Journal of
Materials Chemistry A

REVIEW

Cite this: J. Mater. Chem. A, 2025, 13, 832

Received 7th October 2024
Accepted 13th November 2024

DOI: 10.1039/d4ta07127a

rsc.li/materials-a

Artificial intelligence assisted nanogenerator applications

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Piezoelectric and triboelectric nanogenerators are at the forefront of converting ambient mechanical energy into electricity. These devices have experienced significant advancements in functionality and autonomy through integration with artificial intelligence (AI). This integration not only enhances their performance in autonomous operations by improving mechanical-to-electrical energy conversion efficiency, but also forges new pathways in robotics and intelligent systems. By increasing responsiveness and adaptability, these innovations expand the potential applications of nanogenerators. Looking ahead, the combination of nanogenerators with AI is poised to play a crucial role in developing sustainable, eco-friendly energy solutions. Their dual impact in advancing intelligent systems and promoting environmental sustainability signifies a significant milestone in nanogenerator technology for robotics. This review highlights the essential role of AI in refining nanogenerators, charting a path toward energy autonomy and sustainability.

1 Introduction

In the dynamically advancing field of renewable energy technologies, piezoelectric and triboelectric nanogenerators (PENGs and TENGs) have emerged as cutting-edge approaches for converting ambient mechanical energy into electricity.[1–10] Since their inception more than a decade ago, these technologies have evolved rapidly, rekindling interest in sustainable energy amid a global energy crisis and concerns surrounding traditional fossil fuels. By leveraging piezoelectric and triboelectric effects, PENGs and TENGs can harvest energy from diverse environmental sources, including motion, temperature changes, and structural vibrations, outperforming conventional energy harvesters in terms of electrical efficiency.[11–17]

The efficacy of PENGs and TENGs is significantly influenced by their design and material composition, which presents both substantial opportunities and challenges for enhancing their electrical characteristics. This has spurred vigorous multidisciplinary research efforts focused on optimizing these technologies for a broad range of applications, including energy harvesting, sensing, monitoring, soft robotics, and electronic skins (e-skins).[8,18–40]

The integration of artificial intelligence (AI) with PENGs and TENGs has ushered in a novel phase in boosting their functionality.[41,42] AI offers solutions to the challenges of developing portable, reliable, and eco-friendly energy sources.[43–45] By mimicking human cognitive processes, AI significantly improves computational efficiency in the structural design and material selection for nanogenerators.[46–48] Early efforts to integrate AI with PENGs and TENGs have shown promising results, addressing design, prediction, and optimization challenges[49] and marking a pivotal shift from conventional statistical methods. AI excels at uncovering complex relationships among variables,[23,50] greatly enhancing the exploration of design and material possibilities for these nanogenerators.

This synergy between AI and nanogenerators not only drives advancements in energy harvesting technologies but also heralds in a new era for robotics and intelligent systems. AI-powered nanogenerators enhance robotic perception, cognition, and interaction with their surroundings. This review aims to illuminate recent progress in nanogenerators, with a focus on the transformative impact of AI integration and its potential to revolutionize robotics and intelligent systems while paving the way for a more sustainable future.

2 Fundamentals of PENGs and TENGs

PENGs and TENGs are pioneering energy-harvesting technologies that convert mechanical energy from the environment into electricity. This operation is grounded in Maxwell's displacement current theory, with PENGs utilizing the piezoelectric effect and TENGs harnessing the triboelectric effect in combination with electrostatic induction.

Introduced in 2006, PENGs convert mechanical stress or deformation directly into electrical energy through the piezoelectric effect.[51] This phenomenon is observed in materials that generate an electrical charge in response to mechanical stress. A typical PENG features a piezoelectric material sandwiched between two electrodes in a metal–insulator–metal

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configuration. When mechanically deformed, these structures produce a voltage that drives an electrical current through an external circuit. Materials such as ZnO and PVDF are commonly used to maximize the efficiency of this mechanical-to-electrical energy energy conversion.

TENGs, first developed in 2012, operate through the triboelectric effect,[52] which involves generating electrical energy *via* contact and separation between two distinct materials. This interaction causes the surfaces to acquire opposite charges, and the relative motion between them creates an electrostatic potential that drives an electrical current through a connected load. TENGs can be engineered in various configurations, including vertical contact-separation, lateral sliding, single-electrode, and freestanding triboelectric layer modes, to accommodate diverse mechanical energy inputs. Enhancing TENG performance relies on selecting materials with highly contrasting triboelectric polarities to optimize charge transfer and improve electrical output.

3 Computation for nanogenerator integrations

AI-augmented nanogenerators introduce advanced capabilities to on-device and cloud-based systems by enabling continuous learning mechanisms, which allow these systems to adapt dynamically over time.[53] Handling noisy data is a critical challenge for both platforms, as sensor readings from nanogenerators are often influenced by environmental factors and background interference.[54] Robust statistical models, such as regression and resistant measures of central tendency, help maintain performance by down-weighting outliers and mitgating noise.[55,56] These models provide a stable baseline by focusing on core data patterns, minimizing the influence of erratic points. Outlier detection methods, such as isolation forests and distance-based algorithms, further enhance model reliability in noisy environments by identifying and managing data points that deviate significantly from expected patterns.[57]

Data preprocessing and filtering steps can enhance data quality before inputting into models. For instance, low-pass filters effectively remove high-frequency noise, enhancing data fidelity.[58] By integrating continuous learning capabilities with robust noise management techniques, AI-augmented nanogenerators achieve high accuracy, adaptability, and resilience across various applications.

3.1 On-device processing

On-device processing is essential for real-time applications like wearable monitoring, tactile sensing, and health management, where low latency is critical to provide immediate feedback, ensuring functionality and user satisfaction.[59] In prosthetics and smart clothing for health monitoring, slight delays in response time can disrupt user control, coordination, and timely health alerts.[60] Rapid on-device processing helps prevent these issues by supporting energy-intensive algorithms like Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) for image classification and predictive modeling,[61] as well as less demanding algorithms like Artificial Neural Networks (ANNs), Deep Belief Networks (DBNs), and linear techniques such as Principal Component Analysis (PCA), Linear Classification Algorithms (LCA), and Linear Discriminant Analysis (LDA) (Fig. 1).

On-device datasets, such as biometric data, sensor readings, and activity logs, are processed in real time to provide immediate insights.[62] Efficient algorithms prioritize responsiveness within resource constraints, making them ideal for real-time motor control and sensor feedback. These algorithms often operate in bursts, activating only during specific time windows when sufficient energy is available, thus conserving power.[63] For example, Recurrent Neural Networks (RNNs) may analyze heart rate data intermittently, performing computations during peak energy generation.[63] However, on-device systems are limited by processing power and energy efficiency, restricting the complexity of algorithms and potentially hindering tasks like complex image processing or extensive data analysis.[64]

In addition to energy efficiency, balancing energy consumption and decision accuracy is critical in energy-limited applications like wearables and Internet of Things (IoT) devices, where small batteries and low-latency responses are essential for effective user interaction.[65] While wearables face strict energy constraints, larger IoT or robotic systems have fewer power limitations. Efficient algorithms are necessary to maintain high accuracy and reliability, particularly for real-time monitoring. Pruning,[66] quantization,[67] and lightweight models like MobileNets[68] streamline neural networks by reducing complexity, memory footprint, and computational load, enhancing processing speed without significantly compromising accuracy.

Adaptive processing also adjusts model intensity based on task demands; for instance, RNNs, particularly Long Short-Term Memory (LSTM) networks, may activate only when vital signs deviate significantly, such as in abnormal heart rates, switching to simpler models under stable conditions to conserve energy.[69,70] This approach extends battery life and efficiency in health monitoring while enabling quick responses to health changes.

Continuous health monitoring systems should ensure high accuracy in tracking vital signs, necessitating energy-efficient algorithms capable of sustaining long-term operation. In contrast, environmental sensors, which monitor slowly changing conditions, need only intermittent data collection, allowing for reduced power consumption.[71] To maximize efficiency and precision, AI-augmented nanogenerators employ lightweight models for less critical tasks and shift to complex algorithms when necessary, optimizing energy use.[72] Additionally, integrating energy harvesting and storage solutions, like nanogenerators and supercapacitors, buffer power supply for peak demands, ensuring consistent performance. Advances in nanogenerator energy conversion efficiency, alongside micro-batteries and supercapacitors, stabilize power for intensive tasks, like deep learning and real-time analytics.[73] Low-power hardware and application-specific integrated circuits (ASICs) enhance efficiency, supporting self-powered applications.[74] By effectively combining these strategies, AI-augmented

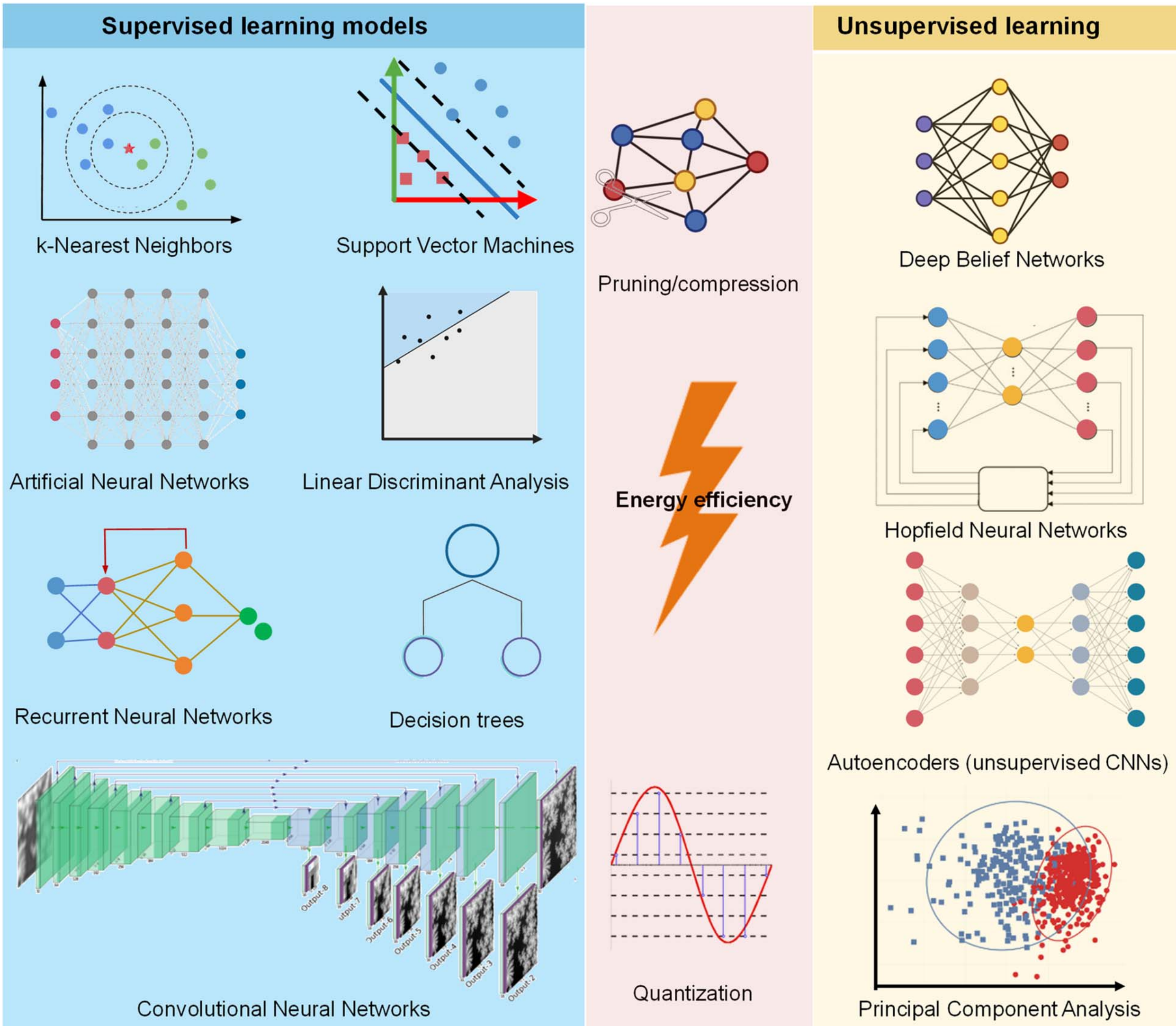

Fig. 1 Machine learning models for AI-augmented nanogenerators. In supervised learning, models like *k*-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANNs), Linear Discriminant Analysis (LDA), Recurrent Neural Networks (RNNs), decision trees, and Convolutional Neural Networks (CNNs) are included. These models, trained on labeled data, are effective for tasks such as classification, pattern recognition, and real-time monitoring in energy-sensitive systems. In unsupervised learning, Deep Belief Networks (DBNs), Hopfield Neural Networks (HNNs), autoencoders (unsupervised CNNs), and Principal Component Analysis (PCA) operate without labeled data for clustering and dimensionality reduction. Energy efficiency strategies like pruning/compression and quantization can optimize these algorithms for low-power environments typical in wearables and IoT devices powered by nanogenerators. CNNs,[124] copyright 2020, Springer Nature.

nanogenerators can maximize functionality while minimizing energy consumption, ultimately enhancing user experience across various applications.

3.2 Cloud-based processing

Cloud-based processing excels in handling computationally intensive, less latency-sensitive tasks, allowing extensive datasets to be offloaded for advanced data analysis and pattern recognition.[75] Security and document management applications benefit from this, as tasks like data encryption and complex pattern analysis require high processing power but are not critically time-sensitive. A hybrid approach is often used, with on-device processing for immediate feedback and cloud processing for in-depth analysis, such as long-term trend detection in gait analysis.[76] While latency-sensitive applications require fast response times, on-device processing can meet this need but may lack resources for complex analyses.[77] In contrast, cloud solutions handle intricate tasks, including deep learning and extensive pattern recognition, though data transmission may introduce delays,[78] as cloud speeds range from hundreds of milliseconds to seconds depending on network conditions and task complexity.[79] Transmission rates vary widely, with 4G long-term evolution (LTE) networks typically offering 10–50 Mbps,[80] while cloud tasks require higher bandwidth. On-device systems also conserve power to prolong battery life, while cloud servers, although more energy-intensive, support larger loads.[81] Integrating AI with nanogenerators for on-device and cloud-based processing enables adaptive, intelligent systems, balancing real-time responsiveness with complex data capabilities.

4 AI-integrated nanogenerators

AI algorithms play a pivotal role in predicting and improving the efficiency, responsiveness, and adaptability of nanogenerators, paving the way for developments in robotics, self-powered sensing, energy-efficient actuation, and intelligent human–machine interactions.[22,23,38,82–98]

The implementation of AI encompasses supervised learning models (classification and regression) and unsupervised models (clustering and dimensionality reduction).[99,100] Unsupervised learning models like DBNs to capture complex hierarchical data representations, and Hopfield Neural Networks (HNNs) to perform associative memory tasks, operate on unlabeled data to identify inherent structures or patterns without predefined outputs. In contrast, supervised learning, such as Support Vector Machines (SVMs) for classifying data by identifying the optimal hyperplane that separates different classes[101] and decision trees to split data based on feature values for interpreting user activities,[102] are trained on labeled data, where each input is paired with its corresponding output, allowing the algorithm to learn patterns and make predictions. ANNs are trained on labeled data for tasks like classification and regression,[103] while LCA and LDA serve for dimensionality reduction and class separation, respectively.[104] LCA uses linear decision boundaries to classify labeled data, and LDA identifies the linear combination of features that best separates classes, maximizing inter-class distance while minimizing within-class variance by leveraging the mean and variance of each class.

K-Nearest Neighbors (KNN) is a supervised, instance-based algorithm that classifies data points by proximity to labeled training instances,[105] enabling rapid gesture recognition by comparing real-time sensor data with recorded movements for quick responses.[47,106–109] CNNs, versatile in machine learning, are primarily used in supervised tasks like image classification, object detection, and segmentation,[110] but can also function unsupervised, as in autoencoders, to learn data representations without labels. Similarly, RNNs are often used for supervised tasks like speech recognition and time-series prediction but can adapt to unsupervised tasks like sequence prediction,[111] allowing for flexible application across diverse machine learning challenges. DNNs, composed of multiple interconnected layers, effectively learn complex data relationships, making them suitable for pattern recognition tasks and multidimensional sensor data processing for applications requiring high accuracy in classification and prediction.[112,113]

Fig. 2 illustrates the integration of AI and nanogenerators to enhance daily life, industrial monitoring, and advanced interactive platforms.[114–116] In wearable technology, nanogenerators enable biometric and health monitoring by supporting advanced machine learning algorithms, such as SVMs, neural networks, and decision trees, for health tracking and activity analysis.[14,37,47,117–121] Decision trees classify user activities by branching on feature values, while neural networks capture complex behavior patterns, and SVMs identify physiological signals (*e.g.*, heart rate and skin temperature) for personalized monitoring by identifying the optimal hyperplane that separates different classes of data points.[39,122,123] E-skins, which simulate touch, typically utilize CNNs to process spatial data, extracting features from tactile interactions to respond to stimuli accurately by applying convolutional layers that filter input data and pooling layers that reduce dimensionality.[124–136] In environmental monitoring, nanogenerators paired with CNNs and SVMs enhance tasks like object recognition,[137,138] liquid leakage detection,[139,140] and gas sensing,[47,141,142] with SVMs classifying environmental conditions and CNNs analyzing patterns for improved sensor detection.

RNNs are well-suited for sequential data tasks where the order of data points is crucial, such as speech classification and lip decoding, by managing temporal dependencies in speech signals.[63,69,109,114,143,144] However, standard RNNs struggle with retaining long-term information due to the vanishing gradient problem.[145] This limitation leads to challenges in learning long-term dependencies for applications requiring sustained contextual awareness.

LSTMs, a specialized RNN type, address this by using memory cells to track behavior changes and predict future actions over extended periods,[111] making them effective in user activity recognition and health monitoring applications.[146,147] LSTMs enable continuous monitoring of vital signs like blood pressure with improved accuracy by maintaining important information across longer sequences, offering timely health updates essential for medical intervention.[148–150] ANNs, consisting of interconnected layers of nodes, are also used for monitoring, including tasks like marine environmental surveillance and pressure mapping,[103] as they can learn to identify patterns and make predictions based on diverse inputs to model complex relationships within data and handling intricate datasets.[17,23,151–154] HNNs, another form of RNNs for associative memory, excel at pattern recognition by managing complex patterns with hierarchical structures derived from data, such as typing dynamics and tactile information.[155] HNNs can retrieve stored patterns based on partial inputs, making them suitable for applications that require quick and reliable recognition of previously learned information, thereby improving user experience in systems that rely on human interaction.

DBNs, combining multiple layers of stochastic, latent variables to facilitate feature learning and classification,[8] can capture hierarchical representations in high-dimensional data through unsupervised feature learning, useful in applications with unlabeled or poorly structured data. PCA aids in reducing the dimensionality of data from human interactions and typing dynamics, retaining key features while enhancing classification accuracy by transforming them into a smaller set of uncorrelated variables known as principal components.[143]

The interplay between nanogenerators and various machine learning algorithms marks a step toward intelligent systems that augment human capabilities and experiences. This integration can achieve improved accuracy, efficiency, and user interaction, involving a range of algorithms (Table 1), such as SVM for object and character recognition,[156,157] KNN through

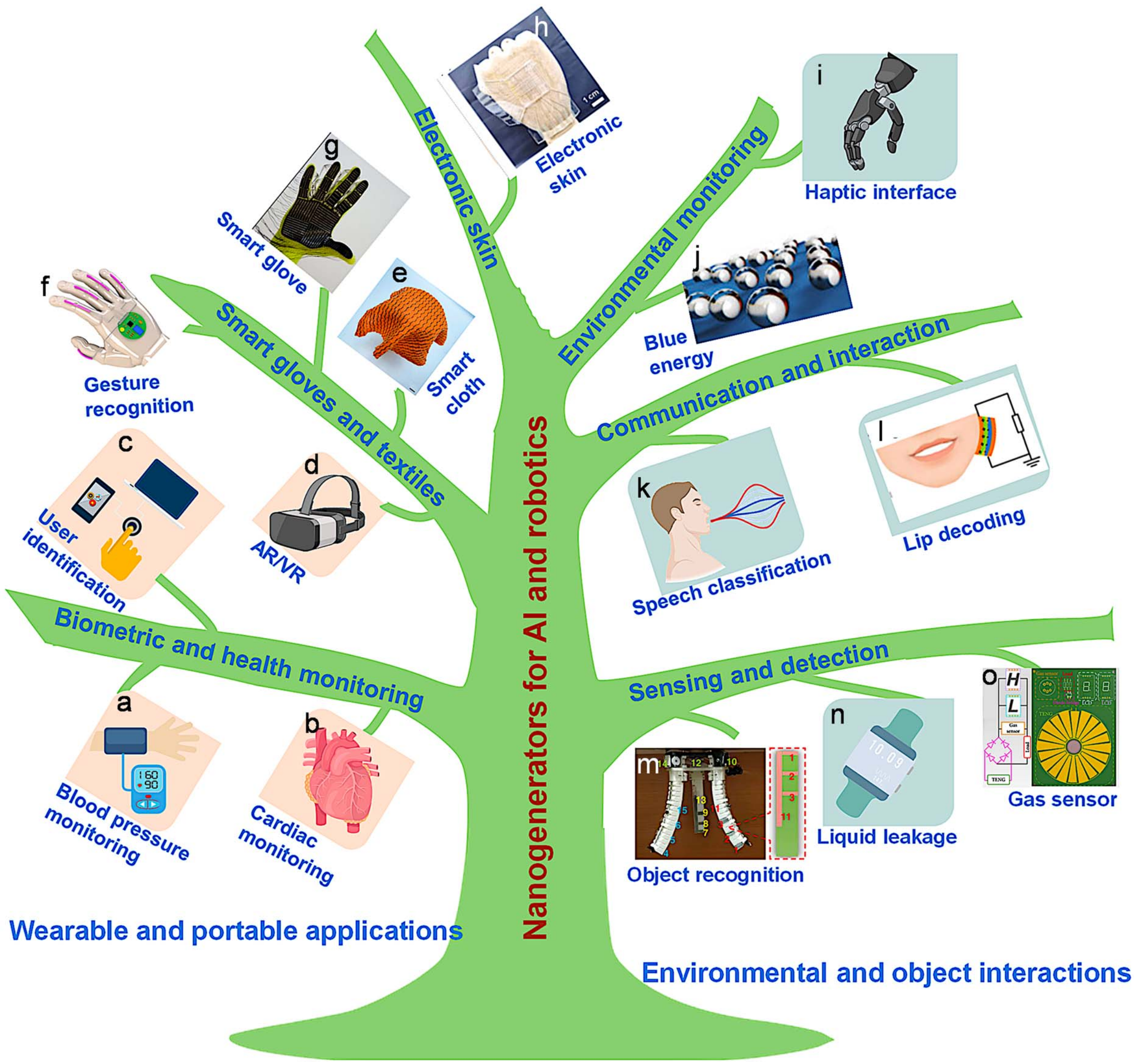

Fig. 2 Applications of AI-enhanced nanogenerators. AI-assisted nanogenerators provide responsive, efficient, and intelligent solutions in advancing human–machine interfaces. In wearable and portable applications, nanogenerators power biometric and health monitoring devices, such as (a) blood pressure monitors, (b) cardiac monitoring systems, and (c) user identification tools. For smart wearables, AI-augmented sensors enable (d) augmented reality/virtual reality (AR/VR) interfaces, (e) smart clothing,[37] copyright 2022, Springer Nature; and (f) gesture-recognition glove,[109] copyright 2020, Springer Nature; (g) tactile sensing glove,[136] copyright 2019, Springer Nature; and (h) e-skin,[40] copyright 2019, Elsevier. In environmental monitoring, (i) haptic interfaces and (j) blue energy harvesting,[17] copyright 2017, Elsevier, represent advancements in sustainable interactions. In communication and interaction, nanogenerators facilitate (k) speech classification and (l) lip decoding,[114] copyright 2022, Springer Nature. In advanced sensing and detection, AI-augmented nanogenerators improve capabilities for (m) object recognition,[138] copyright 2020, Springer Nature; (n) liquid leakage detection, and (o) gas sensing, including the detection of volatile organic compounds (VOCs)[142] copyright 2021, AAAS.

instance-based learning for analyzing signal sequences and handwriting features,[108] ANN for time-series analysis in sensory networks,[23,151] CNN for image and pattern recognition,[125,158–160] and RNN for sequential tasks such as speech processing.[151]

One key approach to reusing AI models without the need for full retraining is transfer learning, which involves utilizing pretrained models that have already learned general features from large datasets and fine-tuning them for new applications.[161] For example, a health monitoring model can be fine-tuned for fitness tracking by modifying layers to target metrics like steps or heart rate.[162] Another effective strategy is modular AI design, where specific components of a model can be reused across different applications.[163] Foundational layers that have been trained on common features, such as motion patterns or general image features, can be repurposed for various tasks like differentiating between types of physical activity or detecting anomalies in sensor data. This modularity allows for significant savings in retraining efforts, enabling systems to adapt quickly to new challenges while maintaining efficiency. Moreover, distributed processing approaches where

Table 1 Overview of algorithms with nanogenerator integration[a]

Algorithm	Roles	Deployment	Energy-efficiency	Reusability	Pros	Cons
PCA	Dimensionality reduction for enhanced classification efficiency	On-device	High (relatively low data dimensionality)	Limited	Efficient for dimensionality reduction, improves data processing speed	May lose critical information in reduced dimensions; sensitive to scaling variations
SVM	Classifies data using hyperplanes; effective in high-dimensional spaces	Cloud	Moderate (memory for large datasets)	Limited; often needs retraining for different data	Effective in high-dimensional spaces; robust to overfitting, enhances classification accuracy	High computational demand, may slow down real-time processing
RNNs	Temporal data analysis, ideal for sequential data like time-series signals	On-device	Low (sequential processing)	Adaptable, with limited retraining for different patterns	Short sequential data and time-series analysis	Computationally expensive, vanishing gradients, challenging for long sequences
LSTM	Enhanced RNN capable of long-term dependencies; suitable for adaptive interfaces	Cloud	Low (memory cells)	Partially reusable through fine-tuning for sequential tasks	Effective for long-term dependencies, addresses vanishing gradient issues in RNNs	Resource-intensive, requires high computational power for training and inference
CNNs	Hierarchical feature extraction, especially effective in image and spatial feature recognition	On-device/cloud	Requires substantial power	Transfer learning allows reuse for similar tasks	Excellent at spatial data recognition, suitable for image and spatial feature extraction	High computational cost; risk of overfitting in deep architectures without sufficient data
DNN	Models complex relationships; versatile in complex pattern detection	Cloud	Low (memory requirements)	Reusable with fine-tuning; transfer learning possible	Capable of modeling complex patterns, versatile for diverse applications	Requires substantial computational resources and large datasets; prone to overfitting in small data
DBN	Unsupervised feature learning for enhanced classification accuracy	Cloud	Moderate (high computational load)	Reusable with adjustments to layers; retains learned features	Effective for hierarchical feature extraction, enhances classification accuracy	Training is complex and time-consuming, demanding computational resources
KNN	Instance-based learning, good for small datasets; suitable for recognition tasks	On-device	Low energy efficiency with large datasets; energy-efficient in small, targeted datasets	Requires retraining for different classes; limited reus	Simple and effective for small datasets, suitable for real-time applications	Inefficient with large datasets; performance degrades with irrelevant features
ANN	Models nonlinear relationships across diverse applications	On-device	Moderate; lightweight architectures viable	Moderate reusability with layer-specific fine-tuning	Highly accurate for complex relationships; versatile across applications	Computationally demanding and requires large amounts of labeled data for training
HNN	Associative memory tasks, handling complex hierarchical data patterns	Cloud	Low (relatively high cost and energy consumption)	Good reusability; effective for memory-intensive tasks without full retraining	Effective for associative memory, retrieves stored patterns from partial input	High computational complexity, often requires cloud-based processing for real-time use

[a] Reusability: pretrained models or parts of the models can be reused for energy-efficient adaptation to new tasks.

Table 2 Algorithmic requirements for various applications in AI-integrated nanogenerators

Application	Algorithms	Roles	Example applications	Data
Tactile sensing and recognition	2D CNNs (spatial)	Spatial feature extraction	E-skins (texture/pressure recognition)	Tactile logs, pressure mappings
	1D CNNs (temporal), KNN, RNN	Sequential and instance-based learning	Smart gloves (gesture recognition), AR/VR interfaces	Gesture sequences, spatial motion data
	1D CNNs (temporal), SVM, ANN, RNN	Classification, pattern recognition, sequential data	Wearable health monitors (heart rate, activity)	Biometric data, sensor readings
	SVMs (classification)	Classifying touch or pressure types	Haptic feedback systems	Tactile data logs
	LSTMs (sequential)	Sequential data processing	Adaptive human–machine interfaces	Sequential tactile data
Security and document management	SVM + PCA	High-dimensional data classification	Document authentication, user biometric verification	Biometric data, document signatures
	Decision trees	Decision-making in workflows	Document categorization, access control	Encrypted signatures, security protocols
	LDA	Class separation	Document type classification	High-dimensional data
Pattern recognition and memory	HNNs (associative memory)	Pattern recognition with stored memory	Typing behavior analysis, user authentication	Sequential logs, sensory interaction patterns
	DBNs (feature learning)	Unsupervised feature extraction	Sensory memory for robots, pattern detection	Sensory data, hierarchical patterns
	RNNs (sequential)	Sequential pattern analysis	Repetitive behavior recognition	Time-series data
	Autoencoders (unsupervised)	Feature extraction without labels	Data compression for sensor logs	Unlabeled data logs
Advanced sensory detection	CNNs (feature extraction)	Feature extraction for detection tasks	Object and sound recognition	Environmental readings
	RNNs (real-time analysis)	Sequential data analysis	Continuous auditory analysis	Real-time sound patterns
	PCA, DBN, HNN outlier detection	Dimensionality reduction, feature learning, associative memory	VOC detection, unusual pattern identification, air quality monitoring	VOC sensor readings, environmental data logs

computational tasks are spread across multiple systems or devices, allow for handling more complex tasks while maintaining performance.[164] In larger systems, this can involve cloud computing resources that complement local processing, enabling advanced data analytics and machine learning operations that exceed the capabilities of individual devices.

4.1 On-device AI-integrated TENGs for tactile sensing and recognition

Nanogenerators are pioneering a new era in artificial sensory systems and human–machine interfaces (HMIs) by creating self-powered, intelligent devices inspired by the biological sensory nervous system.[165]

Various AI models, such as CNNs, SVMs, and RNNs, are tailored to handle the data types in tactile sensing and gait analysis (Table 2). For gait analysis, 1D CNNs excel at processing sequential, time-series data along a single temporal dimension.[166] These layers, adapted with broader strides, capture temporal dependencies within each gait cycle, supporting accurate classification of gait patterns for applications like sports training and rehabilitation. Pooling layers reduce the data size while retaining key features, ensuring efficiency. 2D CNNs are well-suited for tactile sensing, using convolutional layers to capture spatial relationships such as texture and shape.[167] By pairing these layers with the max-pooling layer, which down-samples by retaining only the most prominent features, 2D CNNs reduce data dimensionality while preserving essential spatial features. Fine-tuning stride and kernel settings enhances localized sensitivity, enabling precise, high-resolution data processing for real-time, responsive interactions. In complex scenarios requiring analysis across spatial and temporal dimensions, like robotic tactile systems and environmental monitoring, 3D CNNs capture evolving three-dimensional patterns.[168] When used in tandem with CNNs, SVMs enhance the tactile peripheral nervous system (TPNS) sensor's ability to classify structured data, recognizing high-dimensional patterns like pressure or texture variations by identifying optimal hyperplanes, making them ideal for nuanced recognition tasks.[169] RNNs, particularly LSTMs, handle the sequential nature of tactile data by capturing short- and long-term dependencies, essential for interpreting touch sequences in real time, benefiting prosthetics and robotics.[170]

The integration of these AI models—2D CNNs for spatial data, 1D CNNs for temporal data, and SVMs and LSTMs for classification and sequential analysis—demonstrates the flexibility and adaptability of AI-augmented, nanogenerator-powered systems.

4.1.1 SVMs, 2D CNNs, and RNNs for a tactile peripheral nervous system. The TPNS sensor, powered by TENG-based nanogenerators, exemplifies the synergy of nanotechnology and machine learning in mimicking human tactile responses. By converting mechanical touch into electrical signals, TENGs enable real-time, nuanced tactile perception, enhanced through advanced machine learning algorithms like SVMs, CNNs, and RNNs, which classify and interpret complex tactile data with high accuracy.

SVMs analyze the structured, high-dimensional data (datasets with numerous features) from TENG sensors, including touch intensity, duration, and texture, by identifying optimal hyperplanes that separate tactile classes, such as different pressures and textures, with high precision.[139,169,171] By maximizing the distance between data points from different classes, SVMs achieve high classification accuracy, making them useful for recognizing structured patterns in tactile data. This capability enriches the TPNS by distinguishing tactile stimuli in applications like prosthetics and robotics. Additionally, 2D CNNs work in tandem with SVMs to extract spatial hierarchies in tactile data.[167] Through convolutional layers, CNNs capture local features like edges and textures, creating a hierarchical understanding of tactile inputs. As the data move through deeper layers of the CNN, increasingly complex spatial features are extracted, creating a hierarchical understanding of tactile input. Pooling layers further enhance this by downsampling while retaining essential details, enabling tasks such as identifying textures akin to braille[172] (Fig. 3a). SVMs classify these patterns, ensuring high accuracy in differentiating tactile sensations.

For temporal tactile data, the TPNS employs RNNs, specifically LSTM networks, to handle the dynamic nature of tactile data that unfolds over time.[170] RNNs process sequential data by retaining information about previous inputs for interpreting patterns that change or evolve, while LSTM networks enhance this capability by incorporating memory cells that manage both short-term and long-term dependencies in data sequences, allowing the TPNS to analyze the occurrence of touch and its duration and intensity over time.[173] In prosthetics and robotics, LSTMs support real-time adaptive responses, imitating human touch perception effectively.

TENGs generate power autonomously by converting mechanical touch into electricity, eliminating the need for external batteries and enhancing the sensor's eco-friendliness. This self-sustained energy generation supports continuous, real-time tactile processing, allowing the TPNS to deliver rapid, precise responses for applications in prosthetics and intelligent robotics that rely on immediate, reliable feedback to function effectively.[174–186] These advancements position the TPNS as a transformative technology in future sensory networks, where energy-efficient, intelligent sensors can provide human-like tactile sensitivity in environmentally sustainable ways.

4.1.2 2D CNNs for handwriting human–machine interfaces. The development of TENG-powered handwriting HMIs demonstrates the integration of AI and nanogenerators for interactive applications. TENG-based touchpads convert mechanical handwriting energy into unique electrical signals, capturing the nuances of each user's style[187] (Fig. 3b). Given the complex, multidimensional nature of these signals, CNNs play a key role in accurately processing and converting them.

In handwriting HMIs powered by TENGs, CNNs manage spatial data from the grid-like TENG sensor array, which records variations in pressure, texture, and shape.[188,189] These spatial data form hierarchical levels of detail, with CNNs progressively abstracting and refining information from basic outlines to

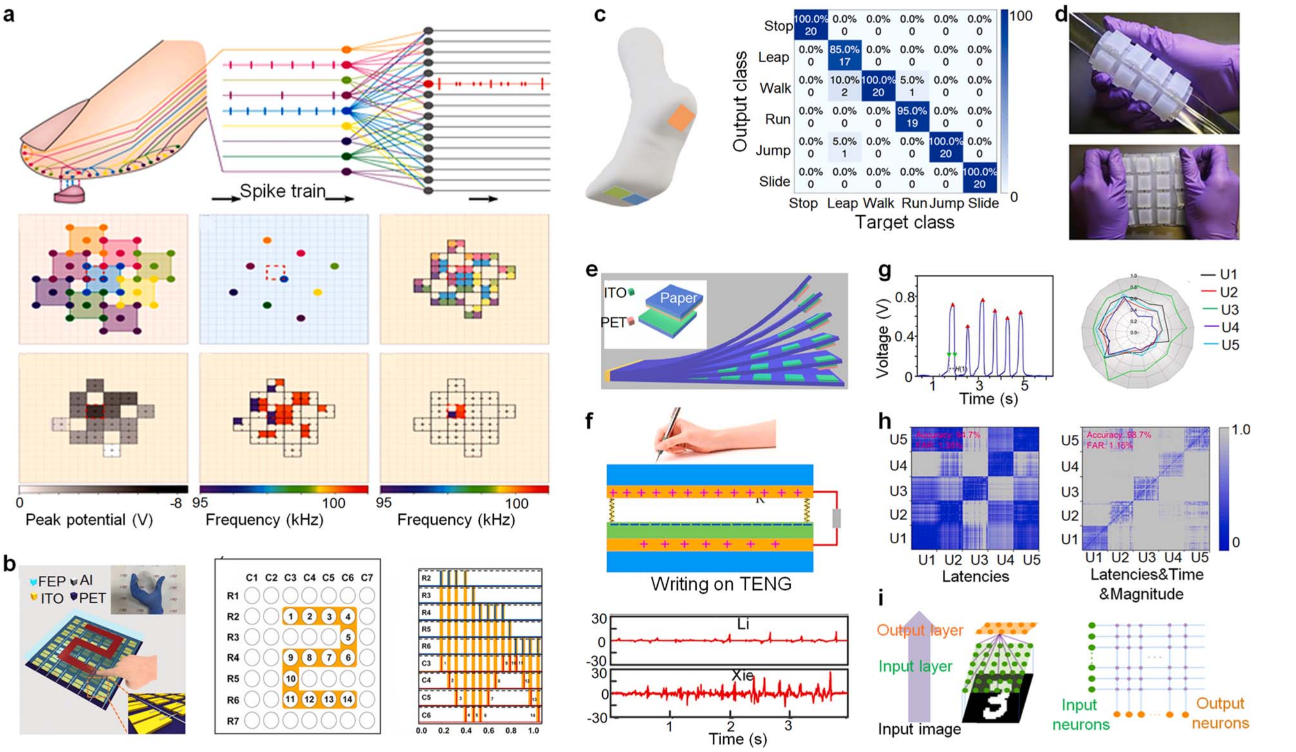

Fig. 3 AI-assisted TENGs for self-powered systems and interfaces. (a) A self-powered artificial tactile peripheral nervous system using TENG, simulating biological sensory circuits using CNN.[172] Copyright 2021, Elsevier. (b) Self-powered handwriting HMI *via* TENG, with structure and recognition principles using CNN.[187] Copyright 2020, Elsevier. (c) Smart socks with TENG sensors for recognizing sports gait data using CNN.[195] Copyright 2020, Springer Nature. (d) Training and recognition process for a 16-key stretchable keyboard security system using SVM.[202] Copyright 2018, Elsevier. (e) Self-powered TENG sensor for document management: page-turn recording and book theft prevention.[205] Copyright 2014, Springer. (f) Handwriting recognition with self-powered TENG for machine learning-based user classification using SVM.[207] Copyright 2020, Elsevier. (g and h) Electrical signal–time curve and feature radar chart for user typing, alongside a cross-user difference score matrix with feature combinations using PCA and SVM.[202] Copyright 2018, Elsevier. (i) TENG matrix-based artificial sensory memory using HNN.[143] Copyright 2020, Elsevier.

intricate handwriting characteristics through multiple convolutional and pooling layers.

Convolutional filters slide across the sensor grid, capturing fine details in pressure and contact that distinguish individual handwriting styles.[167] As data pass through layers, CNNs build hierarchical representations, from basic shapes to complex strokes, allowing for high-resolution interpretation of handwriting. Max-pooling layers further streamline data by retaining prominent features like high-pressure zones and distinct edges, reducing noise and data complexity.[190]

Tactile inputs in flexible, wearable devices often vary due to changes in pressure, contact angle, or surface area, particularly when devices undergo bending or twisting. To accommodate these variations, CNNs employ fine-tuned stride settings and adaptive kernel sizes. Finer stride settings (smaller movement steps across the data) enhance the CNN's sensitivity to minor changes, capturing subtle differences in texture or pressure.[191,192] Meanwhile, adaptive kernel sizes allow the model to focus on different scales of spatial features, adjusting its "field of view" to capture both fine details and broader strokes.[193] This adaptability is crucial for applications requiring real-time feedback, allowing CNNs to maintain accuracy even under physical distortions.

The synergy of TENGs and CNNs enables real-time data processing and instant feedback in handwriting HMIs. TENGs generate continuous electrical signals from handwriting, which CNNs rapidly interpret, supporting applications like virtual keyboards and digital notetaking where seamless interaction is expected. This integration sets a benchmark in self-powered HMIs, balancing energy efficiency with adaptability to physical changes.

4.1.3 1D and lightweight CNNs for smart socks and sports gait analysis. In sports and personal fitness, integrating TENGs with AI in smart wearables, like smart socks and shoes, is revolutionizing gait analysis. These devices embed TENG sensors that harvest kinetic energy from foot movements, converting it into electrical signals that reflect gait characteristics, walking phases, and pressure distributions[46,106,194,195] (Fig. 3c). The self-powered feature allows for long-term continuous, discrete monitoring, fitting seamlessly into daily wear. Gait details, like stride length, cadence, and weight distribution, are analyzed for insights into balance and stability.

Unlike tactile sensing, which relies on spatial data, gait analysis involves time-series data—a sequence of signals that represent movement patterns over time. 1D CNNs are well-suited as they can detect temporal dependencies across sequential movements, enabling the system to interpret complex gait cycles.[166,194] 1D convolutional layers slide filters across the time-series data, capturing recurrent patterns and subtle shifts in foot pressure over each step. This process enables the system to classify various gait types (*e.g.*, normal walking and limping) by detecting recurring signal patterns that correspond to different types of movement. The use of broader strides in 1D CNNs allows the network to observe multiple time steps at once, capturing sequential relationships within the gait cycle that provide a complete, coherent view of movement patterns. This enhances classification accuracy by allowing the network to integrate and contextualize data over a sequence, rather than focusing solely on individual points in time.

Lightweight CNNs, which require minimal computational resources, further optimize on-device analysis, capturing essential features of foot pressure and movement for real-time feedback.[196] Unlike typical CNNs, which demand substantial processing power, lightweight CNNs use fewer parameters and streamlined layer structures, making them ideal for energy-efficient wearable devices. They process data from embedded sensors that monitor foot pressure and movement across gait stages. This capability supports instant adjustments in sports training and rehabilitation, where small gait corrections enhance performance and reduce injury risk.

Real-time feedback is vital for high-performance sports and rehabilitation, enabling athletes, coaches, and therapists to make precise adjustments based on accurate gait data. CNN-enhanced wearables offer valuable insights, including stability, balance, and load distribution, critical for athletic performance, injury prevention, and recovery tracking. In personalized medicine, detailed gait analysis assists in diagnosing mobility issues and customizing rehabilitation exercises to an individual's movement patterns.[197,198] This technology allows coaches to refine technique, monitor fatigue, and proactively address injury risks by identifying asymmetries in movement.[199] In rehabilitation, CNNs provide precise progress tracking, allowing therapists to adjust treatment plans based on quantifiable, real-time feedback, fostering more effective recovery.[200] By enabling data-driven decisions, AI-powered smart wearables optimize performance and minimize injury risks.[201]

4.2 Cloud-based AI-integrated TENGs for security and document management

4.2.1 SVM and PCA for high-dimensional document classification. The integration of nanogenerators with SVM and PCA is advancing energy-efficient solutions in user authentication, security, and document management. When implemented in devices like keyboards and touchpads, TENGs can capture individual typing dynamics such as rhythm, pressure, and speed—producing unique, high-dimensional data patterns for each user[47,117,202] (Fig. 3d). SVM is suited for handling these high-dimensional data due to its ability to create an optimal hyperplane that maximally separates data classes, which correspond to distinct typing behaviors associated with each user. This separation ensures robust, precise user authentication, as SVM effectively classifies nuanced variations in typing patterns, making it difficult for unauthorized users to replicate.

PCA, on the other hand, plays a complementary role by simplifying high-dimensional datasets for efficient data processing and storage.[203] PCA works by identifying the main components (features) of the data, reducing complexity while preserving the most significant patterns, thereby optimizing the data for classification by SVM. This combination of PCA and SVM improves processing efficiency and enhances classification accuracy, as PCA distills the data to its most relevant features before SVM performs classification. In cloud-supported systems, this setup allows for large-scale data analysis, making it a viable solution for secure user authentication and document management across distributed networks.

In document management applications such as library archives and secure facilities, this approach is beneficial for monitoring document interactions. Systems can capture electrical signals generated by handling documents and analyze these signals with SVM and PCA to track user interactions in real-time and prevent theft[117,204,205] (Fig. 3e). This innovation surpasses traditional radio frequency identification-based systems, providing a smarter, more sustainable solution that leverages cloud capabilities for managing extensive, high-dimensional datasets.

4.2.2 Decision trees for workflow automation in document management. Decision trees are hierarchical models that make classifications or decisions based on a series of branching paths determined by specific criteria, making them ideal for workflow automation in document management.[206] By mapping out logical decisions in a tree-like structure, decision trees can systematically evaluate different features of documents such as classification categories, access levels, and handling requirements without requiring manual input for every step. This systematic branching allows for rapid, consistent categorization of documents, ensuring efficient management and access control. In document storage and retrieval systems, a decision tree could automatically categorize documents by type, assign appropriate access permissions, or flag documents requiring special handling. This automation minimizes manual oversight, streamlining processes in secure environments where handling large volumes of documents is essential.

Handwriting recognition in document management captures an individual's unique writing style through sensors that detect variations in mechanical pressure exerted during writing[207] (Fig. 3f). SVM classifies these distinct writing patterns for reliable identity verification, while PCA simplifies data complexity, making classification more efficient by focusing on key features of the handwriting. This application provides an additional layer of security in document management, as each user's handwriting is treated as a unique biometric signature that can be authenticated alongside other security protocols.

By combining SVM's precision in distinguishing high-dimensional data and PCA's efficiency in reducing data complexity, handwriting recognition systems offer secure, energy-efficient verification methods suitable for document management in high-security environments.[178,208] This integration not only enhances user authentication but also extends the capabilities of document management by adding personalized, biometric-based security options, contributing to a more intelligent, responsive, and energy-efficient system for managing sensitive information.

4.3 Cloud-based AI-integrated TENGs for pattern recognition and memory

4.3.1 PCA and SVM for typing analysis and user authentication. The combination of TENGs with PCA and SVM algorithms has significantly advanced typing behavior analysis, achieving greater accuracy and efficiency. TENGs capture mechanical nuances of typing, such as signal magnitudes, latencies, and hold times, transforming these details into electrical signals that serve as robust datasets. PCA simplifies these high-dimensional data by reducing them to essential components, effectively isolating the core elements of typing patterns without unnecessary complexity[202] (Fig. 3g and h). By distilling the data into their most informative aspects, PCA sharpens the focus for further analysis, improving computational efficiency.

Utilizing the refined data provided by PCA, SVM employs its classification capabilities to differentiate between individuals based on their unique typing signatures. SVM identifies an optimal hyperplane that separates data points across high-dimensional spaces, capturing the subtle distinctions in typing behavior that are critical for accurate user identification and authentication. The synergy between PCA's dimensionality reduction and SVM's high-precision classification allows for a robust, energy-efficient typing analysis system, supporting enhanced security and personalization in applications like user authentication and productivity analysis.

4.3.2 HNNs and DBNs for smart robotics and environmental interaction. HNNs play a pivotal role in developing artificial sensory memory for robotics, particularly in the recognition and recall of complex patterns.[155] HNNs are associative memory networks that excel at pattern recognition and recall based on partial inputs, making them highly effective for sensory memory applications in robotics. In systems with TENG matrix sensors, which capture intricate tactile data from interactions, HNNs process and store these sensory patterns. This capability enables robots to dynamically respond to changes in texture, pressure, and other tactile stimuli by recognizing familiar patterns and recalling previous interactions[209] (Fig. 3i). With their layered architecture, HNNs support a robust framework for recognizing and storing high-dimensional sensory data, allowing robots to adapt to various environmental stimuli with precision and memory recall.[210]

Complementing HNNs, DBNs and layered neural networks that learn hierarchical data patterns without the need for labeled inputs can be used for sensory memory systems where data often lack explicit labels through unsupervised feature learning, which is beneficial for high-dimensional tactile data.[8] In cloud-based tactile memory applications, DBNs extract meaningful features directly from complex, multi-faceted TENG sensor data, including information on texture, pressure, and motion. As DBNs autonomously identify underlying structures and patterns within these data, they allow sensory systems to improve responsiveness and adapt over time.

The use of cloud infrastructure with DBNs supports the substantial computational requirements for processing high-dimensional tactile data. This infrastructure enables DBNs to efficiently manage and organize complex tactile information, facilitating pattern recognition and feature learning that enhances robotic systems' real-time interactions and memory functions. HNNs and DBNs provide a comprehensive framework for artificial sensory memory, allowing intelligent robotic systems to navigate, interpret, and recall tactile experiences with precision, thereby paving the way for responsive and autonomous interactions.

4.4 On-device/cloud-based AI-assisted advanced sensory detection

4.4.1 Cloud-integrated CNNs for object recognition in environmental monitoring. Cloud integration enhances the power of CNNs, enabling them to handle large-scale, high-dimensional datasets while benefiting from cloud-based computational resources. The cloud infrastructure continuously refines CNN models, improving accuracy and allowing them to scale effectively for diverse environmental applications. This setup supports real-time monitoring needs in data-intensive scenarios, as CNNs can quickly update and analyze large datasets from various sensors, providing precise and scalable insights essential for safety and environmental monitoring. The cloud-enabled architecture makes CNNs well-suited for large-scale environmental data analysis, where continuous updates and real-time object recognition play vital roles[211,212] (Fig. 4a and b).

For environmental monitoring, CNNs integrated with cloud computing bring advanced capabilities for object recognition and data classification. CNNs are adept at detecting spatial patterns through their hierarchical structure, which processes data in layers to capture features ranging from simple edges to intricate shapes. This makes CNNs highly effective in identifying objects, patterns, and environmental features, such as recognizing volatile organic compounds (VOCs) or detecting specific items or hazards within complex landscapes[8,142] (Fig. 4c).

4.4.2 RNNs for real-time sound analysis. AI-enhanced sensory detection systems that combine nanotechnology with RNNs are significantly advancing real-time sound analysis capabilities in robotics. Biomimetic tactile sensors, such as those powered by TENGs, autonomously respond to mechanical stimuli akin to human skin, allowing robots to detect and precisely process subtle changes in pressure and strain[213] (Fig. 4d). An important development in this field is a self-powered neural tactile sensor that integrates a graphene layer with a TENG sensor featuring microlines, yielding heightened sensitivity to pressure and vibration[214] (Fig. 4e).

RNNs offer distinct advantages for real-time sound analysis, making them highly effective in applications requiring continuous and rapid processing of audio data. Their unique

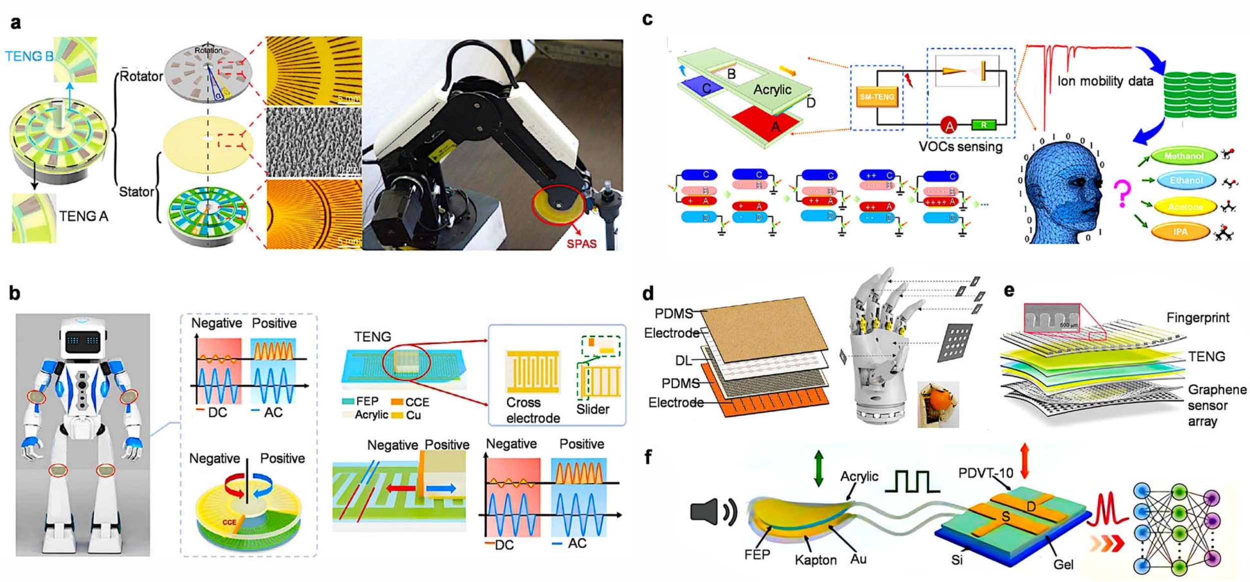

Fig. 4 AI-assisted TENGs for sensory detection. (a) Angle sensor.[211] Copyright 2020, Wiley. (b) Dual-mode vector motion sensors for direction and angle.[212] Copyright 2022, Elsevier. (c) Ionizer with machine learning enhancement.[8] Copyright 2021, RSC. (d) Stretchable sensor for object scanning, pressure measurement, and hardness detection.[213] Copyright 2019, Springer Nature. (e) Neural tactile sensor for pressure detection and texture identification.[214] Copyright 2019, ACS. (f) Artificial auditory pathway.[215] Copyright 2020, Elsevier.

architecture enables them to maintain context across time steps, making RNNs especially well-suited for handling sequential data like sound waves. This capacity to retain information allows RNNs to capture temporal patterns in sound, as they can integrate context from previous inputs—ideal for recognizing complex acoustic signatures that unfold over time. For example, variations in pitch, frequency, and duration in sound waves are effectively analyzed as the RNN processes each element in the sequence, updating its understanding based on previous patterns.

In real-time applications, RNNs operate directly on-device to minimize latency, enabling instant processing of acoustic data and allowing robotic systems to respond to auditory cues with minimal delay. This immediate responsiveness is particularly valuable in robotics, where quick sound recognition and reaction are crucial for navigation, interaction, and environmental awareness. By processing sound data as it arrives, RNNs enable robotic systems to differentiate sounds in dynamic environments—whether identifying speech, mechanical noise, or environmental cues in real-time—enhancing their adaptability, autonomy, and responsiveness to the surrounding world[215] (Fig. 4f). Moreover, the introduction of biomimetic piezoelectric acoustic nanosensors marks a breakthrough in auditory fidelity. These sensors convert vibrations into electrical signals similar to the human hearing process, offering advanced sound detection capabilities[216] (Fig. 5a).

These advancements in CNN-driven object recognition for environmental monitoring and RNN-enhanced real-time sound analysis mark a transformative step toward autonomous, responsive sensory systems in robotics. By merging AI with nanotechnology, these approaches enable real-time learning and adaptive functionality across various fields, including medical diagnostics, environmental monitoring, and smart infrastructure. The combination of on-device and cloud-supported AI bolsters robot interactions with their surroundings, enhancing pattern recognition, decision-making, and sensory precision, furthering the autonomy and intelligence of advanced robotics systems.

4.5 On-device AI-assisted PENG wearables for health monitoring

4.5.1 ANNs and RNNs for wearable health monitoring. The fusion of nanogenerators with AI-driven algorithms, specifically ANNs and RNNs, empowers wearable health monitors to continuously track health metrics in real time.[42,118,209,217–232] ANNs process complex, nonlinear health data patterns by extracting key features from multiple sensor inputs, which is vital for comprehensive health monitoring. RNNs, on the other hand, excel at interpreting time-dependent data, making them ideal for sequential monitoring tasks, such as analyzing heart rate variability, breathing patterns, or prolonged physical activity. By retaining information over time, RNNs allow wearables to recognize evolving patterns in health signals, which is essential for detecting subtle changes that may indicate health risks.

Wearable devices that incorporate ZnO nanorod-based PENGs add an extra dimension to this functionality.[233–235] These materials are highly responsive to motion, generating electrical signals in response to bending, stretching, and other mechanical movements. This sensitivity enables precise measurement of physiological movements and provides valuable input for ANN and RNN models to analyze, enhancing the quality and relevance of real-time health monitoring. This breakthrough lays the groundwork for creating highly sensitive

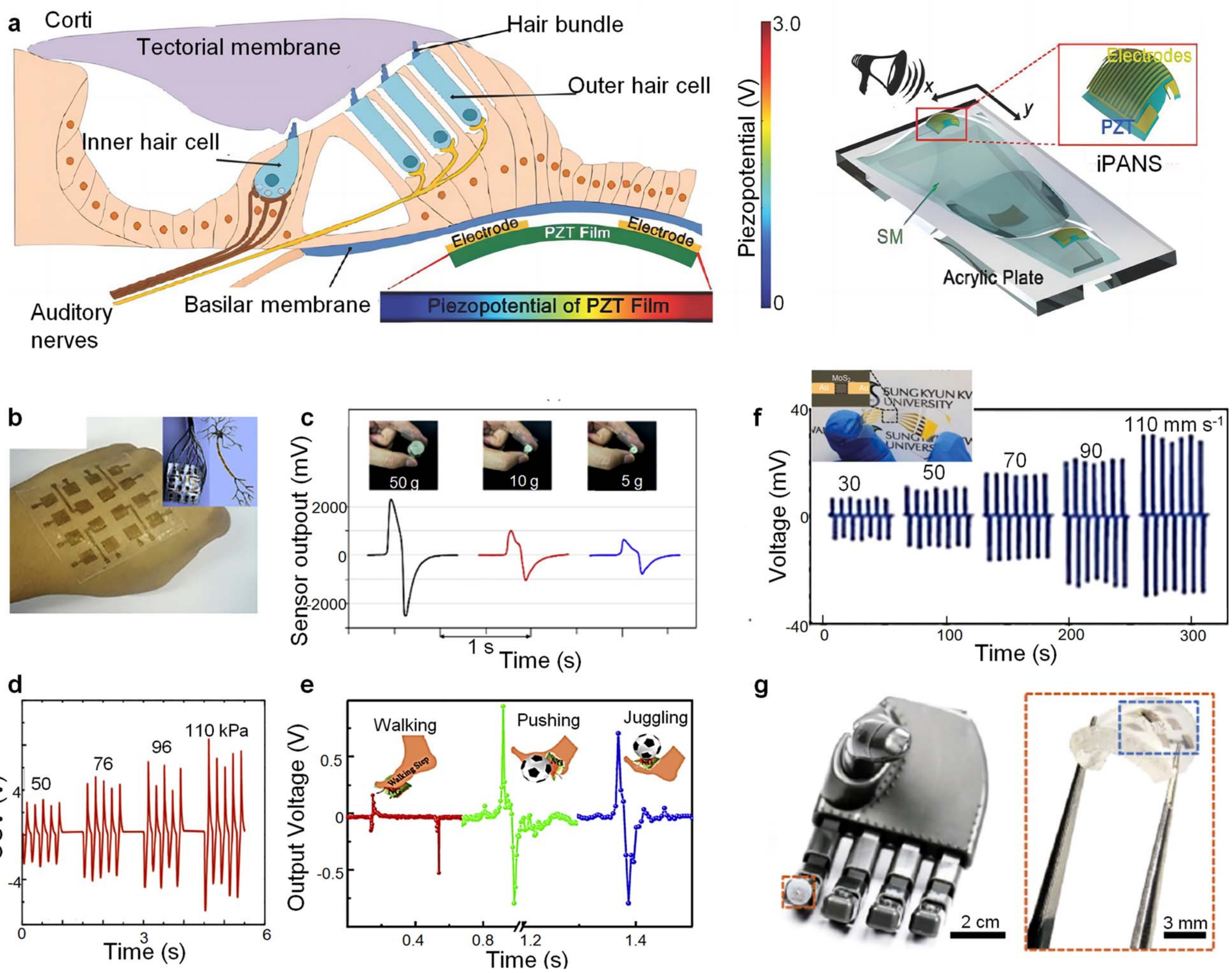

Fig. 5 AI-integrated PENGs for wearables and robotics. (a) Biomimetic inorganic piezoelectric acoustic nanosensor.[216] Copyright 2014, Wiley. (b and c) Multi-sensing e-skin for pressure and temperature detection.[236] Copyright 2018, ACS. (d) Output voltage and pressure for affordable e-skins.[112] Copyright 2020, IOPscience. (e) Wearables inspired by the fish swim bladder.[237] Copyright 2018, Wiley. (f) MoS_{2-x}-based PENG under different bending speeds.[241] Copyright 2018, Wiley. (g) Implanted microsystem in a robotic hand.[213] Copyright 2019, Springer Nature.

e-skins[236] (Fig. 5b and c). When coupled with AI, these devices can interpret complex motions, finding their place in advanced prosthetics and interactive technologies, thus improving the human–machine interface.

4.5.2 SVM, KNN, and decision trees for wearable tactile feedback. Advances in stretchable nanogenerators are revolutionizing wearable tactile feedback, making it possible for devices to deliver responsive sensations directly to users' fingertips[112] (Fig. 5d). These PENG-based devices, designed for industrial-scale production, have transformed touch-sensitive wearables, enabling them to detect and respond to tactile inputs in real time. By integrating these nanogenerators with AI, wearable devices provide users with a more immersive, intuitive interaction, as they can interpret and respond to complex tactile stimuli. The development of bio-PENGs, which utilize eco-friendly materials to generate power from body movements, furthers this approach, supporting sustainable, self-powered wearables capable of adapting to various environmental and physiological cues[237] (Fig. 5e).

In achieving this high degree of tactile feedback, several algorithms play complementary roles, each addressing distinct aspects of tactile data processing. SVMs are pivotal for classifying tactile data by clearly separating various touch inputs, such as different pressures or textures, into specific categories, allowing wearables to differentiate touch types accurately.[238] KNN, a straightforward yet effective algorithm, is useful for classifying tactile sensations by comparing them to known data points. KNN's proximity-based approach is valuable for recognizing textures, pressure levels, or gestures, making it a natural complement to SVM in applications where cumulative sensory data inform tactile feedback.[239] Decision trees and random forests can enhance tactile classification by evaluating input data based on multiple criteria.[240] Decision trees individually assess sensory data, while random forests employ an ensemble of trees for more robust classification.

While SVMs offer foundational classification precision, KNN's historical comparison helps refine touch recognition by drawing on accumulated sensory data. Decision trees and random forests, with their multiple-layered decision-making, add robustness to tactile feedback by providing nuanced classification for a broad range of touch inputs. By dynamically interpreting and adapting to tactile inputs, these algorithms empower nanogenerator-based wearables to deliver advanced, real-time feedback, paving the way for intelligent, self-sufficient, and seamlessly integrated technologies in everyday life.

4.6 On-device/cloud-based AI-integrated PENG biomedical robotics

4.6.1 LSTM for precision control in robotic hands. The integration of LSTM networks with 3D piezoelectric microsystems in robotic hands marks a transformative advancement in biomedical robotics, particularly for cloud-supported applications requiring precision and adaptability. LSTMs are uniquely suited to capture long-term dependencies in sequential data, a critical feature for interpreting tactile inputs that continuously evolve. In robotic hand applications, these dependencies encompass complex tactile feedback patterns that arise as the hand interacts with diverse objects, surfaces, and textures. By retaining contextual information across time steps, LSTMs enable the robotic hand to make intelligent, real-time adjustments based on sequences of past interactions rather than isolated data points. This capability enhances the hand's sensitivity and adaptability, allowing for precise modulation of grip and pressure in response to varying tactile stimuli.

An example of this approach is demonstrated in robotic hands equipped with a monolayer MoS_{2-x}-based PENG designed to optimize electrical outputs in flexible configurations[241] (Fig. 5f) and a PVDF layer with chromium/gold electrodes mounted on a serpentine polyimide ribbon for sensitive tactile feedback[213] (Fig. 5g). By dynamically interpreting tactile data through LSTM algorithms, these systems achieve enhanced sensitivity during manipulation tasks, allowing for highly controlled and responsive actions.

Moreover, AI elevates the functionality of these systems beyond passive data collection, fostering active learning and real-time adaptation. This advanced AI-driven approach utilizes pattern recognition, predictive analytics, and dynamic decision-making processes to boost sensor sensitivity and adaptability under various environmental conditions.[242] For instance, AI's ability to dynamically adjust the electrical output of a sulfur vacancy-passivated MoS_2 PENG in response to changes in pressure and bending angles significantly increases energy efficiency, optimizing system performance and extending operational lifespan.[243]

In the 3D piezoelectric microsystem integrated into a robotic hand, AI can significantly improve the hand's grip and manipulation abilities by continually learning from tactile feedback.[244,245] This adaptability allows the robotic hand to perform a wide range of tasks with enhanced precision and responsiveness to touch, enabling it to handle diverse and unpredictable objects effectively. This fusion of AI with nanogenerator-powered biomedical robotics opens a myriad of possibilities, from self-adjusting prosthetic systems that provide a more seamless user experience to autonomous energy management within these systems, ensuring optimal power distribution. Such advancements are crucial for enhancing the autonomy of robotic and biomedical applications, making them more efficient and user-friendly.

4.6.2 ANN for real-time decision-making in adaptive prosthetics. In adaptive prosthetics, the integration of ANNs on-device enables real-time responsiveness, which is essential for seamless and intuitive user experiences. Unlike LSTMs, which are more suitable for handling sequential dependencies over time, ANNs provide immediate decision-making by analyzing tactile feedback and positional data in real time. This capability allows the prosthetic to react instantly to changes in movement, enabling fluid, adaptive motion that closely aligns with the user's natural actions.

By processing tactile inputs on-device, ANNs eliminate the latency associated with cloud processing, ensuring that the prosthetic can adjust grip, orientation, and movement as the user performs various tasks. This real-time processing is particularly useful for adaptive prosthetic hands, where instantaneous feedback is needed to accommodate changes in grip strength and angle based on the detected force or shape of the object being handled. Additionally, by optimizing response based on real-time inputs, ANNs reduce wear and tear on the device by avoiding unnecessary movements, thereby improving the lifespan and efficiency of the prosthetic system. The PENG-based design, with materials such as sulfur vacancy-passivated MoS_2, enables these prosthetics to harvest energy autonomously, further enhancing their usability and sustainability.

These innovations in AI-integrated PENG biomedical robotics, through cloud-enabled LSTM applications for robotic hands and on-device ANN applications for adaptive prosthetics, mark a significant step towards creating self-sufficient, highly adaptive systems in healthcare. The combination of precise tactile feedback processing and intelligent adaptability enables these systems to provide a more personalized, responsive experience for users, with applications that span both medical and robotic fields.

5 Conclusions and outlook

The fusion of artificial intelligence with nanogenerators is transforming the conversion of mechanical energy into electrical energy, leading to more efficient and sustainable energy solutions. This breakthrough is paving the way for the creation of self-powered devices, crucial for advancing autonomous robotics and intelligent systems independent of external power sources. Moreover, AI's integration is refining the accuracy and responsiveness of robotics sensors and actuators, significantly improving healthcare wearables for precise monitoring of vital signs and enabling real-time data analytics. These advancements promote predictive maintenance and adaptive learning, tailoring devices to user-specific requirements.

However, this integration presents several challenges, including complexities in analysis, design, fabrication, and the broad application of these technologies. There is an urgent need for a universal framework that can thoroughly understand the piezoelectric and triboelectric effects, optimize structures, innovate new materials, effectively scale current outputs, and expand the application domains. This advancement should extend beyond sensing functions to include computational capabilities as well.

Ongoing research offers promising directions for incorporating active materials that can respond dynamically to external stimuli, such as pressure, heat, or electrical fields into nanogenerator-powered soft robotics and intelligent machine systems. These materials are useful in robotic systems requiring adaptive responses, such as soft sensors, e-skins, actuators, and microfluidic devices, where flexibility and responsiveness are essential.

Combining TENGs and PENGs within a single system can offer dual capabilities in both sensing and actuation. This combination leverages TENGs' sensitivity to surface contact and movement and PENGs' ability to generate stable output under deformation, creating a more comprehensive energy-harvesting and sensory network. This integration may be accomplished by layering materials or designing hybrid circuits where each generator type contributes to specific functions. These hybrid systems support the development of self-powered, untethered robotic devices capable of responding to environmental cues.

For soft robotics, low-power actuation mechanisms are crucial as they allow for motion without requiring high energy input. Further development of electroactive polymers, dielectric elastomers, and shape-memory alloys enables movements like bending, contracting or expanding with minimal electrical power for soft actuators in robots. When paired with TENG or PENG devices, these materials support sustained operation in autonomous systems that rely on limited power sources.

Microscale TENG- and PENG-based robots, due to their compact size, hold significant potential for biomedical applications within confined spaces, such as vascular systems. These miniature devices could navigate narrow blood vessels or other internal pathways to perform diagnostics, deliver targeted drugs, or even conduct minor repairs within the body. Biocompatible materials, such as hydrogels and flexible polymers, enable safe interactions with biological tissues, while advanced microfabrication techniques like photolithography, 3D printing, and laser micromachining allow for the precise construction of robots at the microscale, essential for delicate medical applications. In the development of flexible tactile sensors, innovations in materials science and structural design have led to substantial improvements in sensitivity. Flexible substrates, such as elastomers and conductive polymers, combined with structured micro/nano-patterns on the surface, enhance the device's ability to detect and differentiate between subtle pressure changes, temperature variations, and other material properties. These advances also support enhanced auditory and olfactory sensing, enabling more precise sound and gas detection, respectively, in soft robotics and wearable devices.

Moving forward, key areas for nanogenerator-based systems include addressing performance limitations, ensuring stability in challenging conditions, and advancing production techniques for scalability. Strategies to enhance output performance include using multilayered structures and optimizing the surface area to boost energy capture. Ensuring device stability in harsh environments may involve material coatings that protect against high temperature, humidity, or mechanical stress, as well as encapsulation techniques to shield sensitive components. Scaling production can benefit from automated fabrication techniques, such as roll-to-roll processing or 3D printing, to achieve consistent, high-quality manufacturing at a large scale.

Addressing these challenges will be essential for advancing the practical applications of nanogenerator systems. By enhancing durability, efficiency, and scalability, the potential of AI-enhanced nanogenerators can be unlocked across diverse fields, from medical devices and biosensors to self-powering buildings, ultimately marking a substantial step toward sustainable, autonomous technological solutions.

Data availability

No primary research results, software or code have been included and no new data were generated or analyzed as part of this review.

Author contributions

The manuscript was written through the contributions of all authors. All authors have approved the final version of the manuscript.

Conflicts of interest

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.

Acknowledgements

This is an invited submission for the Nanogenerators themed collection. The authors acknowledge the Henry Samueli School of Engineering & Applied Science and the Department of Bioengineering at the University of California, Los Angeles for their startup support. J. C. acknowledges the Vernroy Makoto Watanabe Excellence in Research Award at the UCLA Samueli School of Engineering, the Office of Naval Research Young Investigator Award (Award ID: N00014-24-1-2065), National Science Foundation Grant (Award Number: 2425858), NIH Grant (Award ID: R01 CA287326), the American Heart Association Innovative Project Award (Award ID: 23IPA1054908), the American Heart Association Transformational Project Award (Award ID: 23TPA1141360), the American Heart Association's Second Century Early Faculty Independence Award (Award ID: 23SCEFIA1157587), the Brain & Behavior Research Foundation Young Investigator Grant (Grant Number: 30944), and the NIH National Center for Advancing Translational Science UCLA CTSI (Grant Number: KL2TR001882).

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