, while Ca^{2+} was varied independently as an additional compositional dimension for fingerprint discrimination. Each composition generated a distinct transient current response with characteristic peak amplitude, rising behavior, and relaxation profile (Fig. 5f).

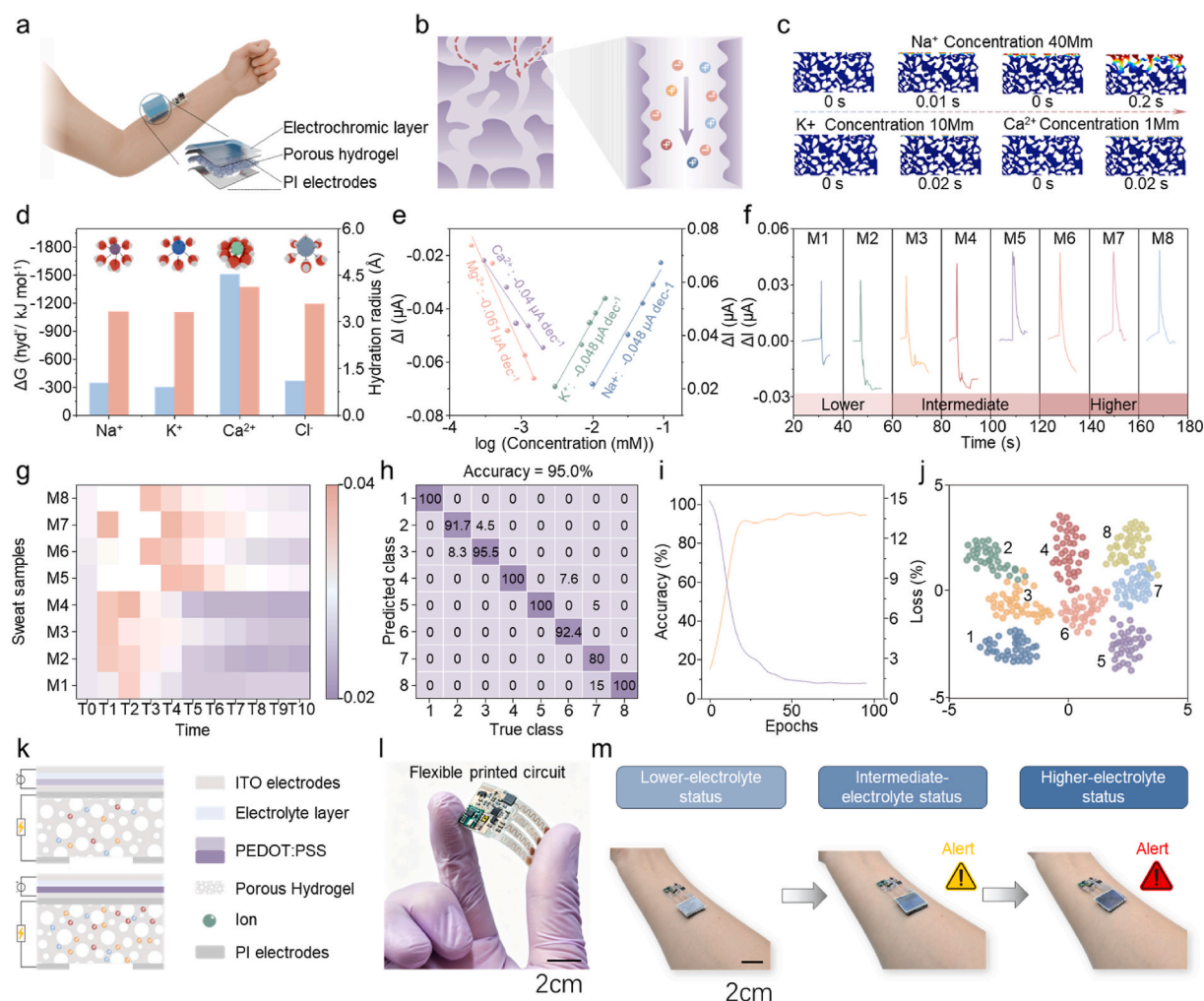


Fig. 5. PHES with ion-diffusion dynamics-based sweat fingerprint identification and electrochromic feedback. (a) Schematic illustration of the wearable PHES attached to the human arm. (b) Schematic illustration of sweat uptake and ion diffusion within the interconnected porous hydrogel network. (c) Simulated concentration evolution of Na^+ , K^+ , and Ca^{2+} in the porous hydrogel, showing ion-dependent diffusion behavior under a concentration gradient. (d) Comparison of hydration-related parameters of representative sweat ions, including hydration free energy and hydration radius. (e) Current responses of the PHES toward different ion concentrations, showing ion-specific diffusion-current characteristics. (f) Representative transient current responses generated by eight artificial sweat samples with different Na^+ , K^+ , and Ca^{2+} compositions. (g) Ion-diffusion dynamics-based sweat fingerprint patterns constructed from time-dependent current features extracted from T0 to T10. (h) Confusion matrix for the classification of eight artificial sweat samples, with an overall accuracy of 95.0%. (i) Training accuracy and loss curves of the deep-learning model. (j) t-SNE visualization of the extracted sweat fingerprint features. (k) Schematic illustration of the integrated sweat-ion sensing layer and electrochromic display layer. (l) Photograph demonstrating the flexibility and lightweight nature of the flexible circuit board. Scale bar 2 cm. (m) Wearable demonstration of sweat electrolyte-status monitoring and visual feedback, where lower-electrolyte, intermediate-electrolyte, and higher-electrolyte statuses are converted into different electrochromic color levels. Scale bar 2 cm. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Because a single peak current cannot fully represent the coupled transport of multiple ions, time-dependent current values from T0–T10 were extracted to form an 11-dimensional feature vector for each sample (Fig. S27). These features contain information related to the diffusion rate, peak formation, decay behavior, and recovery of the mixed ions. The extracted features from M1–M8 were arranged into a two-dimensional heat map to construct ion-diffusion-dynamics-based sweat fingerprints (Fig. 5g). Clear differences appeared in both the magnitude and temporal distribution of the current features among the eight compositions. These patterns arise from the coupled time-dependent fluxes of Na^+ , K^+ , and Ca^{2+} , as described in Supplementary Note S3. A deep-learning model trained on these fingerprints achieved 95.0% classification accuracy for the eight artificial sweat compositions, with clear class separation in the t-SNE map (Fig. 5h–j).

To translate the classification result into an intuitive output, an electrochromic layer was integrated above the sweat-ion sensing layer

(Fig. 5k). The electrochromic section consists of indium tin oxide (ITO) electrodes, a photocurable electrolyte, and a poly(3,4-ethylenedioxythiophene):poly(styrene sulfonate) (PEDOT:PSS) color-changing film. Fig. S28 shows the progressive coloring and bleaching processes over approximately 20 s, indicating that the optical state can be reversibly regulated by the applied electrical input. After artificial sweat recognition, the predicted electrolyte-status level is converted into an appropriate electrochromic driving condition. Signal acquisition and electrochromic control are implemented through a customized flexible circuit. The circuit includes power-management, current-acquisition, wireless-control, and H-bridge driving sections, as illustrated in Fig. S29. The fabricated flexible printed circuit incorporates serpentine interconnects and multiple sensing terminals, enabling conformal placement on the human body (Fig. 5l and Fig. S30). Current signals from the sweat-ion sensing patch are collected and transmitted for analysis, after which the classified sweat status is subsequently visualized by the

electrochromic layer. As demonstrated in Fig. 5m, the recognized artificial sweat compositions are translated into three visually distinguishable electrolyte-status levels. For lower-electrolyte samples M1 and M2, the electrochromic layer shows no obvious color change. For intermediate-electrolyte samples M3–M6, the electrochromic layer exhibits a slight color change, while higher-electrolyte samples M7 and M8 induce a pronounced color change. This three-stage visual feedback enables the sweat-ion sensing result to be read without complex external interpretation (Video S2). Through artificial sweat uptake, ion-diffusion-dynamics sensing, sweat fingerprint identification, and electrochromic electrolyte-status indication, the PHES provides a proof-of-concept route for artificial sweat electrolyte-status classification and direct visual feedback.

Although the present study demonstrates proof-of-concept classification using predefined artificial sweat compositions, real human sweat presents a substantially more complex sensing environment. Interindividual variations in sweat electrolyte composition and sweat rate, together with additional metabolites, proteins, skin-derived contaminants, evaporation, and environmental factors, may influence ion-diffusion dynamics and the resulting electrical fingerprints. Therefore, future studies will focus on validation with real human sweat and evaluation of the robustness of the fingerprinting strategy under these complex physiological and environmental conditions.

3. Conclusions

We have developed a raccoon-paw-inspired porous hydrogel electronic skin for self-powered tactile perception and artificial sweat fingerprint recognition. The porous PVA hydrogel provides mechanical compliance, reversible water uptake, and continuous ion-transport pathways. By combining thermogalvanic voltage generation with pressure-dependent resistance modulation, the PHES enables self-powered pressure sensing and surface-texture recognition. The porous network also converts ion-dependent diffusion dynamics of mixed electrolytes into time-resolved fingerprints, enabling eight artificial sweat compositions to be classified with 95.0% accuracy and translated into electrochromic visual feedback. These results demonstrate the capability of a single porous hydrogel platform to integrate tactile and ionic sensing through distinct physical transduction processes. The present study is limited to predefined artificial sweat compositions. Future work will focus on regulating pore architecture and polymer-ion interactions to improve fingerprint selectivity and stability, together with validation using real human sweat and integration of more comprehensive physiological-state recognition and feedback.

4. Methods

4.1. Materials

PVA (molecular weight, 120,000 to 140,000), Dimethyl Sulfoxide (DMSO, $\geq 99.5\%$), $\text{K}_3\text{Fe}(\text{CN})_6$ (MW = 329.2, $\geq 99\%$), and $\text{K}_4\text{Fe}(\text{CN})_6 \cdot 3\text{H}_2\text{O}$ (MW = 422.4, $\geq 99\%$) were purchased from Sigma-Aldrich. Polyimide (PI, 50 μm) tape, carbon electrode, indium tin oxide (ITO, 0.125 mm), Ecoflex silicone, aqueous electrochromic ink based on PEDOT:PSS, and aqueous photocurable electrolyte were purchased from Zhuhai Kaivo New Materials Tech Co., Ltd. All materials were used as received without further purification.

4.2. Fabrication of the PHES

The PHES was prepared via a four-step procedure. The sucrose proportion was defined as the mass fraction of sucrose in the precursor mixture before freeze–thaw treatment. The 66% sucrose hydrogel was prepared using a precursor mixture containing approximately 66 wt% sucrose and 33 wt% PVA/DMSO solution. Sucrose particles with a particle size of 0.1–0.2 mm were used as the sacrificial template. Briefly,

0.3 g PVA was dissolved in 3.7 g of DMSO and stirred in an oil bath at 95 °C and 800 rpm for 2 h until a transparent, homogeneous solution was obtained. Subsequently, 8 g of sucrose particles were added, and the mixture was stirred with a glass rod until the sucrose particles were uniformly dispersed in the PVA/DMSO solution. The resulting suspension was poured into a hollow polydimethylsiloxane mold with a bottom electrode comprising PI tape and a carbon electrode. After the solution had leveled, a matching top electrode (PI tape with carbon electrode) was placed, and the assembly was allowed to stand at 253 K for 24 h. The formed hydrogel was subsequently immersed in deionized water for 24 h to exchange DMSO and remove the sucrose porogen. For the thermogalvanic sensing module, the porous hydrogel was loaded with 0.2 M $\text{K}_4\text{Fe}(\text{CN})_6 \cdot 3\text{H}_2\text{O}$ and 0.2 M $\text{K}_3\text{Fe}(\text{CN})_6$, corresponding to a molar ratio of 1 to 1.

4.3. Integration of the PHES with the honeycomb-structured contact layer

To enhance surface-texture perception, Ecoflex silicone was cast into a custom honeycomb mold and cured at room temperature for 24 h. The resulting honeycomb contact layer had a side length of 1.0 mm, a cell size of approximately 1.75 mm, a wall width of 0.5 mm, and a layer thickness of 0.5 mm, with the detailed geometric parameters summarized in Table S4.

4.4. Assembly of the visual feedback electrochromic module

An aqueous PEDOT:PSS-based electrochromic ink was uniformly coated onto the bottom ITO electrode and dried at 80 °C for 5 min. An aqueous photocurable electrolyte was then applied, the top ITO electrode was placed to seal the device, and the assembly was cured under a 365 nm ultraviolet light-emitting diode lamp.

4.5. Artificial sweat testing

After each artificial sweat measurement, the PHES sensor was thoroughly rinsed with deionized water and allowed to recover until a stable baseline comparable to the initial level was obtained. The subsequent sample was tested only after the residual response became negligible.

4.6. Material characterization

Tensile and compressive mechanical tests were carried out with a universal testing machine (QT-1196) under ambient conditions (293 K, 30% relative humidity). The hydrophilicity of the porous hydrogel was evaluated at room temperature using a contact angle goniometer (OCA20, USA).

4.7. Electrical characterization

Temperature differentials were imposed using Peltier elements controlled by a temperature controller (SenseFutures TEC215L) and monitored with a Napui TR230X thermocouple under ambient conditions (293 K, 30% relative humidity). Electrochemical impedance spectroscopy and CV of the hydrogel were performed on an electrochemical workstation (CHI660e, Shanghai Chenhua Instrument Co., Ltd.). Additional experiments investigating contact position and material dimensions were conducted under the same environmental conditions.

4.8. Training and optimization of the deep-learning model

For surface-texture recognition, nine surface categories were tested with 100 independently acquired sensing samples per category, yielding a total of 900 samples. For sweat-fingerprint identification, eight artificial sweat compositions were tested with 100 samples per composition, yielding a total of 800 samples. Each complete sensing response was

treated as an independent sample. For both recognition tasks, the datasets were randomly divided into training, validation, and testing subsets at a ratio of 8:1:1. The training subset was used for model optimization, the validation subset was used to monitor model performance during training, and the testing subset was kept independent from training and used for final classification evaluation. A ResNet-34 architecture was employed for feature extraction and multiclass classification. The model was trained for 80 epochs using the Adam optimizer with categorical cross-entropy loss. A learning rate of 1×10^{-4} and a batch size of 32 were used during model optimization. Classification performance was evaluated using the independent testing subset through recognition accuracy and confusion matrices, while t-SNE was used to visualize the distribution of the extracted features. No cross-validation was performed in the present study.

CRediT authorship contribution statement

Suyi Wen: Writing – original draft, Methodology, Conceptualization. **Ning Li:** Writing – original draft, Methodology, Conceptualization. **Kunjiao Liu:** Methodology, Investigation. **Yu Niu:** Methodology, Investigation. **Xinru Yang:** Methodology, Investigation. **Yuxiu Yao:** Methodology, Investigation. **Zhichao Gao:** Methodology, Investigation. **Xiaojing Cui:** Writing – review & editing. **Shengli Cao:** Writing – review & editing. **Zhou Li:** Supervision. **Hulin Zhang:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.bios.2026.119180>.

Data availability

Data will be made available on request.

References

- Alsaid, Y., Wu, S., Wu, D., Du, Y., Shi, L., Khodambashi, R., Rico, R., Hua, M., Yan, Y., Zhao, Y., Aukes, D., He, X., 2021. Adv. Mater. 33, 2008235. <https://doi.org/10.1002/adma.202008235>.
- Bai, C., Dong, X., Liu, Q., Zhao, M., Yang, K., Niu, Y., Zhang, H., Zhai, W., 2026. Nat. Commun. 17, 2675. <https://doi.org/10.1038/s41467-026-69450-9>.
- Bai, N., Xue, Y., Chen, S., Shi, L., Shi, J., Zhang, Y., Hou, X., Cheng, Y., Huang, K., Wang, W., Zhang, J., Liu, Y., Guo, C.F., 2023. Nat. Commun. 14, 7121. <https://doi.org/10.1038/s41467-023-42722-4>.
- Baker, L.B., De Chavez, P.J.D., Ungaro, C.T., Sopena, B.C., Nuccio, R.P., Reimel, A.J., Barnes, K.A., 2019. Eur. J. Appl. Physiol. 119, 361–375. <https://doi.org/10.1007/s00421-018-4048-z>.
- Bariya, M., Nyein, H.Y.Y., Javey, A., 2018. Nat. Electron. 1, 160–171. <https://doi.org/10.1038/s41928-018-0043-y>.
- Chang, Z., Wang, F., Wang, Z., Yu, J., Ding, B., Li, Z., 2026. Prog. Mater. Sci. 156, 101579. <https://doi.org/10.1016/j.pmatsci.2025.101579>.
- Childs, A., Mayol, B., Lasalde-Ramírez, J.A., Song, Y., Sempionatto, J.R., Gao, W., 2024. ACS Nano 18, 24605–24616. <https://doi.org/10.1021/acsnano.4c10344>.
- Davis, N., Heikenfeld, J., Milla, C., Javey, A., 2024. Nat. Biotechnol. 42, 860–871. <https://doi.org/10.1038/s41587-023-02059-1>.
- Fu, J., Zhao, C., Tian, W., Gao, X., Zhang, Y., Ma, W., Wang, K., Song, D., Zhang, X., 2025. Fundam. Res. <https://doi.org/10.1016/j.fmre.2025.09.018>.
- Griffanti, G., Nazhat, S.N., 2020. Int. Mater. Rev. 65, 502–521. <https://doi.org/10.1080/09506608.2020.1735828>.
- Guo, X., Sun, Z., Zhu, Y., Lee, C., 2024. Adv. Mater. 36, 2406778. <https://doi.org/10.1002/adma.202406778>.
- He, X., Fan, C., Luo, Y., Xu, T., Zhang, X., 2022. Npj Flexible Electron. 6, p. 60. <https://doi.org/10.1038/s41528-022-00192-6>.
- Hu, S., Lu, W., Li, H., Shi, X., Peng, Z., Cao, X., 2023. Nano Energy 114, 108658. <https://doi.org/10.1016/j.nanoen.2023.108658>.
- Hui, Z., Zhang, Z., Wang, Y., Zhang, R., Liu, X., Jiang, M., Ju, F., Hou, W., Xia, Z., Wang, D., Wang, P., Pei, Y., Yan, R., Zhang, Y., Chen, Q., Huang, W., Sun, G., 2024. Adv. Mater. 36, 2314163. <https://doi.org/10.1002/adma.202314163>.
- Ji, W., Liu, H., Liu, Y., Zhang, Wei, Zhou, T., Liu, X., Tao, C., Dai, J., Zha, B., Xie, R., Wu, J., Wu, Q., Zhang, Weina, Li, L., Huo, F., 2023. Npj Flexible Electron. 7, p. 53. <https://doi.org/10.1038/s41528-023-00285-w>.
- Jiang, Y., Ye, H., Zhang, S., Pan, Y., Huang, Z., Li, H., Guo, J., Zhu, C., Yuan, M., Dai, B., Li, J., Yang, W., Gao, L., Xie, Y., 2024. Nano Energy 131, 110329. <https://doi.org/10.1016/j.nanoen.2024.110329>.
- Kim, K., Sim, M., Lim, S.-H., Kim, D., Lee, D., Shin, K., Moon, C., Choi, J.-W., Jang, J.E., 2021. Adv. Sci. 8, 2002362. <https://doi.org/10.1002/advsc.202002362>.
- Kumar, M., Singh, R., Kang, H., Kim, S., Seo, H., 2020. Nano Energy 73, 104756. <https://doi.org/10.1016/j.nanoen.2020.104756>.
- Li, J., Xia, B., Xiao, X., Huang, Z., Yin, J., Jiang, Y., Wang, S., Gao, H., Shi, Q., Xie, Y., Chen, J., 2023. ACS Nano 17, 19232–19241. <https://doi.org/10.1021/acsnano.3c05797>.
- Li, N., Wang, Z., Niu, Y., Li, Y., Wen, S., Zhang, H., Lin, Z.-H., 2025. Adv. Sci. 12, e05873. <https://doi.org/10.1002/advsc.202505873>.
- Li, N., Wang, Z., Yang, X., Zhang, Z., Zhang, W., Sang, S., Zhang, H., 2024. Adv. Funct. Mater. 34, 2314419. <https://doi.org/10.1002/adfm.202314419>.
- Li, Y., Li, N., Zhang, X., Zhang, J., Sun, L., Huang, Z., Zhang, H., 2025. J. Mater. Chem. A 13, 10531–10539. <https://doi.org/10.1039/d5ta00253b>.
- Liang, J., Cai, X., Huang, L., Cheng, L., Tan, F., Qiu, J., Zhang, Y., Yan, W., Lin, W., Zhong, G., Ye, R., Zhao, J., Yu, X., Tan, C., 2026. ACS Nano 20, 9699–9710. <https://doi.org/10.1021/acsnano.5c17767>.
- Linghu, C., Liu, Y., Yang, X., Chen, Z., Feng, J., Zhang, Y., Li, Yan, Zhao, Z., Seo, Y.-J., Li, J., Jiang, H., Su, J., Fang, Y., Li, Yuhang, Wang, X., Wang, Y., Gao, H., Hsia, K.J., 2025. Sci. Adv. 11. <https://doi.org/10.1126/sciadv.adt4765> eadt4765.
- Liu, T., Zhang, M., Li, Z., Dou, H., Zhang, W., Yang, J., Wu, P., Li, D., Mu, X., 2025. Nat. Commun. 16, 2363. <https://doi.org/10.1038/s41467-025-57629-5>.
- Liu, W., Shi, X.-L., He, X., Zhu, S., Li, Z., Li, C., Zhang, D., Li, M., Wu, X., Zhang, H., Wang, L., Qin, X., Chen, Z.-G., 2026. Nat. Commun. 17, 1294. <https://doi.org/10.1038/s41467-025-68055-y>.
- Liu, Y., Tao, J., Mo, Y., Bao, R., Pan, C., 2024. Adv. Mater. 36, 2313857. <https://doi.org/10.1002/adma.202313857>.
- Liu, Y., Zhou, B., Xu, G., Luo, W., Hu, X., Guan, F., Shi, S., Ge, Z., Shen, S., Chen, A., Guo, L., Lau, C., Lim, C.T., Lu, J., 2026. InfoMat 8, e70085. <https://doi.org/10.1002/inf2.70085>.
- Lloyd, E.C., Dhakal, S., Amini, S., Alhasan, R., Fratzl, P., Tree, D.R., Morozova, S., Hickey, R.J., 2025. Nat. Commun. 16, 3792. <https://doi.org/10.1038/s41467-025-59171-w>.
- Sang, S., Bai, C., Wang, W., Khan, S.A., Wang, Z., Yang, X., Zhang, Z., Zhang, H., 2024. Nano Energy 123, 109366. <https://doi.org/10.1016/j.nanoen.2024.109366>.
- Singh, N.K., Wang, Yixun, Wen, C., Davis, B., Wang, X., Lee, K., Wang, Yong, 2024. Nat. Biotechnol. 42, 1224–1231. <https://doi.org/10.1038/s41587-023-01973-8>.
- Sung, D., Han, S., Kim, Sumin, Kang, H., Jekal, B., Kim, G., Kim, J., Hong, M., Moon, G., Kim, Sungseun, Lee, Y., Hwang, S.-W., Jeong, H., Ryu, Y.-S., Kim, Sungbong, Koo, J., 2025. Sci. Adv. 11. <https://doi.org/10.1126/sciadv.adu2142> eadu2142.
- Wang, X., Ji, H., Gao, L., Hao, R., Shi, Y., Yang, J., Hao, Y., Chen, J., 2024. Chem. Eng. J. 495, 153382. <https://doi.org/10.1016/j.cej.2024.153382>.
- Wang, Y.-F., Zhang, X.-Y., Liu, J.-Y., Song, Y.-J., Ni, Y.-Q., Chen, Z.-X., Li, Y.-C., Zhang, T., 2025. Chem. Eng. J. 507, 160501. <https://doi.org/10.1016/j.cej.2025.160501>.
- Wang, Z., Huang, Y., Xu, K., Zhong, Y., He, C., Jiang, L., Sun, J., Rao, Z., Zhu, J., Huang, J., Xiao, F., Liu, H., Xia, B.Y., 2023. Nat. Commun. 14, 69. <https://doi.org/10.1038/s41467-022-35721-4>.
- Wei, R., Cui, X., Khan, S.A., Bai, C., Wang, C., Zhang, J., Hao, R., Huang, Z., Li, Z., Zhang, H., 2025. Chem. Eng. J. 522, 167739. <https://doi.org/10.1016/j.cej.2025.167739>.
- Xiao, M., Meng, J., Zhang, H., Wu, Z., Li, Z., 2025. Adv. Mater. 37, e06436. <https://doi.org/10.1002/adma.202506436>.
- Xu, G., Huang, X., Shi, R., Yang, Y., Wu, P., Zhou, J., He, X., Li, Jialin, Zen, Y., Jiao, Y., Zhang, B., Li, Jiayu, Zhao, G., Liu, Y., Huang, Y., Wu, M., Zhang, Q., Yang, Z., Yu, X., 2024. Adv. Funct. Mater. 34, 2310777. <https://doi.org/10.1002/adfm.202310777>.
- Xu, Z., Yu, M., Li, Q., Wang, C., Yao, Y., Wei, R., Chi, C., Yan, C., Zhang, X., Xu, Y., Huang, B., Xu, D., Shen, Y., Zhao, Z., Feng, S.-P., Liu, W., Zhang, H., Lin, S., 2026. Natl. Sci. Rev. nwag283. <https://doi.org/10.1093/nsr/nwag283>.
- Yang, X., Niu, Y., Li, N., Cui, X., Li, Z., Zhang, H., Lin, Z.-H., 2026. ACS Sens. accssensors.5c04692. <https://doi.org/10.1021/acssensors.5c04692>.
- Yin, L., Cao, M., Kim, K.N., Lin, M., Moon, J.-M., Sempionatto, J.R., Yu, J., Liu, R., Wicker, C., Trifonov, A., Zhang, F., Hu, H., Moreto, J.R., Go, J., Xu, S., Wang, J., 2022. Nat. Electron. 5, 694–705. <https://doi.org/10.1038/s41928-022-00843-6>.
- Zhang, H., Yang, X., Cui, X., Niu, Y., Wang, C., Li, N., Cao, S., Zhang, J., Sang, S., 2026. Adv. Funct. Mater. 36, e00015. <https://doi.org/10.1002/adfm.202600015>.

Zhang, X., Li, H., Liang, B., Zou, Z., Yang, Z., Xiong, S., Yang, L., Wang, X., Chen, Y., Xu, Y., Li, Y., 2026. Sci. Bull. 71, 1153–1164. <https://doi.org/10.1016/j.scib.2025.12.045>.

Zhi, X., Ma, S., Xia, Y., Yang, B., Zhang, S., Liu, K., Li, M., Li, S., Peiyuan, W., Wang, X., 2024. Nano Energy 125, 109532. <https://doi.org/10.1016/j.nanoen.2024.109532>.
Zou, K., Xia, X., Xu, Y., Wei, J., Jiao, T., Chen, Q., Chen, M., Chen, X., 2026. Biosens. Bioelectron. 296, 118309. <https://doi.org/10.1016/j.bios.2025.118309>.