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Applications of flexible materials in health management assisted by machine learning

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In recent years, the demand for improved health management has become increasingly higher; however, the existing medical resources have made it difficult to meet this demand. The field of health management is in urgent need for self-help monitoring equipment, intelligent identification technology and personalized medical services. This article reviews the application of flexible materials in health management, particularly the application of flexible wearable sensing devices combined with machine learning technology in various medical scenarios, and classifies them into several types of applications such as health monitoring and prevention, disease diagnosis and treatment, rehabilitation treatment and assistance. Flexible materials can be used to fabricate or integrate various types of high-sensitivity sensors with the characteristics of high flexibility and self-adhesion, resulting in a wealth of health monitoring equipment. These devices can self-monitor various physiological indicators in various parts of the human body. The integration of machine learning (ML) makes it possible to analyze and identify subtle, massive, multi-channel and multi-modal sensor data, accelerating the intelligent process of health management and personalized medicine. This paper not only elaborates on various flexible materials and ML algorithms commonly used in the field of health management, but also focuses on discussing the application of ML-assisted flexible materials in different stages of health management, and puts forward prospects for the future development direction, providing reference and inspiration for major changes in the field of health management.

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1 Introduction

Currently, amidst the advancements in social productivity and medical standards, individuals have placed increasing emphasis on physical health, fostering an urgent demand for health management. Traditional manual monitoring, diagnosis, and auxiliary methods have fallen short in meeting this escalating need. Consequently, the construction of an autonomous and intelligent health management system has become imperative. The harmonious integration of flexible materials and sensing technologies has spawned a myriad of intelligent home health monitoring devices, such as smart blood pressure monitors and glucometers capable of remote connectivity and surveillance as well as smart bracelets and watches that continuously track vital physiological indicators such as the heart rate and blood oxygen saturation.[1–4] Wearable health monitoring devices, characterized by their real-time capabilities and comfort, are highly practical for the general population, particularly the elderly, ensuring effective disease management while enhancing their overall well-being.[5] Furthermore, the continuous advancements in microprocessor technology, wireless communication, and artificial intelligence have facilitated the integration of wearable devices with ML techniques, thereby broadening the horizons of health management research and offering new avenues for scientific inquiry.[6,7]

In recent years, wearable health monitoring systems primarily composed of flexible materials such as gels, textiles, and plastics have garnered significant attention.[8–12] Traditional rigid materials based on metals are often dense and heavy, limiting their applicability in fields requiring lightweight designs.[13] Their high stiffness also compromises comfort and fails to establish seamless contact with the skin, leading to air gaps that introduce motion artifacts that can distort or disrupt the accurate capture of physiological or biological signals. Conversely, flexible materials typically exhibit superior stretchability and mechanical strength, which enable them to conform to human skin and accommodate movement.[14–16] Through judicious material selection or design, these devices can further enhance sensing capabilities or drug delivery functions, catering to diverse scenarios like daily exercise and adjuvant therapy, embodying multifunctionality and integration.[17–23] Additionally, flexible materials facilitate ease of processing, satisfying the portability requirements of home health monitoring devices

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while offering users a more comfortable and convenient experience.

The application of ML algorithms in healthcare has attracted considerable interest. ML algorithms can leverage physiological parameters and behavioral data collected by wearable devices to predict individuals' health status and disease risks, thereby assisting physicians in devising personalized treatment plans. This approach not only empowers individuals to self-manage their health but also provides doctors with more precise and comprehensive diagnostic insights.[24–26] ML algorithm helps identify data collected by wearable devices, and it greatly improves the recognition accuracy of motion states.[27] This includes steps, duration and intensity, as well as specific activities such as running, swimming, cycling, and even individual exercise patterns, which significantly improve the intelligence of family health monitoring.[28,29] Above all, ML algorithms enable the maximization of the use of flexible sensors in people's daily lives, thereby further propelling the advancement and application of flexible sensing technologies in a scholarly and technological context.

However, the current relevant reviews mainly focused on a single monitoring project or lacked systematic discussions on the combination of machine learning techniques and applications. This study aims to provide a comprehensive review of the application of ML-assisted flexible material devices in health management. To summarize the current progress in this field, we first categorize and introduce existing flexible materials. Subsequently, we investigated the mechanisms of various ML algorithms employed for signal data processing, thereby highlighting the strengths, limitations, and suitable scenarios of different models. Lastly, we focus on classifying and discussing relevant research on the application of ML-assisted flexible sensors in health management, encompassing daily healthcare, disease treatment, nursing rehabilitation, and assistance for individuals with disabilities. In summary, this paper offers a clear overview of the technological innovations and theoretical frameworks of flexible materials assisted by ML in the current health management landscape, providing a forward-looking perspective and reference for intelligent development trends in health management.

2 Flexible materials

Flexible materials are characterized by high extensibility, sensitivity, and self-adhesiveness and play a critical role in wearable electronics and electronic skin. Owing to their diversity, these materials exhibit distinct properties and are suitable for various application scenarios. However, achieving a comprehensive yet non-redundant classification of such complex and versatile materials poses significant challenges. Based on extensive research and the integration of ML techniques in intelligent health management, we categorized flexible materials into four main types: gel-based materials, textile-based materials, plastic-based materials, and others.

2.1 Gel material

The gel material is a three-dimensional porous polymer network formed by physical or chemical crosslinking of hydrophilic polymer molecules with immiscible polymer molecules and solvents.[30–33] It can be divided into hydrogels, organogels, ionic liquid gels and eutectogels according to the different solvents.

Gel materials containing different solvents have completely different properties. Hydrogel materials with unique three-dimensional mesh structures have high water content and similar structures to natural soft tissues, which has an advantage in the biomedical field,[26] Moreover, a large number of hydrophilic groups enable them to show good biocompatibility,[34,35] and thus be widely used in the field of intelligent medical treatment. However, hydrophilic groups can also cause certain limitations in hydrogel materials. For example, hydrogels cannot resist water loss and freezing at low temperatures.[36] To increase the scope of application of the gel material, the researchers found that a new gel material can be formed by adding a certain amount of binary solvent to the hydrogel, that is, the organogel with organic liquid as the main solvent.[37] Due to the addition of binary solvents, the cross-linking density of hydrogen bonds between organic compounds and water molecules increases, which effectively hinders the formation of ice crystals and reduces the evaporation of water to a certain extent to achieve the effect of low-temperature anti-freezing.[38] Nevertheless, the use of organic solvents also has drawbacks, such as poor biocompatibility and the same problems with ionic liquid gels.[39] An ionic liquid gel is a gel material with a designable structure that is confined to a three-dimensional crosslinked network by chemical or physical means.[40] Because it is mainly composed of two parts of ionic liquid and polymer, it also has the advantages of high chemical and thermal stability of ionic liquid.[41] In addition, ionic liquid gels have good mechanical strength and self-healing properties,[42,43] which can be widely used in the field of flexible sensing. However, ionic liquids have a series of problems such as expensive, poor biocompatibility and complicated follow-up treatment.[44] Therefore, eutectogels containing green deep eutectic solvents composed of HBD and HBA have become the focus of researchers recently.[45,46] This device not only combines the advantages of the high conductivity of an ionic liquid and a wide electrochemical operation window but also has the advantages of non-toxic, low cost and easy to operate. This effectively compensates for the limitations of hydrogels and ionic liquid gels.[47] With the progress of biomaterial technology, an increasing number of gel species have been discovered and applied in intelligent detection combined with ML (Fig. 1A).[48–51]

2.2 Textile materials

Textile materials include filaments, fibers, and yarns, which can be made into a series of textiles by weaving, felting, bonding, tufting and other methods. According to different sources, textile materials can be divided into natural textile materials and synthetic textile materials, which are important parts of flexible materials.

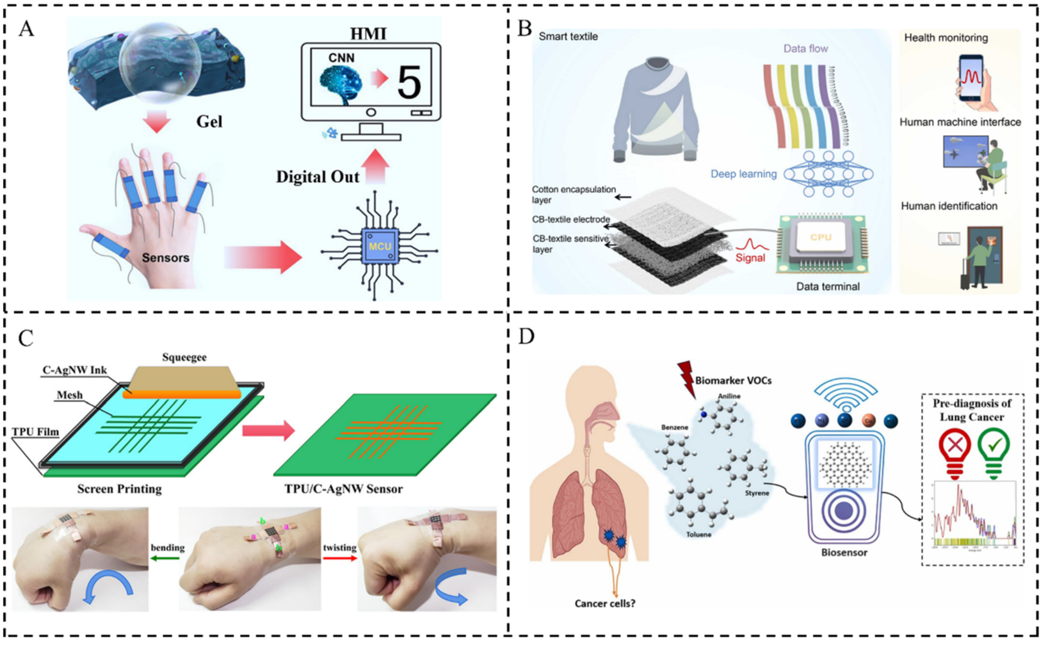

Fig. 1 Sensing devices based on different flexible materials are applied in the field of health management combined with ML. (A) Gel-based gesture recognition system. This figure has been reproduced from ref. 51 with permission from ACS publication, copyright 2023; (B) textile-based human monitoring and identification systems. This figure has been reproduced from ref. 52 with permission from Elsevier publication, copyright 2024; (C) TPU-based sensor for monitoring the full range of human motion. This figure has been reproduced from ref. 53 with permission from ACS publication, copyright 2021. (D) Metal-doped graphene sensors for lung cancer diagnosis. This figure has been reproduced from ref. 54 with permission from Elsevier publication, copyright 2024.

Textile materials have the general properties of flexible materials such as stretchability. Wearable sensing devices made of textile materials can be woven into gloves and antennas of various shapes with porous structures (nonwoven fabrics),[55] which have good air permeability.[56] To realize flexible electronics better, people usually use electrospinning, chemical vapor deposition, and solution methods to prepare textile materials with the expected properties. For example, PVDF can be transformed into conductive nanofibers with high piezoelectric properties through electrospinning technology.[57] At the same time, to expand the application range of wearable textile-sensing equipment, the prepared textiles are generally multi-layered structures to ensure high performance and functional diversification. For example, SWCNTs powder, isopropyl alcohol, and water mixed solution sprayed on cotton fabric made of triboelectric layer, super hydrophobic textile material made of waterproof layer and other prepared multi-layer structure textiles have high sensitivity, high electrical conductivity, excellent waterproof and sweat resistance.[58] With the support of ML, wearable textile-sensing devices made of textile materials are often used in the field of human–machine interfaces, such as health monitoring and human identification (Fig. 1B).[52]

2.3 Plastic materials

Plastic materials are organic polymer materials synthesized with resin as their main component. They can be divided into thermosetting plastics and thermoplastic plastics based on the different heat changes of the resin. Various plastic materials, including TPU, PLA, PI, and PVC are widely used in the field of flexible electronics.

As a common flexible substrate, TPU exhibits good flexibility, chemical stability, and high electrical conductivity which can be obtained by doping with conductive fillers such as carbon or NMC.[59] PLA is a polyester synthesized from lactic acid as a raw material.[60] The properties of PLA can be combined with wearable technology, biocompatibility and biodegradability. PLA films prepared by low-temperature solvent dissolution spin-coating technology also exhibit good stability.[61] PI exhibits good flexibility and mechanical properties, and high thermal conductivity can be obtained when mixed with 1D or 2D fillers (AgNW and BN).[62] PVC is a widely used polymer with low cost, good recyclability, and good electrical and corrosion resistance.[63] By modifying PVC through a series of reactions such as nucleophilic substitution, it can be made more flexible and diversified based on its unchanged inherent properties.[64] There are many examples of plastic materials, which have the general properties of flexible materials, such as flexibility and variability, present outstanding advantages in a certain performance (such as electrical conductivity, and thermal conductivity), and have rich research value. Wearable sensing devices based on flexible plastics combined with ML can be widely used in the field of intelligent monitoring of human movements, such as blinking, smiling, and joint bending (Fig. 1C).[65]

2.4 Others

In addition to the aforementioned three typical flexible materials, we further elaborate on other flexible materials to complement the discussion. Widely used in intelligent health management, these additional materials encompass carbon-based flexible materials, inorganic semiconductor materials, printable materials, and certain composite materials with unique characteristics.

The most common carbon-based flexible materials are CNT and GN, both of which are ideal materials for making soft electronics. CNTs are 1D quantum materials, often prepared by dry or solution methods. CNT is often combined with NMC, silicone and other materials, showing excellent mechanical and electrical properties and high sensitivity.[66,67] GN is a single-atom-thick material arranged in a 2D hexagonal lattice,[68] prepared by "top-down" or "bottom-up" methods. GO has rich functional groups, adjustable structures and properties and can achieve simultaneous multimodal detection.[69] Inorganic semiconductor material is a kind of material with special electronic properties. Different inorganic semiconductor materials have unique properties. For example, ZnO and ZnS have high piezoelectric properties, resulting in wearable sensing devices and electrodes with high sensitivity.[70,71] Ag_2S-based flexible materials have good flexibility, and wearable sensing devices can withstand various shape changes.[72] Printable materials are defined as those capable of being processed and shaped *via* advanced printing technologies, such as 3D printing, inkjet printing, and screen printing.[73,74] These materials, including resins, metals, ceramics, and others, demonstrate superior stretchability and processability. Wearable sensing devices fabricated from printable materials can collect health-related data in real time; when integrated with ML, these devices enable early disease detection and personalized health management strategies.[75] Composite functional materials exhibit diverse properties derived from multiple material types, offering broader applications in health management. For example, polydimethylsiloxane (PDMS) combines the processability of plastics with the elasticity of gels, allowing for the creation of complex structures suitable for wearable health monitoring through specialized manufacturing techniques.[76] Thermoplastic elastomers (TPE) integrate the plasticity of plastics, the flexibility of gels, and excellent biocompatibility. When combined with ML, TPE-based materials can be used to develop smart bracelets, health-monitoring patches, and other innovative devices, further advancing their application in health management.[77]

There are many kinds of flexible materials with properties such as flexibility, conductivity and variability. Various wearable sensing devices, such as electronic textiles,[58] gloves[78] and wristbands[69] are prepared based on flexible materials to collect sensor data, such as pulse and gesture signals and perform data analysis combined with ML technology to realize efficient prediction, early warning, diagnosis and assistance in the field of health management (Fig. 1D).[57,79,80] These flexible materials were fused with different components to fabricate health monitoring equipment. The applications of ML algorithms in the field of health management are summarized in Table 1.

3 Mechanism and evaluation of ML models

ML is an artificial intelligence technology that enables computers to automatically improve their performance by learning from data without the need for explicit programming instructions. By building and training models, ML algorithms can discover patterns and rules in the data, which allows them to make predictions and classifications on new data. This technology is widely applied across various fields, including image recognition, speech recognition, natural language processing, recommendation systems, medical diagnosis, and financial analysis, where it enhances efficiency and accuracy, addresses complex problems, and provides personalized solutions.[112–115]

Traditional disease prediction and diagnosis rely on doctors' experience and limited data, whereas ML improves accuracy by uncovering complex patterns in vast medical data. ML models can analyze sensor data, medical imaging, and pathological information to predict disease risk and assist in accurate diagnoses, reducing misdiagnosis. For example, IBM Watson and Google DeepMind have successfully used ML for detecting conditions like glomerulosclerosis, diabetic retinopathy, and age-related macular degeneration, highlighting its significant applications in health management.[116–118] Commonly used ML algorithms and model evaluation indicators in the field of health management are summarized below.

3.1 ML algorithms

3.1.1 Regression class model. Linear regression predicts the value of the dependent variable by fitting a straight line (or hyperplane) to minimize the difference between predicted and actual values. Logistic regression is a widely used classification algorithm that is primarily designed for classification tasks, especially binary classification. It works by establishing a logistic function (typically a sigmoid function or other simple linear functions) to map the output of a linear regression model to the (0,1) interval, thereby providing a probability for classification. In simple terms, data points are distributed across two distinct regions, representing two categories of outcomes. Logistic regression fits a curve to separate these data points, allowing it to predict which category new data belongs to.

In the medical and health domains, both linear and logistic regression models are frequently used to validate correlations between two or more features. For instance, Agier *et al.* used linear regression to explore how various social and environmental exposure factors impact health.[112] Linear regression solves the model parameters using the least squares method, which involves finding a set of parameters that minimizes the loss function. Linear regression assumes a linear relationship between independent and dependent variables. If the actual relationship is nonlinear, the predictive performance of linear regression may be compromised. In health-related fields,

Table 1 Components, monitoring signals, ML algorithms and applications of various flexible materials

Material	Component	Signal (monitoring site)	ML algorithm	Application field
Gel materials	NaCl/PVA	Pressure (neck)	CNN	Driving fatigue, safety and health monitoring[81]
	PVA/PEI/$CaCl_2$	Pulse wave signal (wrist)	LDA	Disease diagnosis[50]
	PDMS/PR/PAAm	pH (body)	Linear regression	Disease diagnosis[82]
	Catechol/Chitosan/Diatom	Tremor (hand)	SVM/KNN	Disease diagnosis[83]
	Ecoflex/Silicone	Sound (chest/back)	CNN	Disease diagnosis[84]
	HACC-PAM	pH (wound)	CNN	Disease treatment[85]
	gel@PANI/Cu_2O NPs	Voltage (wound)	ANN	Disease treatment[86]
	PAM/SA/TG	Deformation (finger flexion signals)	CNN	Finger rehabilitation training[51]
	NaCl/TA/PAM	EMG and FMG (arm)	MNN	Finger rehabilitation training[87]
	MXene/HA-PBA/TA	EMG (right arm)	CNN	Sign language recognition[88]
	PAM/DAS/Gly	Deformation (five fingers)	ANN	Sign language recognition[89]
	P(AA-*co*-AM)/MXene@PDADMAC	Deformation (five fingers and wrist)	ANN	Sign language recognition[90]
Textile materials	PTFE/PA	TES (back)	Logistic regression/DT/RF	Sitting posture recognition and early warning[91]
	EPE/EVA	Pressure (hip)	KNN; SVM; DT	Sitting posture recognition and early warning[92]
	TPU/WPU/DMF/[Bmim][BF_4]	Pressure and temperature (hip)	LDA	Prevention and rehabilitation of pres-sure injuries[93]
	Nitrile/Silicone rubber/Polyester copper	Pressure (feet)	CNN	Disease diagnosis[94]
	Ecoflex/Ag	Pressure (finger)	Linear regression	Finger rehabilitation training[55]
	PVDF/PPy/$Cs_2AgBiBr_6$	Pressure (finger, elbow, knee and arterial pulse)	SVM	Disease diagnosis[57]
	PDMS/FEP/CNTs/Al	Pressure (wrist)	FFNN	Blood pressure monitoring[58]
	Ag/PE	Pressure (elbows and knees)	SVM	Gait recognition and rehabilitation[95]
	TPU/PES/Ni/Ecoflex	Pressure (heel and toe)	ANN	Gait recognition[96]
Plastic materials	PET/GS	ECG (chest), GSR (palm)	DT	Fatigue monitoring[97]
	PI/Cu/Polystyrene/Ecoflex	ECG (chest)	CNN	Disease diagnosis[98]
	PDMS/PI	EMG (human body)	[a]	Disease diagnosis[99]
	PI/MPN/PI	Pressure (wrist)	[a]	Disease diagnosis[100]
	Ecoflex/PDMS/PI/Cu	ECG/SCG/PPG (sternum)	FFNN/CNN/KNN/SVM/TCNN	Disease diagnosis[101]
	Ecoflex/PI	Sound (sternum)	CNN	Disease diagnosis[102]
	PMMA/PI/AgNPs	EOG/VOG (eye)	KNN/SVM	Disease treatment[103]
Others	Ecoflex/silbione gel	ECG (chest)	CNN	Health monitoring and movement recognition[104]
	PES	Pressure (hip)	RF	Sitting posture recognition and early warning[105]
	GO/SA/Au	Pressure (wrist; hand)	PCA	Pulse monitoring[69]
	PVDF/ZnO/PDMS/Cu	Pressure (wrist; throat)	[a]	Pulse and vocal cord vibration detect-ion[71]
	CNT/Silicone/BA	Pressure (lung; heart)	Linear regression	Disease diagnosis[67]
	CB/PDMS	Pressure (hand)	KNN/SVM/LSTM/DT	Disease treatment[106]
	PVA/DHBS	Temperature/pH/trimethylamine/uric acid/moisture (wound)	NN	Disease treatment[107]
	AuNP/SWCNT	Electrical signal	LDA	Drug identification[66]
	Au–ZnS NPs	Electrical signal	Linear regression	Drug identification[70]
	Ag_2S	Pressure (finger)	[a]	Gesture recognition[72]
	BTO/SU-8	Pressure (feet)	CNN	Gait recognition[108]
	PDMS	Pressure (left/right biceps brachii, left/right triceps brachii, left/right tibialis anterior and left/right gastrocnemius)	PCA/DT/KNN/Gaussian NB	Detection and recognition of muscle force in rehabilitation training[65]

Table 1 (*Contd.*)

Material	Component	Signal (monitoring site)	ML algorithm	Application field
	MoS_2/HEC/PU	Pressure (neck)	SVM	Silent speech recognition[109]
	CNT/PDMS	Pressure (sensor array)	SVM	Braille reading recognition[110]
	LIG/PDMS/FEP	Pressure (robot finger)	CNN	Braille reading recognition[111]

[a] Indicates that the name of the specific ML algorithm is not mentioned in the cited reference.

primary applications include disease screening when clear patterns exist.

Logistic regression, due to its simplicity and strong interpretability, is widely used in disease risk assessment. By analyzing clinical data, lifestyle habits, and other patient information, logistic regression can be used to build disease risk assessment models, assisting doctors in evaluating a patient's risk of developing a disease.[119–121]

3.1.2 DT and RF. DT can be simply explained as follows: imagine a tree where each branch represents a question or decision point, such as "Is this feature value greater than a certain number?" Based on the answer, the data is split into different paths, eventually reaching the tree's leaf nodes, where a classification or prediction is made (Fig. 2A). An RF, on the other hand, is a collection of many DTs. Each tree independently makes predictions, and the RF combines these predictions by "voting" or averaging the results to produce the final prediction. The proposed method is more robust than a single decision tree because it can better handle complex and diverse data (Fig. 2B).

Mechanistically, a DT structure mimics human thought processes by making decisions through a series of "if-then" rules. An RF is an ensemble of multiple trees where errors made by individual trees do not significantly impact the overall prediction, making it highly effective for dealing with noisy data. This robustness shows that RF is well-suited for handling data with many dimensions and features because it does not rely on a single sample set and exhibits excellent noise resistance. For example, Song *et al.* leveraged these characteristics to develop an intelligent surface ML gesture recognition system for health management,[122] and Zhang *et al.* utilized the RF's strong noise resistance to create a health monitoring system based on blood pressure data.[123]

3.1.3 SVM. In a two-dimensional coordinate system, the goal of SVM is to find an optimal separating hyperplane that clearly distinguishes between two classes of data points. Unlike conventional classification methods, SVM not only seeks a boundary that separates the data but also maximizes the margin between this boundary and the nearest data points, known as support vectors to enhance the model's generalization capability (Fig. 2C). This margin maximization process allows SVM to perform exceptionally well in handling high-dimensional data, particularly in classification tasks where robustness is crucial, This makes it one of the most commonly used classification methods in ML.

SVM has been widely applied to disease classification and diagnosis. By learning from the clinical biomarkers and imaging data, the proposed SVM can construct effective classification models that can assist doctors in diagnosing diseases. For example, in cancer diagnosis, SVM can analyze gene expression data and imaging features of patients to achieve accurate classification and early diagnosis of various cancer types. In addition, SVM can be used for the prediction and risk assessment of chronic diseases, such as cardiovascular diseases and diabetes. For example, Shen *et al.* used an improved SVM (OFSSVM) to improve genome-based cancer prediction by balancing interpretability and accuracy,[114] whereas Wang *et al.* used an extended SVM (WT-SVM) to advance eye movement signal classification and healthcare applications.[115] The improved PSVM method proposed by K. Drosou *et al.* effectively addresses the challenge of imbalanced medical datasets. These advancements highlight the adaptability of SVM for managing imbalanced data and its significance in medical classification tasks.[124]

3.1.4 KNN and *K*-means. The KNN makes predictions based on information about the *K* "neighbors" closest to the test sample in the training set. In the classification task, the category mark that appears most among the *K* "neighbors" is often selected as the prediction result, and in the regression task, the average value of the *K* "neighbors" is generally used as the prediction result. The KNN model is a lazy learner, meaning it does not create a model in advance; rather, it makes decisions based on the data at the moment. It works well for smaller datasets and is simple to understand; however, it can be slow with large datasets because it requires comparing each new data point to all existing ones (Fig. 2D).[125]

K-Means, on the other hand, is like organizing a party in which guests are grouped into different circles based on similarities. The proposed method divides data into *K* distinct clusters and minimizes variance in each cluster. The *K*-means model is an eager learner, meaning that it actively creates a model (clusters) by iteratively refining the cluster centers. It is efficient on large datasets but may struggle to find the optimal number of clusters or handle irregularly shaped clusters. This kind of algorithm is often used to classify existing data with or without labels which is suitable for the classification and identification of health and sub-health status in the field of health management.[126]

3.1.5 ANN, CNN, RNN and LSTM models. The algorithm based on neural networks has a very important application in the field of health management. The ANN can be visualized as

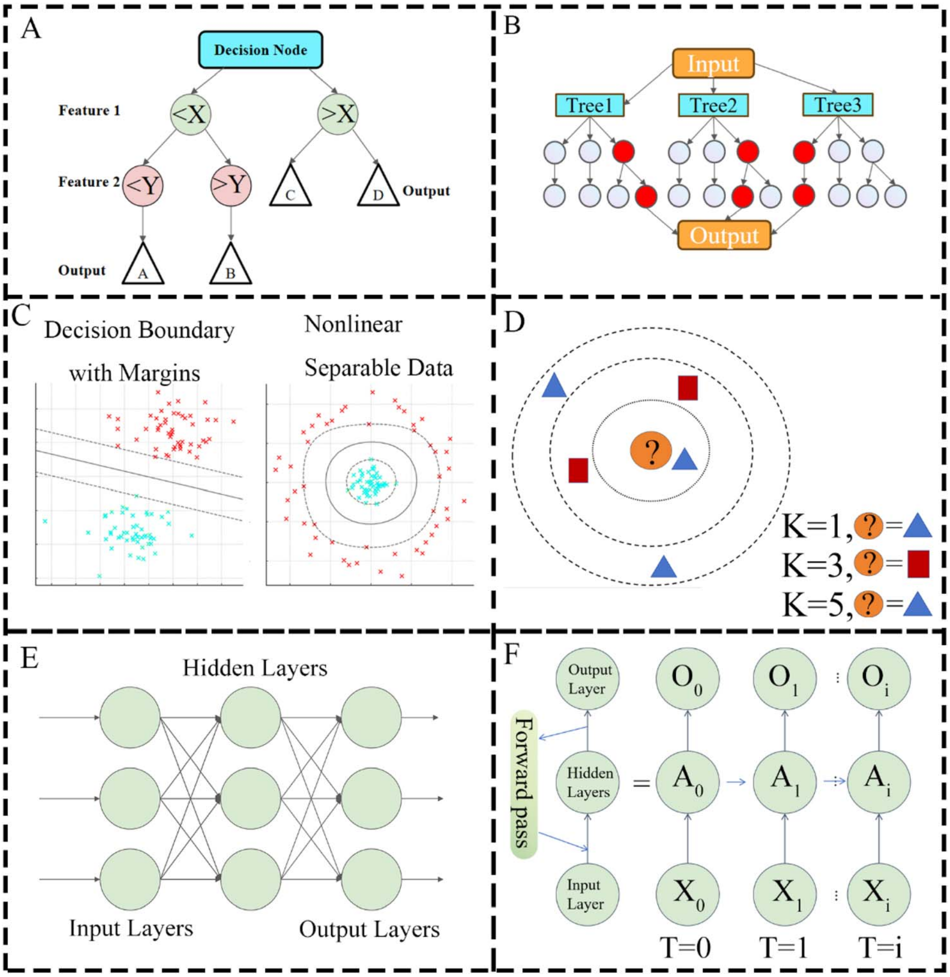

Fig. 2 ML algorithm mechanism diagram. (A) Schematic of DT. (B) Schematic of RF. (C) SVM model diagram including linear and nonlinear models. (D) Schematic of KNN; (E) schematic of an ANN. (F) Schematic of RNN.

a multilayer connection graph, where each node represents a neuron and each line represents the connections between neurons. Each node represents a specific output function called an activation function and the connections between each node represent a weight. The input data are transmitted through these connections, processed at each node and finally reach the output layer to generate prediction or classification results. Typically, the input layer neurons receive the external input, and the hidden and output layer neurons process the signal. The final result is the output by the output layer neurons (Fig. 2E). This structure, similar to the nervous system of the human brain, enables learning and memory by adjusting the "weights" of these connections.

DL can be considered a more complex and deeper neural network with no less than 2 hidden layers. Each layer acts as a feature extractor, progressively extracting simple patterns (such as edges or colors) into more complex patterns (like objects or scenes). Through deep layer-by-layer calculation, DL models can automatically discover and learn complex structures in data, thereby demonstrating powerful learning and recognition capabilities. CNN, RNN and LSTM are DL algorithms commonly used in data analysis in the field of health management.

A CNN is a type of DL model specifically designed for image processing. Each layer in the CNN is like a filter (convolutional kernel) that scans the input image to extract local features. Each filter focuses on different image details (such as edges, corners, or textures), and these details are gradually aggregated to form an understanding of the entire image. The structure of a CNN makes it particularly strong and efficient for handling visual data. A CNN is commonly used for further data processing in health management, especially in medical imaging and signal processing. Complex sensor identification problems such as biometrics, baby care, and wound status detection can be easily solved by such algorithms.[127–130]

For applications in which data exhibit temporal dependencies, both RNN and LSTM offer significant potential. RNN can be visualized as a cyclic chain, where each node acts as a link in the chain. The input data flows through this chain like a signal, with each node not only receiving the current input but also passing on the "memory" from the previous node. This memory is propagated through the network *via* cyclic connections,

Table 2 Advantages, drawbacks and applications of common algorithms

Algorithm	Advantage	Drawback	Health management applications
Linear regression	Simple and easy to implement, suitable for scenarios where there is a linear relationship between data features	Unable to handle nonlinear data; if the actual relationship is nonlinear, the predictive performance may be limited	Disease diagnosis[67,82] Finger rehabilitation training[55] Drug identification[70]
Logistic regression	Strong interpretability, suitable for binary classification problems, widely used in disease risk assessment	Performs poorly in scenarios where features are non-linearly separable	Sitting posture recognition and early warning[91] Precise drug delivery[139]
DT	Easy to understand and interpret, simulating human decision-making processes, suitable for handling noisy data	Prone to overfitting with a single decision tree, leading to poor generalization performance	Fatigue monitoring[97] Sitting posture recognition and early warning[91,92] Recognition of muscle force[65] Disease diagnosis[106]
RF	By integrating multiple DTs, it enhances the ability to handle complex and noisy data	The computational cost is relatively high, and the training time is lengthy, especially when the number of decision trees is large	Sitting posture recognition and early warning[91,105] Precise drug delivery[139,140]
SVM	Performs well in high-dimensional spaces, suitable for classification tasks, especially in disease classification and diagnosis	High computational complexity for large datasets, and sensitive to noise	Gait recognition[95,141] Sitting posture recognition and early warning[92] Silent speech recognition[109] Braille reading recognition[110] Disease diagnosis[57,83,101] Disease treatment[103,106]
KNN	KNN algorithm is highly intuitive, performing classification or regression prediction by finding the *K* nearest neighbors to the test sample	As the dataset grows, KNN requires calculating the distance between each new sample and all training samples, leading to rapidly increasing computational and storage demands, resulting in low efficiency	Sitting posture recognition and early warning[92] Recognition of muscle force[65] Disease diagnosis[83,101] Disease treatment[103,106]
K-Means	*K*-Means is a suitable algorithm for large datasets, simple and easy to understand and implement, improving clustering efficiency through iterative optimization of cluster centers	K-means requires specifying the number of clusters (*K*) in advance, but determining the optimal *K* value is often difficult in practical applications. The choice of initial cluster centers can affect the final clustering result, potentially leading to a local optimum	Health and sub-health state prediction[126]
ANN	Capable of automatically discovering complex structures in data, with strong learning and recognition capabilities	It requires a large amount of data for training with high computational costs and is difficult to interpret	Sign language recognition[89,90] Gait recognition[96] Disease treatment[86]
CNN	Particularly adept at handling spatial data such as images, capable of extracting local features, widely applicable	Complex, high time and resource consumption, the generalization ability decreases when the training data is small, with weak performance on non-spatial data sets	Driving fatigue, safety and health monitoring[81] Gait recognition[108] Health monitoring and movement recognition[104] Finger rehabilitation training[51] Sign language recognition[88] Braille reading recognition[111] Disease diagnosis[84,94,98,101,102] Disease treatment[85]
RNN	Can capture temporal dependencies in sequential data, suitable for handling time series tasks	As sequence length increases, early input information is easily forgotten	Fall prediction in the elderly[131] Speech pathology detection[132] Electronic medical record recognition[133,134] Electronic medical record information extraction[135]
LSTM	Effectively retains information over long sequences, suitable for handling long-term dependency data	More complex in structure compared to traditional RNNs, with higher computational demands	Prediction of athlete health status[129] Disease diagnosis[137,138] Disease treatment[106] Dementia prevalence prediction[136]

which allows the RNN to capture temporal correlations in sequential data. However, as the chain length increases, the information from earlier inputs tends to become blurred or forgotten (Fig. 2F). RNNS can be used for fall prediction in the elderly,[131] speech pathology detection,[132] electronic medical record recognition[133,134] and information extraction.[135]

STM can be considered a short-chain within the RNN, capable of retaining information over a short period. LSTM can be viewed as an enhanced version of the RNN chain, where each node is equipped with "memory cells" and "control gates". These memory cells store important information, whereas control gates (gate mechanisms) determine which information should be retained or discarded. The memory cells in each node are regulated by these gates and can maintain critical long-term dependency information. As a result, even when the chain length is long, LSTM can effectively transmit information from earlier inputs. The proposed architecture allows LSTM to handle more complex and extended sequential data tasks. LSTM has the advantage of processing time series; thus, it can be used to predict the prevalence of dementia,[136] diabetes,[137] cardiovascular health trajectory,[138] and athlete health status[129] based on previous health record data and regional statistical data.

The above ML algorithms have various range of applications in data analysis in the field of health management. The advantages and disadvantages of these algorithms in use and the application scenarios are presented in Table 2.

3.2 Model evaluation

The model evaluation is a critical step to ensure that the ML model performs well. Below are detailed explanations of some commonly used evaluation metrics in the classification task, which apply to different types of ML models.

3.2.1 Accuracy. Accuracy (formula (1)) is the most intuitive performance metric, measuring the proportion of correctly predicted samples to the total number of samples. While accuracy is a quick way to assess model performance, it may not be a good indicator when dealing with imbalanced data. In cases in which the model predicts only the majority class, it may still exhibit high accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

TP (True Positive): positive samples correctly predicted by the model. TN (True Negative): negative samples correctly predicted by the model. FP (False Positive): negative samples incorrectly

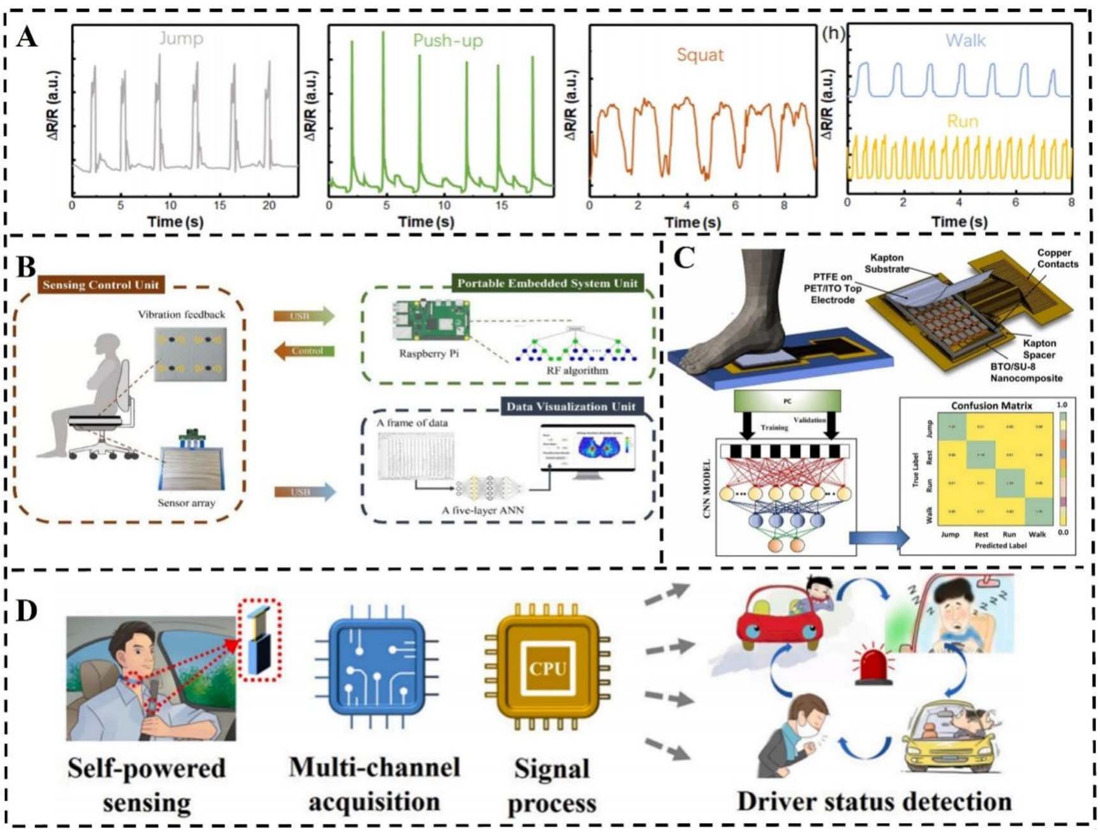

Fig. 3 Healthcare management of the flexible materials in different scenes. (A) Motion recognition. This figure has been reproduced from ref. 143 with permission from ACS publication, copyright 2017; (B) sitting position recognition. This figure has been reproduced from ref. 105 with permission from Elsevier publication, copyright 2021; (C) gait recognition. This figure has been reproduced from ref. 108 with permission from Elsevier publication, copyright 2023; (D) fatigue identification and early warning. This figure has been reproduced from ref. 81 with permission from Elsevier publication, copyright 2023.

predicted as positive. FN (False Negative): positive samples incorrectly predicted as negative.

3.2.2 **Recall.** Recall (formula (2)) measures the proportion of actual positive samples that the model correctly identifies as positive. It is particularly important in applications sensitive to missed detections, such as medical diagnosis and fraud detection, where missing a true positive case can have serious consequences.

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{2}$$

3.2.3 **Precision.** Precision (formula (3)) measures the proportion of correctly predicted positive samples out of all samples predicted as positive by the model. It is crucial in scenarios where false positives carry significant costs, such as when falsely diagnosing a person with a disease can lead to expensive or harmful medical interventions.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{3}$$

3.2.4 ***F_1* score.** The F_1 score (formula (4)) is the harmonic mean of precision and recall. This metric considers both precision and recall and is useful in situations where both need to be balanced, especially when one cannot afford to prioritize the other.

$$F_1 = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{4}$$

3.2.5 **AUC-ROC curve.** AUC (Area Under the Curve) represents the area under the ROC (Receiver Operating Characteristic) curve. The ROC curve is a graphical tool used to illustrate the performance of a model for different threshold settings. The *X*-axis represents the False Positive Rate (FPR), which is calculated as FP/(FP + TN), while the *Y*-axis represents the True Positive Rate (TPR), which is the same as Recall. A higher AUC value generally indicates better model performance, and this metric is widely used to evaluate binary classification models.

3.2.6 **Model-specific evaluation methods.** For models like Support Vector Machines (SVM), the choice of kernel functions and parameter tuning are crucial for evaluating performance. Different kernel functions can significantly affect the classification boundaries, and tuning hyperparameters (such as *C* and gamma) directly affect the model's complexity and tendency to overfit.

For DL models (such as CNN, RNN, and LSTM), monitoring the loss function is essential because it reflects the model's performance during training. Observing overfitting and comparing the validation loss to the training loss provides key insights into the need to adjust the model architecture and parameters. The following substances describe the application of ML-assisted flexible materials in the intelligent process of health management.

4 Applications

Flexible materials have been widely used as highly ductile substrates. Researchers have designed or modified these materials to give them favorable properties, such as good biocompatibility and high adhesion, enabling their application in the fabrication of wearable sensing devices for health management. The integration of ML technology has further facilitated the intelligentization of health management processes, including personal healthcare, medical treatment, and rehabilitation nursing. This section categorizes and discusses these processes in detail.

4.1 Healthcare management, physiological status monitoring and early warning system

4.1.1 **Healthcare management.** Healthcare involves effective measures aimed at maintaining and enhancing individual physical and mental well-being. Healthcare management employs a range of methods and technologies to preserve and elevate an individual's overall health status and significantly improve their quality of life. The continuous advancement and synergy between flexible materials and ML technologies have revolutionized the monitoring and evaluation of daily exercise routines, fostering intelligent and personalized healthcare management. On the one hand, owing to their flexible characteristics, they can conform seamlessly to detection sites, greatly enhancing the comfort and adaptability of wearable devices. On the other hand, through big data analysis and algorithm optimization, ML can tailor training plans to an individual's physical conditions, exercise habits, and health goals.[142]

Wearable sensors based on flexible materials enable real-time monitoring of various exercise types and intensities, helping users in assessing their health status. As shown in Fig. 3A, these sensors can be incorporated into textiles, artificial skin, and other wearable devices to monitor ongoing activities like jumping, push-ups, squatting, walking and running.[143] The sensors detect body movements, such as knee and elbow joint bending, through changes in resistance or optical loss caused by strain, thereby achieving human motion tracking.[14,15,23,143–148] Additionally, with the improvement of the sensitivity of the flexible sensor, some of the subtle data indirectly related to movement, such as pulse rate and mouth and abdominal breathing patterns, can be accurately detected, which not only helps fine-tune movement monitoring but also assists in the monitoring of patients with diseases such as heart disease and asthma.[143,149] In summary, these real-time feedback mechanisms enable individuals to adjust their exercise pace and intensity promptly, ensuring safe and effective workouts, and thereby achieving the goals of healthcare management.

Furthermore, research has extended the applicability of flexible materials to underwater motion monitoring. The core lies in the incorporation of hydrophobic materials like PDMS[145] and stearic acid-modified polydopamine/reduced GO.[150] For instance, Ren *et al.* developed an underwater strain sensor based on ionically conductive hydrogels using [2-(methacryloyloxy) ethyl]dimethyl-(3-sulfopropyl) ammonium hydroxide, which not only boasts excellent sensing properties for identifying underwater activities like breaststroke but also exhibits robust anti-swelling and self-recovery properties suitable for long-term underwater monitoring. Such studies hold immense potential for identifying potentially dangerous situations like improper underwater postures or drowning.[151–154]

Moreover, ML technology enables the classification of multiple exercise types in real time and the efficient processing of vast amounts of motion data.[155] For example, N. Rodeheaver *et al.* leveraged an ML technology algorithm based on residual CNN in a soft bioelectronic system to mitigate motion artifacts and achieve real-time activity recognition and classification with an overall accuracy of up to 99.3% and promptly uploaded valid exercise data to smartphones for health status assessment.[104] In conclusion, sensors based on flexible materials can recognize motion in most scenarios, providing users with relevant exercise data for healthcare management. Integration with ML technologies significantly enhances the usability of motion recognition technology, which promotes its application in healthcare management.

4.1.2 Physiological status monitoring and early warning system. Physiological status monitoring and early warning represent a systematic approach that comprehensively assesses and provides early alerts for an individual's health condition. The core of this approach lies in the continuous monitoring of physiological states and the early detection of potential health risks, such as low back pain arising from prolonged improper sitting postures[105] or the likelihood of falls. The integration of ML technologies enables intelligent, timely interventions and prevention, thereby providing individuals with more precise and personalized health management strategies.

In contemporary times, the ubiquitous use of smart devices like computers and mobile phones, along with online work and study lifestyles, has fostered sedentary habits among most people. Incorrect sitting postures or extended sedentary periods can readily lead to sub-optimal health conditions, including obesity, musculoskeletal disorders, and metabolic health risks.[156] To address these risks, Zhang *et al.* used thermoplastic polyurethane and 1-butyl-3-methylimidazolium tetrafluoroborate ionic liquid as raw materials for wet spinning to fabricate a smart cushion with dual-modality sensing capabilities for temperature and strain. Furthermore, they developed an IMS that visualizes pressure and temperature distribution images, coupled with an LDA prediction model, achieving a recognition accuracy of 99.65% for five different sitting postures.[93] Numerous similar studies have harnessed various ML models, including KNN, RF, LR, and NB, to enable sensors to identify sitting postures with high accuracy, promptly issuing prompts or alerts.[91,156–158] As depicted in Fig. 3B, Ran *et al.* designed a portable sitting posture monitoring system based on a flexible polyester substrate, utilizing an RF algorithm with an 11×13 sensor array, achieving a classification accuracy of 96.26% for sitting postures and reminding users to correct their posture through vibration feedback.[105]

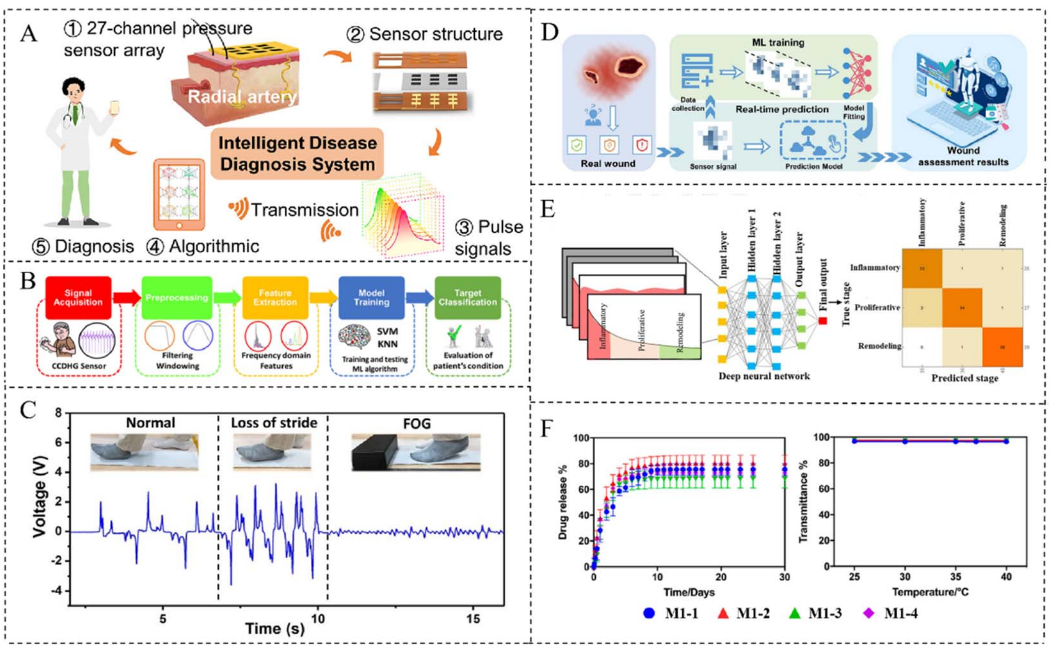

Fig. 4 Intelligent diagnosis and treatment of diseases in different contexts. (A) Intelligent pulse diagnostic system. This figure has been reproduced from ref. 100 with permission from ACS publication, copyright 2023. (B) Tremor sensor assessment of Parkinson's disease. This figure has been reproduced from ref. 83 with permission from Elsevier publication copyright 2021. (C) Walking pattern recognition of patients with Parkinson's disease. This figure has been reproduced from ref. 166 with permission from ACS publication, copyright 2019. (D) Individualized management of wounds. This figure has been reproduced from ref. 85 with permission from Elsevier publication, copyright 2022. (E) Wound identification at different stages. This figure has been reproduced from ref. 86 with permission from ACS publication, copyright 2022. (F) Predicted structure and optimized hydrogel properties. This figure has been reproduced from ref. 167 with permission from ACS publication, copyright 2020.

Walking is a ubiquitous daily activity, and gait recognition research can contribute to the prevention of abnormal gait patterns, such as splayfoot and flatfoot.[159] As shown in Fig. 3C, Beigh *et al.* employed a self-powered pressure sensor based on a flexible hybrid transduction BTO/SU-8 nanocomposite and integrated it into sensor insoles for gait recognition. Combined with CNN, they developed a hindfoot deformity recognition system with an accuracy rate exceeding 98%, indicating significant potential for assisting athletes, the elderly, and others in the early detection of knee and ankle abnormalities.[108] In addition, abnormal gait patterns can be precursors to falls in children and the elderly.[141] The current research primarily focused on capturing real-time data on normal walking and identifying falls through abnormal signals.[94] ML algorithms like SVM can classify walking states (*e.g.*, slow/fast walking, turning, and reversing) to predict potential falls based on the wearer's movement patterns.[160]

Fatigue can significantly reduce work efficiency, impair health, and even threaten life safety, particularly for professions requiring prolonged, intense concentration and mental exertion, such as drivers and surgeons. Researchers have designed flexible sensors in the form of neckbands to recognize neck movements, combined with ECG, respiratory rate, and GSR signals, ML models were used to predict mental fatigue levels.[97] Luo *et al.* created an intelligent neckband primarily composed of NaCl/PVA hydrogel, leveraging its flexibility, stretchability, self-healing properties, and NaCl's strong conductivity and sensing sensitivity for long-term wear and fine motion recognition. As shown in Fig. 3D, when a driver (wearer) engages in distracting activities like chatting, the ML model analyzes the electrical signal data to make judgments and alerts the wearer with different colored lights.[81]

In physiological status monitoring and early warning systems, the combination of flexible sensors and ML technologies can be tailored to specific professions and domains, including pressure injury rehabilitation for wheelchair users and real-time monitoring for excavator operators, catering to the needs of unique groups in real-life scenarios.[92,93] Currently, the integration of flexible sensors and ML technologies into comprehensive health assessment systems is highly demanded and essential, promising significant development prospects.

4.2 Disease diagnosis and treatment

Disease diagnosis, treatment and drug development and design are the core of monitoring the health status of patients, developing reasonable medical plans and improving quality of life. Most current technologies rely on large equipment and doctors, which may cause radiation threats or damage the impact on the human body. The risks associated with continuous medical treatment and off-target drug use are all difficulties we are facing now. The technology integrating ML algorithm and flexible materials can effectively improve these conditions and realize targeted quantitative, scientific and non-invasive intelligent diagnosis and medical treatment.

4.2.1 Disease diagnosis. Diseases of the nervous system,[161] circulatory system,[162] respiratory system[163] and other systemic diseases affect the organs and systems of the human body and pose a serious threat to people's physical and mental health. Many of these diseases have been studied and sensors made of flexible materials enable real-time monitoring. Using ML techniques to analyze data, the accuracy of PD, CVD, and COPD diagnosis can be improved.

CVD is a kind of circulatory system disease related to the cardiovascular system, including hypertension and coronary heart disease, and has become one of the main diseases endangering human health.[164] The traditional diagnosis of CVD is often a combination of imaging techniques and blood biochemical tests, which can cause discomfort to patients and cannot be monitored for a long time. Combining flexible wearable sensing devices with ML algorithms to solve these problems can also remotely monitor and diagnose CVD, such as AF.[50] Pulse detection is a clinically validated detection method for CVD. Researchers often attach the sensor to the skin surface to receive the change signal of the sensor resistance caused by the deformation of the skin with the blood vessel and then convert it into a pulse wave after processing, such as filtering and denoising (Fig. 4A).[100] The classification by MiniRocket and RF algorithm can be used for the diagnosis of ASD, AF and other diseases.[58,165] The patient's monitoring ECG can also be collected by a wearable sensor, and the collected waveform can be accurately analyzed for their heart rate and respiratory rate, and then combined with ML algorithms for diagnosing CVD.[98]

PD is a degenerative neurological disorder that causes hand and foot tremors, and muscle stiffness, and severely affects daily movement.[168] Traditional PD diagnosis methods rely on medical observation and clinical examination and are easily affected by subjectivity, leading to misclassification or symptom neglect, which further affects the diagnosis of PD.[169] TENG based on flexible materials are often made into sensors to realize self-powered wearable devices, extract characteristic peaks by detecting voltage signals or gait signals generated by tremors, and diagnose PD with KNN, linear SVM and other algorithms (Fig. 4B).[83] Kim *et al.* synthesized a CCDHG-TENG and prepared a tremor sensor. The KNN and linear SVM algorithms were used to classify the frequency characteristics of the signals. The linear SVM distinguished normal, mild and severe tremors with 100% accuracy, which was more accurate than KNN. FOG is a state of walking intention, but the pace suddenly stops or decreases, which is a major risk factor for falls and injuries in patients undergoing PD.[170] Patients usually experience stride loss before FOG. Researchers have created a low-cost, portable and comfortable tribon-electric smart sock. At the same time, it is used as a wearable sensor to collect gait information and uses an ML algorithm to judge the three conditions of normal walking, stride loss and FOG with high accuracy (Fig. 4C).[166] A walk recognition system can provide energy and electricity by itself.[94]

COPD and OSA are respiratory diseases that can aggravate sleep-breathing disorders.[163] Flexible instruments, combined with algorithms such as CNN and SVM, can capture lung sound waves and seismocardiogram data to identify lung abnormalities, such as burst sounds, wheezing and rales, or apnea and respiratory insufficiency. It can be used for the early diagnosis of COPD or OSA and also for monitoring cardiac activity caused by it.[84,101] Flexible sensors with integrated ML algorithms track cough frequency and intensity and can be used to classify patients with COVID-19 (ref. 171) and healthy controls.[102]

In addition to the aforementioned diseases, other diseases can also be monitored and diagnosed using flexible sensors and ML, such as severe skin acne, intestinal obstruction, and muscle atrophy. Due to radiation limitation[172] and the inconvenience of operation, the traditional intestinal detection method cannot obtain the true intestinal status. The integrated device based on a 3D-printed elastomer resonator and flexible electronic device can be attached to the abdomen, and the BPNN algorithm can be used to evaluate intestinal sounds during digestion. For example, in Wang's work, the average recognition rate is 76.89%, which is expected to be used for the evaluation of digestive function and auxiliary diagnosis of intestinal diseases, but there is still a lot of room for improvement.[173] In the detection and diagnosis of inflammatory skin diseases such as acne, pH-responsive hydration and ML technology can be used to quantify pH levels promptly according to their color and then diagnose early signs of skin diseases such as acne, which has the advantage of being instantaneous and reusable.[82] The integration of ML algorithms with non-invasive flexible surface EMG sensors can be used to assist in the diagnosis of muscle atrophy due to fracture and to distinguish between muscle atrophy due to nerve damage or limb fixation, enabling non-invasive and comfortable cause assessment.[99]

Flexible sensors combined with ML algorithms are widely used for disease diagnosis. Compared with traditional disease detection technology, it has the following characteristics: accuracy, high sensitivity and real-time monitoring. It can be used to track and decode pulse, blood pressure, gait and other signals, which can realize remote condition monitoring of patients and intelligent and efficient diagnosis and provide a new idea for realizing fast, non-invasive, remote, economical, accurate and intelligent diagnosis.

4.2.2 Disease treatment. Flexible wearable sensing technology can be used in the fields of auxiliary surgery,[174,175] wound dressing,[176,177] eye treatment,[178] *etc.* Combined with ML algorithms, it can intelligently identify and classify the hand movements of surgeons during surgery, the severity and healing status of wounds during treatment, and eye movements (convergence and dispersion) with high efficiency and accuracy.

A piezoresistive flexible tactile sensor with high sensitivity and reliable linear response characteristics is fixed on the human body or the robot system,[179] and the ML model can be used to monitor and classify the resistance change value of the hand movement during surgery. Al-Handarish *et al.* inserted a carbon black evenly distributed porous sugar/PDMS sponge flexible sensor into the robot operating system, combined with LSTM and five traditional ML algorithms to recognize surgeons' gestures on the main interface of the robot system during endovascular catheter insertion, among which LSTM had the highest overall recognition accuracy of 87.38%. The robotic system, which acts as an interface between the physician and the tool, demonstrates the potential of piezoresistive tactile sensors for force sensing in surgical robots.[106] In addition, similar flexible sensor technologies demonstrate broad application prospects in fields such as human–machine interaction and smart wearable devices. For instance, the self-powered flexible sensor array based on TENG developed by Dong *et al.* has achieved the monitoring of human gestures in different parts of the human body, such as elbows, necks, and wrists, through LSTM, with an accuracy of up to 90%, and has been successfully applied to control the movement of two-wheeled robots;[180] TENG flexible sensors were fabricated for the design of robot electronic skin for non-contact and contact pressure measurement. During the robot grasping process, the neural network algorithm was adopted to fully utilize the dual-channel sensing data of the sensor to identify different materials and different hardness values, and the recognition rates were 93.49% and 92.22%, respectively.[181] This self-powered flexible sensor not only can detect deformation during the complex movement of the human body but can work continuously without external circuits, providing a new solution for flexible wearable devices and portable health monitoring systems.

Wound healing proceeds in four stages: hemostasis, inflammation, proliferation, and remodeling. Traditional wound dressings cannot monitor the wound healing status over time, and frequent dressing changes can cause wound infection. Wound dressings made of flexible materials and sensors are flexible and can be used for *in situ* wound sensing without removal, and they can have hemostatic, antibacterial and other effects (Fig. 4D).[85] Through the detection of temperature, pH, uric acid and other biomarkers related to wound inflammation and infection, combined with the ML algorithm, it can be used for the diagnosis of wound type or skin healing stage, and even the assessment and classification of wound healing status can be carried out on the smartphone to accelerate the wound healing process.[107] The intelligent wearable sensor integrated with the ANN algorithm by Kalasin *et al.* can diagnose the healing stage of inflammation, proliferation and remodeling through pH and predict the wound recombination of skin disease subjects with an accuracy rate of 94.6% (Fig. 4E), realizing real-time monitoring and management of personalized wounds and clinical use.[86]

Factors such as electronic devices and genetics have an increasing influence on human eye diseases, with CI and strabismus being two types of troublesome eye diseases. Current treatment techniques, including OBVT[182] and pencil push-ups,[183] have a lower success rate in-home therapy and require ongoing outpatient visits. Therefore, flexible sensors combined with VR technology and ML algorithms can be used as an alternative method for treating eye diseases and tracking convergence and divergence. The detection of eye convergence and divergence is also expected to be useful in the diagnosis of neurodegenerative diseases and children with learning disabilities. Mishra *et al.* created a “virtual therapy” in which wearable soft electronics combined with a virtual reality environment detect convergence and divergence, achieving a classification accuracy of 91% when combined with ML algorithms. Three subjects showed improved convergence and divergence after continuous use of the VR program, demonstrating that the

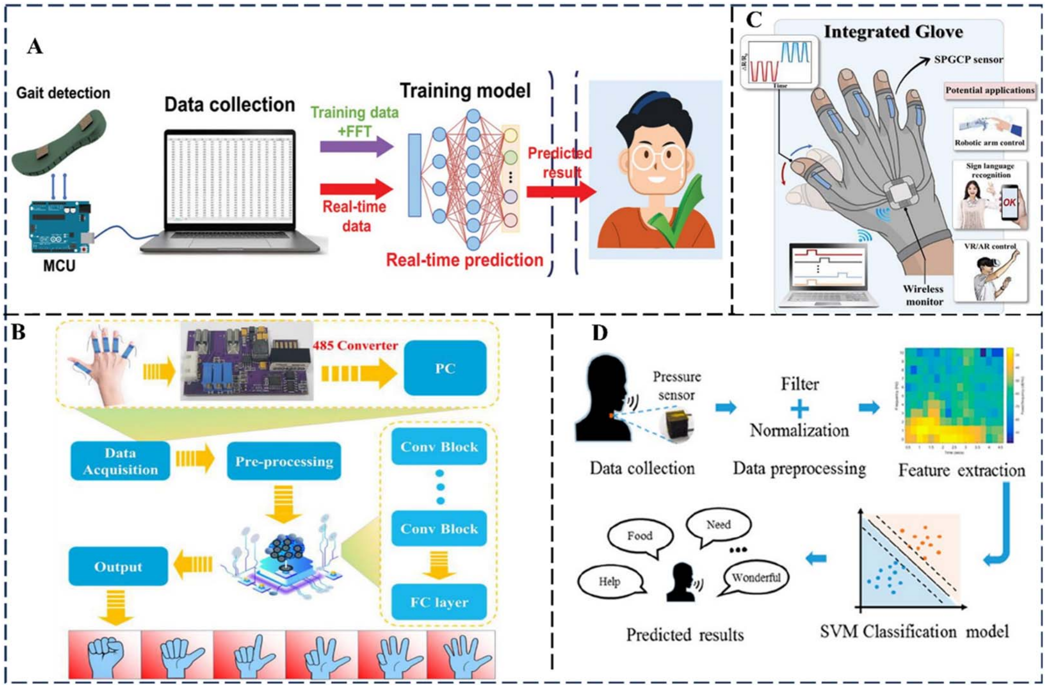

Fig. 5 Application of flexible materials and ML in rehabilitation and assistance. (A) Schematic of patient identification using smart insoles and ML. This figure has been reproduced from ref. 96 with permission from Wiley Publications copyright 2021. (B) Diagram of the HMI gesture recognition system. This figure has been reproduced from ref. 51 with permission from ACS publication, copyright 2023. (C) Smart glove and its potential applications. This figure has been reproduced from ref. 194 with permission from Elsevier publication, copyright 2022. (D) Silent speech recognition schematic. This figure has been reproduced from ref. 109 with permission from ACS publication, copyright 2023.

system can be used for the office treatment of CI and strabismus.[103]

Flexible sensors with wireless monitoring and comfortable and flexible features combined with ML algorithms have been used for disease treatment. Its application in the fields of auxiliary surgery and wound dressing ensures the safety of doctors and patients and realizes intelligent, quantitative, non-contact, rapid and accurate personalized treatment, which has great application potential in the field of disease treatment.

4.2.3 Drug development and design. With a deep understanding of the pathogenesis of diseases and the rapid development of biotechnology, targeted therapy has become a new strategy for treating specific diseases, that is accurate drug delivery to specific target tissues and cells in the body for fixed-point release and continuous drug administration. Precision treatment with high efficacy, specificity and good safety has become the focus of disease treatment.[184] Reducing the risk of off-target effects has become the focus of attention. The unique three-dimensional hydrophilic network structure of hydrogels and the property of effectively regulating drug release make them widely used as carriers to assist drug release.[185] For example, Nieto *et al.* prepared gellan-supported redox reactive implantable hydrogels with varying degrees of crosslinking to serve as paclitaxel vectors for the treatment of HER2-positive breast cancer.[186] However, determining the optimal hydrogel formulation has become a huge challenge.

To solve this problem with more specificity and accuracy, the researchers found that integrating ML into the development of materials can effectively gain insights from description–prediction-specification strategies, which can quickly achieve the development of the most efficient biological materials.[187] ML can predict and optimize materials design, effectively avoiding several repeated experiments and greatly reducing experimental costs.[188] For example, the use of RF and LR can effectively predict the self-assembly of hydrogels.[139] Xu *et al.* also incorporated ML into the development of hydrogel drug delivery systems. They used PLS and DRM to predict the structure of the hydrogel and then realized a precision drug delivery system for eye protein drugs through numerical optimization to ensure efficient drug release and high transparency of the carrier (Fig. 4F).[167]

In addition, ML can be used not only for drug delivery but also for drug penetration testing. For example, to determine the number of therapeutic agents, such as small molecule compounds, peptides, mRNA, proteins, and cellular extracellular vesicles, that enter the human body, Yuan *et al.* adopted the MLR model in the ML method to link the drug permeability with the physicochemical properties of the materials used in the preparation. The method was used to simulate the penetration process of drugs through the skin to predict the penetration of drugs through the skin.[140] It can be seen that ML plays an important role in drug development and design and has several application prospects.

4.3 Rehabilitation and assistance

4.3.1 Rehabilitation training. Rehabilitation training is an extremely important link for treating diseases or injuries. Neuromuscular and skeletal diseases, traumatic events, stroke and other diseases often leave sequelae of motor dysfunction after treatment, which requires long-term and repeated rehabilitation training to improve. Rehabilitation training can promote functional recovery, reduce complications and sequelae, and prevent re-injury, all of which are of great significance to the comprehensive rehabilitation of patients. Traditional manual rehabilitation training resources are limited, expensive and lack personalized; therefore, it is urgent to introduce an accurate, cheap and personalized self-help rehabilitation training system.

The continuous breakthrough in the preparation process of flexible materials makes them not only comfortable and wearable but also have a wide range of adjustable mechanical properties, creating conditions for the design of precision rehabilitation training equipment.[189] The continuous improvement of wearable monitoring devices based on flexible materials provides a guarantee for the real-time tracking of the whole process of self-help rehabilitation training. The development of various sensors with wide detection limits and high sensitivity has been continuously conducted. They can be seamlessly integrated with flexible materials such as gels, textiles and PDMS and made into wearable devices such as wristbands, belts, insoles, and clothing for monitoring exercise posture and muscle force status during physical rehabilitation training.[51,65,87,95,190] Sensing equipment based on flexible materials produces extrusion, stretching and other deformations due to motion contact, resulting in electrical signals such as charge transfer and resistance changes.[65,95,96,191] These real-time electrical signals are transmitted through wireless transmission devices to mobile phones, computers and other devices. The multi-directional accurate monitoring of self-help rehabilitation training was realized, which greatly reduced the cost of human monitoring.

ML technology is rapidly developing and can be integrated into the monitoring data analysis of flexible wearable devices. ML can perform dimensionality reduction, classification and regression processing of multi-channel and multi-modal sensing data, to realize efficient and accurate identification of gestures, gait and force degree in the process of self-help rehabilitation training,[96,192,193] which assists the construction of intelligent medical systems. For example, ML assists the system in determining whether the rehabilitation training goal is achieved according to the data of frequency and amplitude.[95] As shown in Fig. 5A, based on the gait information recorded by the smart insole, ML realizes patient identification and automatically matches the set training plan to the patient *via* IoT remote Settings.[96] At the same time, ML technology helps build various HMI systems to make rehabilitation training personalized, intelligent and interesting. For example, EMG and FMG signals were analyzed by ML algorithm to identify the movement intention of patients and control commercial pneumatic robot gloves to assist complete the training action.[87] As depicted in Fig. 5B, according to the result of gesture recognition, PC instructions are triggered to encourage patients to perform finger function rehabilitation training, and the engaging training experience can improve patients' enthusiasm.[51] In addition, the signals collected by the HMI can be uploaded to the cloud to assist doctors in remote diagnosis. It not only saves medical resources but also avoids the risk of exposure to infection during the COVID-19 pandemic.[87] In brief, HMI expands the interactive ways of rehabilitation training.

In short, the combination of flexible materials and ML technology enables accurate and inexpensive monitoring, promoting autonomous and intelligent processes. HMI improves the privacy of rehabilitation training systems and enhances the rehabilitation training experience.

4.3.2 Care and assistance. High-quality nursing resources are very necessary for the sick, the elderly and the young, but in the high-pressure rhythm and highly aging social environment, nursing resources are scarce and expensive, resulting in these groups having difficulty accepting all-day meticulous manual care, so new nursing methods and ideas are urgently needed.

Non-invasive flexible sensors are not only comfortable to wear but also have excellent sensitivity and responsiveness. They can monitor the body and the surrounding environment in a timely and accurate manner, greatly reducing the burden of monitoring. Wireless transmission networks and ML technology help transmit and identify signals in real-time to help detect early health risks, including the severity of blood leaks,[195] the vulnerable status of the elderly,[196,197] and infant fall risk.[198] Alerts can be sent to nurses' stations or infant guardians promptly, providing an example of creating a new care system in the Internet age.

Assistance is particularly necessary for persons with physical disabilities. Sign language is the primary means by which deaf and mute people communicate with the outside world; however, it is incomprehensible to people without professional training. Therefore, mobile hand language sensing equipment and accurate and efficient decoding technology will greatly contribute to communication. With excellent adhesion, sensitivity and stability, the hydrogel sensor can be attached to the arm or, finger or made into a smart glove for collecting voltage, resistance or EMG signals during sign language expression (Fig. 5C).[88,90,194] CNN, ANN and other ML algorithms can easily achieve the high-precision classification of multi-channel data, so as to achieve efficient decoding of sign language.[88–90] With the Chinese character display system, real-time interpretation of sign language can be completed,[90] which brings great convenience to the lives of deaf and mute people. Compared with sign language, which requires professional learning, silent speech provides an alternative way for people with aphasia. Although people with laryngeal diseases cannot produce sound through vocal cord vibration, the expression of silent speech requires the participation of the throat and facial muscles. Flexible pressure sensors with excellent sensitivity, wide detection limits and fast response, and tattoo electrodes with robust electrical properties that perfectly fit the skin epidermis, have been developed to sense throat muscle movements or facial EMG signals, providing accurate current or high-fidelity EMG signals. SVM, LDA and other ML algorithms are used to achieve highly accurate recognition of silent speech (more than 92%) (Fig. 5D).[109,199] The realization of silent speech provides a guarantee and new idea for communicating with patients with aphasia in dark and noisy environments.

Braille is an important channel through which the blind can acquire and transmit information. It is composed of several raised dots and mainly relies on tactile perception for recognition. Flexible materials are widely used in tactile sensors because of their shape-shifting properties and are integrated into robotic fingers or made into grid-like flexible sensor arrays, which can press, tap, and slide to reach braille bumps.[110,111] In particular, the electrical isolation unit of the grid can effectively eliminate the crosstalk effect of the current and help collect high-quality current signals.[110] Combined with an ML algorithm to classify electrical signals, the proposed algorithm can achieve efficient decoding and effectively recognize Braille letters and numbers. In particular, the ML algorithm can not only recognize signals but can also be reverse-applied to the hardware design of the flexible tactile sensor by fusion of statistical learning criteria to help select the best manufacturing parameters of the sensor.[111]

In short, with the assistance of flexible materials and ML technology, care and assistance is constantly moving toward algorithms that can achieve efficient decoding and effectively recognize Braille letters a new intelligent pattern.

5 Conclusions and prospects

ML-assisted flexible materials have been widely used in the field of health management, mainly in the following aspects: first, flexible materials are used in health monitoring equipment because of their conformability to the body, high flexibility, sensitivity, and the accuracy of data collected in the face of complex human movement. Secondly, ML technology can efficiently process massive, multi-dimensional and multi-channel sensing data, identify hidden patterns and rules, make immediate and accurate predictions of health monitoring status, and realize rapid response and intelligence. Third, the integration of ML technology and flexible sensing devices has promoted the rapid development of HMI in the field of health management, helped build an intelligent medical environment, realized personalized health management, improved user experience, and paid attention to security and privacy protection.

Although flexible materials have made great progress in the research field in the past few years, they are easy to be damaged during repeated bending and are more sensitive to changes in environmental factors. In addition, their lack of reliability and stability limits their application, and they still need to be further improved in terms of material or structural systems. ML also faces many problems in application: insufficient quantity and quality of health data deteriorate ML algorithm performance. The complex model based on neural networks has high accuracy, but its complex internal mechanism makes the model lack explanation and difficult to obtain a decision-making basis, making it difficult to assist doctors in making targeted treatment plans in clinical practice. It is necessary to improve the transparency of models or develop a tool to explain complex models. For huge datasets, it is faced with the problem of high time and high consumption, and imperfect security measures may lead to privacy disclosure, which requires the synchronous improvement of the computer hardware level and the development of more efficient and secure algorithms to reduce the burden of data processing and protect user privacy.

New flexible materials are being developed in the following directions in the field of health monitoring. (1) Multi-functional integration. By adding various functional components and structural designs, new flexible materials can monitor different categories of signals (temperature, humidity, strain, physiological signals, *etc.*) and different intensity signals (joint movement, breathing, heart rate, *etc.*). Flexible materials that integrate printing technology, thermal therapy and other functions will effectively promote the realization of non-sensory monitoring and the integration of monitoring and treatment. (2) Biocompatibility enhancement. Non-toxic, biodegradable natural biomaterials have become the research hotspot for new flexible materials due to their biocompatible properties. (3) Environmental adaptability. New flexible materials are designed to adapt to extreme environments (high temperature, low temperature, *etc.*), which will greatly expand their application scope in the field of health monitoring. (4) Passive energy supply and lightweight design. The development of self-powered flexible sensors through technological innovation in material design and preparation provides a solution to the power dependence and lightweight design of health monitoring devices. In the future, the application of ML-assisted flexible materials in the field of health management is expected to achieve breakthroughs in the following aspects: first, it is necessary to make full use of the advantages of ML data analysis to assist in material design and efficiency prediction, save costs and improve efficiency. Second, using the advantages of big data, the ML algorithm is constantly optimized to include more types of health data (such as mental health data, and environmental data) into the analysis scope to further improve the accuracy of health state prediction and diagnosis. Third, ML technology vigorously promotes the analysis of genomic data and the popularization of HMI, further promoting the development of personalized medicine. Fourth, data encryption, anonymization technology and ML algorithms work together to explore integration ways and ideas to ensure user health data security.

Abbreviation

1D	one-dimensional
2D	two-dimensional
AA	acrylic acid
AF	atrial fibrillation
AM	acrylamide
ANN	artificial neural network
ASD	atrial septal defect
AuNP	gold nanoparticle
Au–ZnS NPs	ZnS and gold nanoparticles

BA	butyl acetate
BN	boron nitride
BPNN	back propagation neural network
BTO	barium titanate
CB	carbon black
CCDHG-TENG	catechol-chitosan-diatom hydrogel triboelectric
CI	nanogenerator
CNN	convergence insufficiency
CNT	convolutional neural network
COPD	carbon nanotube
CVD	chronic obstructive pulmonary disease
DAS	cardiovascular disease
DHBS	dialdehyde starch
DL	sodium 3,5-dichloro-2-hydroxybenzenesulfonate
DMF	deep learning
DRM	*N*,*N*-dimethylformamide
DT	dynamic regression model
ECG	decision tree
EMG	electrocardiogram
EPE	electromyogram
EVA	expandable polyethylene
FEP	ethylene-vinyl acetate
FMG	fluorinated ethylene propylene
FOG	force myography
Gly	gait freezing
GN	glycerol
GO	graphene
GS	graphene oxide
GSR	graphite sheets
HACC-PAM	galvanic skin response
HBA	polyacrylamide and chitosan quaternary ammonium salt
HBD	hydrogen bond acceptor
HEC	hydrogen bond donor
HMI	hydroxyethyl cellulose
IMS	human–machine interface
KNN	intelligent monitoring system
LDA	*k*-nearest neighbor
LIG	linear discriminant analysis
LR	laser-induced graphene
LSTM	logistic regression
MiniRocket	long short-term memory
ML	a very fast (almost) deterministic transform for time series classification
MLR	machine learning
MNN	multiple linear regression
MoS_2	multilabel neural network
MSE	molybdenum disulfide
NB	minimize the loss function
NMC	naive Bayes
NPs	metal nanoparticles
OBVT	in-office vision therapy
OFSSVM	oriented feature selection support vector machine
OSA	obstructive sleep apnea
PA	polyamide
PAAM	polyacrylamide
PANI	polyaniline
PCA	principal component analysis
PD	Parkinson's disease
PDA	polydopamine
PDADMAC	poly(diallyldimethylammonium chloride)
PDMS	polydimethylsiloxane
PE	polyethylene
PEI	poly(ethylene imine)
PES	polyester
PET	poly(ethyleneterephthalate)
PI	polyimide
PLA	polylactic acid
PLS	partial least squares regression
PMMA	polymethyl methacrylate
PPy	polypyrrole
PR	phenol red
PSVM	proximal support vector machine
PTFE	polytetrafluoroethylene
PU	poly(vinyl alcohol)
PVA	polyvinyl chloride
PVC	polyvinylidene fluoride
PVDF	polyurethane
RF	random forest
RNN	recurrent neural network
SA	sodium alginate
SC	sodium casein
STM	short-term memory
SVM	support vector machine
SWCNTs	single-arm carbon nanotube
TA	tannic acid
TENG	triboelectric nanogenerators
TG	tannic acid-reduced graphene oxide
TPE	thermoplastic elastomer
TPU	thermoplastic polyurethane
VR	virtual reality
WPU	waterborne polyurethane
WT-SVM	wavelet transform-support vector machine

Data availability

There is no data in this manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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