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Review

Advances in Machine Learning for Wearable Sensors

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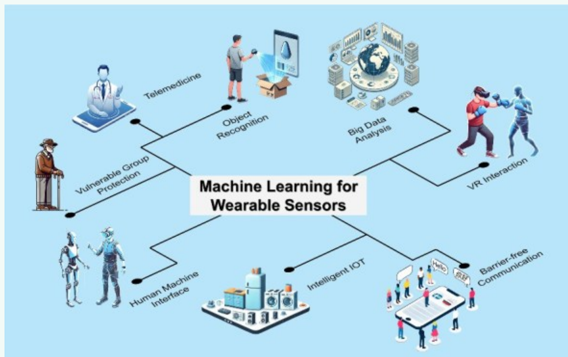
ABSTRACT: Recent years have witnessed tremendous advances in machine learning techniques for wearable sensors and bioelectronics, which play an essential role in real-time sensing data analysis to provide clinical-grade information for personalized healthcare. To this end, supervised learning and unsupervised learning algorithms have emerged as powerful tools, allowing for the detection of complex patterns and relationships in large, high-dimensional data sets. In this Review, we aim to delineate the latest advancements in machine learning for wearable sensors, focusing on key developments in algorithmic techniques, applications, and the challenges intrinsic to this evolving landscape. Additionally, we highlight the potential of machine-learning approaches to enhance the accuracy, reliability, and interpretability of wearable sensor data and discuss the opportunities and limitations of this emerging field. Ultimately, our work aims to provide a roadmap for future research endeavors in this exciting and rapidly evolving area.



KEYWORDS: *machine learning, wearable sensors, personalized healthcare, supervised learning, unsupervised learning, data analysis, real-time monitoring, human−machine interaction, bioelectronics*

INTRODUCTION

Wearable sensors have emerged as a transformative technology in the fields of personalized healthcare and human−machine interaction (HMI).[1−8] By continuously monitoring an individual's physiological states and motions, these devices possess the potential to provide personalized, real-time insights and support.[9−20] Recent technological advancements have catalyzed the development of advanced wearable devices adept at capturing an expansive range of physiological signals, providing opportunities for personalized healthcare and HMI.[21−41] With the increasing availability and demand for such devices, wearable sensors have gained significant attraction in remote patient monitoring, sports performance tracking, and health and wellness coaching.[42−49] For instance, these devices can continuously monitor physiological parameters such as heart rate, blood pressure, physical activity levels, among others.[50−54] This real-time monitoring offers the potential for early detection and intervention of potential health issues, ultimately improving health outcomes.[55−63] Wearable sensors can also provide personalized feedback and support, enabling individuals to make informed decisions to improve their health and wellness.[64−66] The field of wearable sensors has witnessed significant growth in recent years,[64,67−79] as demonstrated by the extensive range of applications and the interdisciplinary nature of related publications (Figure 1a).

Despite these significant benefits, using artificial intelligence (AI) for wearable sensors still faces several challenges. One major obstacle is the processing and analysis of the vast amounts of data generated by these devices.[80,81] High levels of noise and interference can impact the accuracy and reliability of the results.[82,83] Additionally, the compact design of wearable devices limits both data storage and computing capabilities, posing a challenge to conducting intricate on-device analyses.[84] Nevertheless, the rapid evolution of wearable sensing technology and the growing demand for personalized healthcare and HMI solutions make this a field of significant interest and potential.[85,86] In this context, artificial intelligence has the potential to overcome these challenges and make wearable sensors more reliable and effective.[87−89] Using machine-learning (ML) algorithms and statistical models can improve

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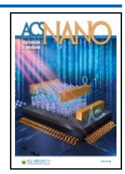

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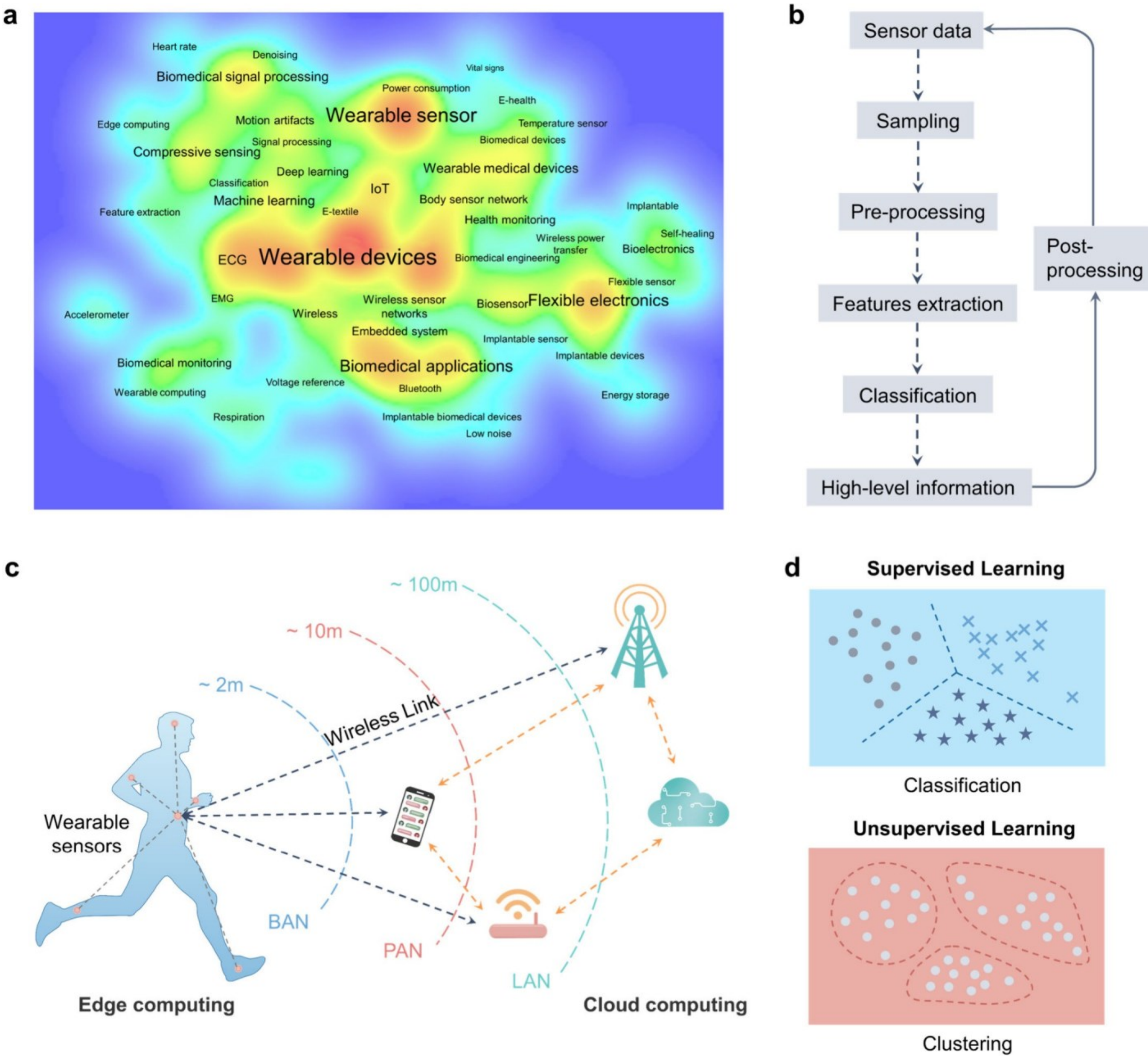

Figure 1. An overview of using ML for wearable sensors. a, The keywords of publications related to wearable sensors demonstrate the extensive application scope and interdisciplinarity of this field. Keywords from Web of Science. b, Typical process of applying ML algorithms to wearable sensors for data collection, preprocessing, feature extraction, and model training. c, Comparison of edge AI and cloud AI approaches in wearable sensors, highlighting their respective advantages and drawbacks. d, Use of supervised and unsupervised learning techniques for wearable sensors, with supervised learning often applied for classification and prediction of health metrics and unsupervised learning for discovering underlying patterns and relationships in the data.

the accuracy of the data collected by wearable sensors and help to identify meaningful patterns in the data that may be useful for healthcare professionals.[90,91] For example, ML algorithms can be trained on large amounts of data from wearable sensors to detect early signs of various health conditions, such as cardiovascular disease, sleep apnea, and even Parkinson's disease.[92,93] This application has the potential to help healthcare professionals diagnose and treat these abnormalities at earlier stages, significantly improving patient healthcare outcomes.[57] Moreover, ML can also help to optimize the sensing performance of wearable sensors.[94] For example, ML algorithms can be used to calibrate wearable sensors and improve their accuracy, by considering the different types of interference and noise that may affect the data.[95]

Herein, we summarize the role of ML in the field of wearable sensors. We describe the various applications of ML in wearable sensors, including the use of algorithms for data analysis and prediction as well as the development of wearable sensors that incorporate advanced ML techniques. Then, we discuss the challenges and limitations of ML in wearable biomonitoring, including issues related to data privacy and security as well as the need for robust and scalable algorithms that can handle large amounts of data. Furthermore, the Review encompasses the latest research and technological advances in this area including the development of algorithms,

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data processing techniques, and wearable sensors designed to improve the accuracy and reliability of biomonitoring. Considering the future of ML for wearable biomonitoring, integration of ML is revolutionizing the accuracy and efficiency of wearable sensors by identifying and correcting errors in the collected data. By addressing the challenges that wearable sensors currently face, ML has the potential to significantly improve people's health and wellness, facilitating healthcare professionals to diagnose and treat various health conditions more effectively.

MACHINE LEARNING

ML algorithms are increasingly harnessed to process vast amounts of data generated by sensors.[96] As shown in Figure 1b, the process typically begins with the collection of raw sensing data, which is then preprocessed to filter the noise and reduce the motion artifacts.[2] Next, feature extraction techniques are applied to identify relevant features in the data. These features may include statistical measures such as mean and variance or more complex ones such as spectral features. Upon the extraction of relevant features, they are used as inputs to ML algorithms, which are trained on a data set of labeled examples. The training process involves adjusting the parameters of the model to minimize the difference between the predicted output and the true output. Once the model has been trained, it can be used to make predictions on unseen data. In the context of wearable sensors, ML algorithms have been used to predict a variety of outcomes, including activity recognition, fall detection, and disease diagnosis. The ability of ML algorithms to learn from data and deliver accurate predictions makes them powerful tools for processing wearable sensor data and extracting meaningful insights about human health and behavior.

Traditionally, data collected by wearable sensors has been processed using methods such as statistical analysis and signal processing.[96] These methods have limitations in terms of the complexity and diversity of the data that they can effectively handle. The main difference between ML algorithms and their traditional counterparts lies in their adaptability and generalization capabilities.[97] Traditional algorithms rely on manually defined rules and features to process sensor data, which often limits their applicability to specific scenarios and data sets.[98−100] ML, on the other hand, has several advantages over traditional methods in the context of wearable sensors.[101−103] First, ML algorithms can handle large and complex data sets, allowing for more accurate analysis and insights. Second, these algorithms can learn from data and continuously improve their performance, leading to better results over time. Third, ML algorithms can detect patterns and relationships in data that may not be easily noticeable with traditional methods. Finally, ML algorithms can handle a wide range of data types and modalities, ranging from physiological signals to behavioral data, rendering them versatile tools for processing data from wearable sensors. These advantages have positioned ML as a valuable tool in improving the performance of wearable sensors and enabling applications in the field of wearable healthcare and wellness.

Edge AI and Cloud AI. In the wearable sensor field, the deployment of ML algorithms can be categorized into two broad approaches: edge AI and cloud AI (Figure 1c).[104] Both approaches offer their advantages and drawbacks, contingent on the specific use case at hand. Edge AI involves the deployment of ML models and algorithms directly on wearable sensors such as smartwatches and fitness trackers. This approach enables real-time data processing and decision-making on the device, which reduces the need for constant communication with the cloud. Furthermore, it also minimizes privacy and security risks associated with the transmission of sensitive health data. On the other hand, cloud AI leverages the computational power and storage capacity of remote servers to process and analyze wearable sensor data. This approach can provide more accurate results, given its access to a larger data set and the ability to leverage more sophisticated algorithms. Additionally, cloud AI facilitates centralized data management and sharing, allowing the combination of data from multiple wearable devices to gain a more comprehensive understanding of a person's health.

The choice between edge AI and cloud AI in wearable sensors depends on the desired balance between privacy, security, and data accuracy. For instance, edge AI is well-suited for use cases where privacy and security are paramount, such as in wearable sensors designed to monitor patients with medical conditions. In contrast, cloud AI finds its forte in use cases where data accuracy is the primary concern such as in wearable sensors used to optimize athletic performance. Both edge AI and cloud AI have important roles to play in the wearable sensor field, and the ongoing advancement of AI technology is expected to further enhance their capabilities and expand their applications. As wearable sensors become more sophisticated and integrated into our daily lives, the role of AI in transforming fields and improving human health is anticipated to become increasingly important.

Supervised Learning and Unsupervised Learning. In the field of wearable sensors, selecting the right machine-learning algorithm can be crucial in achieving the desired outcomes. Figure 1d illustrates two prominently used AI approaches in wearable sensors; supervised learning and unsupervised learning.[105,106] This approach has proven to be highly effective in predicting chronic health conditions, such as diabetes and heart disease, thereby enhancing the accuracy of wearable sensors. On the other hand, unsupervised learning does not require labeled data and instead uses data-clustering techniques to identify patterns and relationships in the data. Particularly beneficial in situations characterized by an abundant amount of data but limited labeled data, unsupervised learning aids in identifying patterns that may not be easily noticeable through manual inspection. In the context of wearable sensors, unsupervised learning is frequently employed to identify trends in large amounts of data such as daily physical activity patterns or sleep quality. The adoption of both supervised and unsupervised learning has tremendously improved the accuracy and capabilities of wearable sensors, positioning them as powerful tools for collecting and analyzing health and wellness data. With the continued integration of AI in wearable sensors, these devices are anticipated to become even more sophisticated and capable of providing detailed insights into human health and wellness. Consequently, the strategic selection of a suitable ML algorithm for wearable sensors is deemed a pivotal step in optimizing their functionality.

BIOMONITORING

Health monitoring constitutes a fundamental aspect of personalized healthcare, empowering clinicians to track and manage real-time health status of their patients.[107−111] By combining ML algorithms with wearable sensors, researchers

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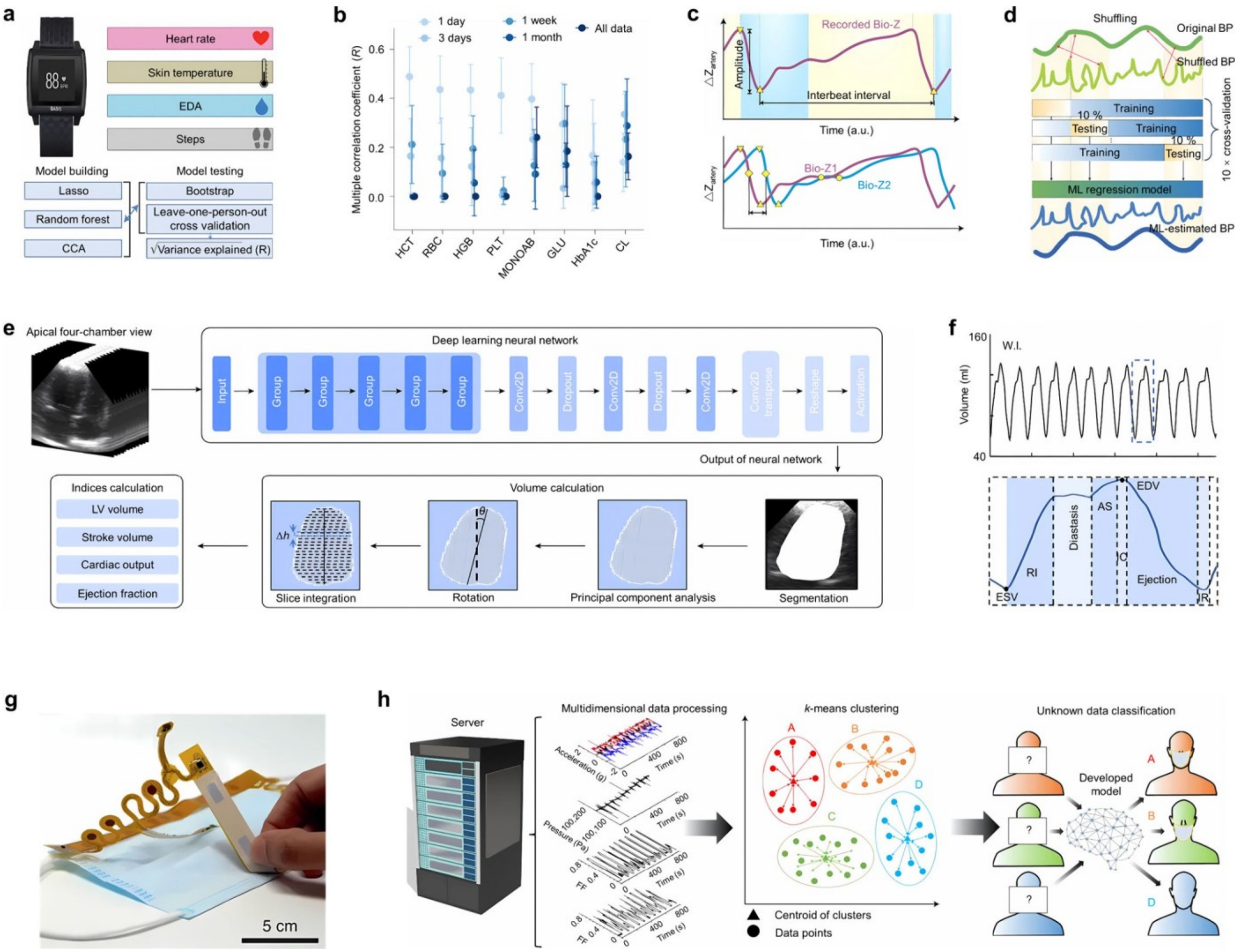

Figure 2. ML-assisted physiological monitoring. a, Statistical moments collected by the wearable smart watch, including heart rate, skin temperature, EDA, and step counts (top). Overview of the statistical learning methods employed and model evaluation methodology (bottom). b, Wearable vital signs calculating features through random forest models using varying time windows. Reproduced with permission from ref 119. Copyright 2021 Springer Nature. c, Illustration of the Bio-Z signal (top), and two Bio-Z signals recorded by two pairs of GETs for collecting data and ML algorithm. d, Training models developed by shuffling hand grip and cold pressor data. Reproduced with permission from ref 120. Copyright 2022 Springer Nature. e, Schematic workflow. Preprocessed images train the FCN-32 model, which predicts left ventricular volume from unprocessed images, enabling derivation of stroke volume, cardiac output, and ejection fraction. f, Left ventricular volume waveform generated from the wearable imager (W.I.) and labeled features in one cardiac cycle. Reproduced with permission under a Creative Commons CC-BY license from ref 118. Copyright 2023 Springer Nature. g, Photograph of the conformable multimodal sensory face mask. h, Schematic of ML model development. Data were loaded from the server, processed, and applied to a k-means clustering-based classification model, with the test data set's predicted positions compared to true values during testing. Reproduced with permission from ref 121. Copyright 2022 Springer Nature.

have developed approaches to health monitoring that showcase the potential to improve the accuracy and efficiency of these systems.[112−116]

One area where ML algorithms prove particularly advantageous in health monitoring is in the development of personalized health monitoring systems.[117,118] By analyzing data from wearable sensors, ML algorithms can identify individual differences in health factors, enabling clinicians to tailor treatment plans to the specific needs of each patient. For example, vital signs are often utilized for detecting and monitoring medical conditions. However, traditional measurements require clinical and laboratory tests for definitive conclusions. Recently, Dunn et al. employed ML models, including random forests and Lasso models, to predict clinical laboratory test results based on vital signs measured by wearable sensors, such as continuous heart rate, skin temperature, electrodermal activity (EDA), and motion (Figure 2a).[119] The study also investigated the impact of time and personalization on the model's accuracy. Results revealed that wearable sensors provided more measurements than those obtained in clinics during the detection period and allowed for the design of more complex model features, resulting in more accurate clinical laboratory test predictions. Additionally, different time windows yielded varying model performances (Figure 2b). Personalized models established by using more observational results or intensive monitoring periods with appropriate monitoring durations exhibited improved accuracy, outperforming population-level models. This study linked specific physiological features to clinical characteristics, enhancing the understanding of the relationship

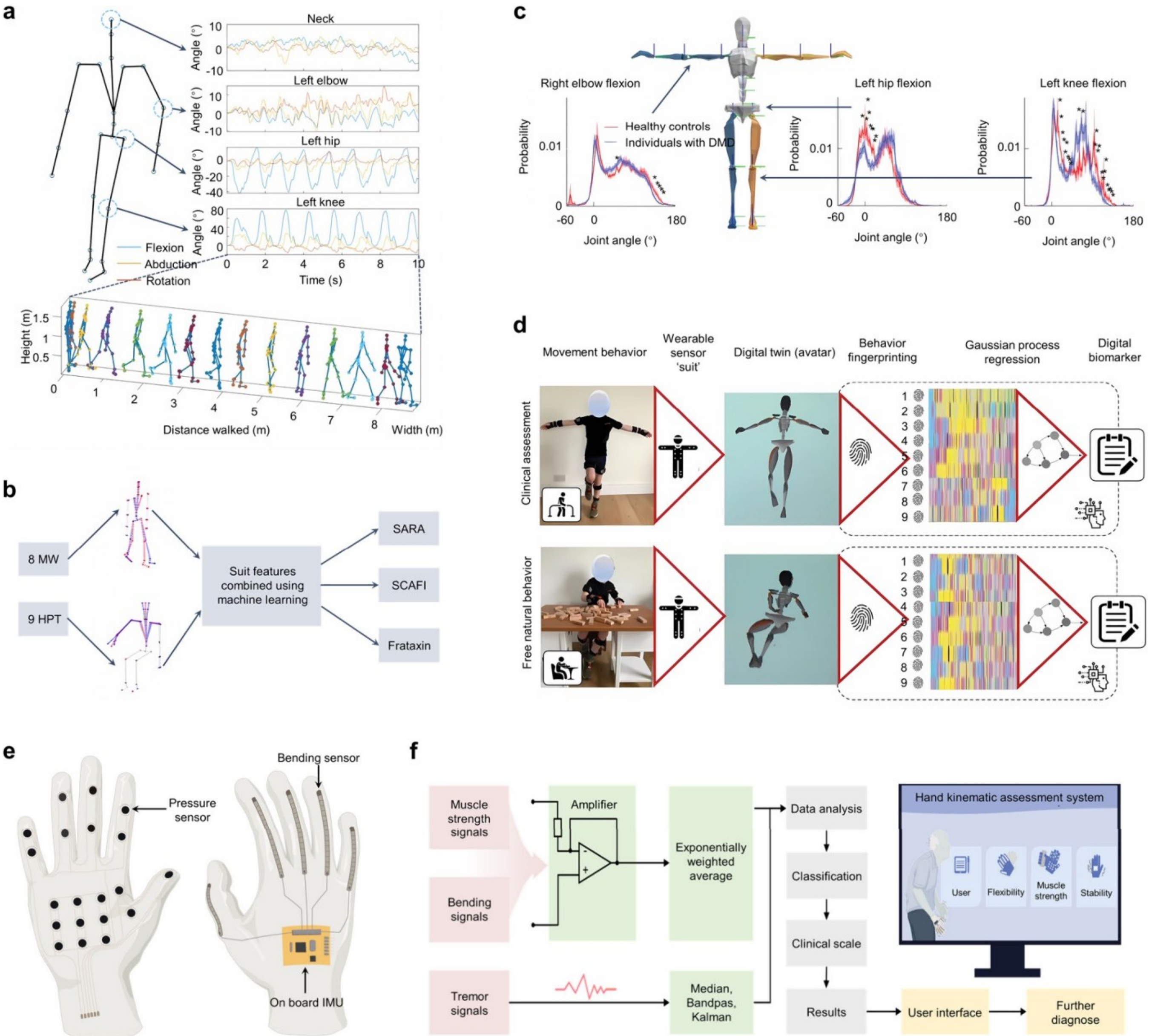

Figure 3. ML-assisted wearable body motion sensing. a, Reconstructed body posture of a participant performing the 8-m walk is captured using a motion suit with inertial sensors monitoring limb movement. The suit records a typical time series of angular positions for neck, elbow, hip, and knee joints, along with a frame sequence of a Friedreich's ataxia (FA) patient's 8-m walk test at 0.5 s intervals. b, Utilizing full-body motion capture and ML to analyze performance markers for reconstructing standard clinical assessments and improving FA disease progression estimation. Reproduced with permission under a Creative Commons CC-BY license from ref 122. Copyright 2023 Springer Nature. c, Probability distribution of joint angles at three skeletal joints comparing natural movement behavior data between individuals with Duchenne muscular dystrophy (blue) and healthy controls (red). d, The system extracts ethomic fingerprints from participants' natural movement behavior using suit data, employing supervised GP regression to derive digital biomarkers from these fingerprints. Reproduced with permission under a Creative Commons CC-BY license from ref 123. Copyright 2023 Springer Nature. e, Multi-sensor-based hand function assessment glove. f, The hand function assessment process includes hand kinematic signals collecting, processing, and analyzing. Reproduced with permission under a Creative Commons CC-BY license from ref 93. Copyright 2023 Wiley-VCH.

between clinical biochemistry tests and physiology. Personalized monitoring and modeling frameworks can be readily extended to other types of data and clinical measurements, enabling the widespread implementation of personalized health monitoring through wearable sensors.

Another area where ML algorithms play a pivotal role is in the development of predictive health monitoring systems. By continuously monitoring health data through wearable sensors, ML algorithms can detect and interpret changes in a patient's health in real-time, allowing clinicians to timely intervene before a condition worsens. Arterial blood pressure (BP) is an essential parameter for understanding various health conditions, including cardiovascular diseases. Dynamic blood pressure monitoring platforms can facilitate the analysis of correlations between diseases and individual behaviors and lifestyles, thereby facilitating proactive disease prevention. However, traditional dynamic blood pressure sensors are cumbersome and invasive. Kireev et al. introduced a self-adhesive, low-impedance graphene electronic tattoo (GET) based on bioimpedance measurements (Bio-Z) for continuous blood pressure monitoring.[120] The Bio-Z waveforms are inversely related to BP (Figure 2c top), and the ΔZ_{artery} curve is used to identify four characteristic points, systolic pressure foot, diastolic pressure peak, mean slope, and inflection point for constructing ML regression algorithms for BP prediction (Figure 2c bottom). Adaptive boosting techniques process approximately 50 feature points extracted from the four Bio-Z signals to train the ML algorithms. Training is typically performed on shuffled data (Figure 2d); the original time trajectories are randomized and divided into ten equal parts, using one part for training and the remaining nine for 10-fold cross-validation analysis. The implementation of 10-fold cross-validation allows the ML model to utilize most of the training data while avoiding overfitting. Post-training, the data are reordered according to their original temporal sequence. The results indicate that the bioimpedance platform achieves higher accuracy than previously reported. The prediction accuracy of the ML regression model trained through cyclic training reaches 0.06 ± 2.5 mmHg (diastolic pressure) and 0.2 ± 3.6 mmHg (systolic pressure). According to the Institute of Electrical and Electronics Engineers (IEEE) standards, these values are equivalent to grade A classification wearable blood pressure measurement devices, providing a solution for wearable blood pressure monitoring.

ML algorithms not only exhibit proficiency in extracting feature points from curves but also demonstrate notable capabilities in extracting information in the field of medical imaging. Recently, Hu et al. reported a wearable ultrasound device for continuous, real-time, and direct assessment of cardiac function.[118] The device achieves effective mechanical coupling with human skin, allowing examination of the left ventricle from different angles during movement. Subsequently, deep learning neural networks are applied to extract key information from continuous image streams, with preprocessed images used to train the Fully Convolutional Networks (FCN)-32 model. The trained model can automatically predict left ventricular volume from continuous image recordings, generating waveforms of key cardiac performance indicators such as stroke volume, cardiac output, and ejection fraction (Figure 2e). By comparing the output information on left ventricular volume waveforms (Figure 2f top) and key features in a detailed cardiac cycle (Figure 2f bottom) from the wearable ultrasound device and commercial imagers, the results validate comparable performance between the wearable and commercial imagers. This technology enables dynamic wearable monitoring of cardiac performance with significantly improved accuracy in various environments and has the potential to extend its benefits to outpatient and athletic populations.

ML algorithms can also be used to enhance the accuracy and reliability of health monitoring systems. By analyzing data from multiple sensors, ML algorithms can detect and correct errors in health monitoring, improving the overall quality and usefulness of these systems. The emergence of COVID-19 and health policies worldwide has highlighted the importance of masks in combating the spread of infectious diseases, and integrating wearable electronic devices into masks can provide valuable insights for both individual and public health. Kim et al. reported a conformable multimodal sensory face mask (cMaSK) that could be integrated with commercial masks (Figure 2g) and simultaneously monitor multiple signals related to both biological and environmental conditions, including mask position, skin temperature, humidity, speech activity, and breathing patterns.[121] An ML algorithm was developed to classify the position of the mask. Here, researchers employed *k*-means clustering, classifying points into *k* clusters based on minimizing the distance between data points and clusters' centroids (Figure 2h). Data stored on the server were processed for training and testing of the algorithm. The accuracy rates for male and female subjects were 92.8% and 77.5%, respectively, reliably decoding mask positions. The precise recognition of mask position effectively contributes to improving the quality of device wear and proactively assists users in optimizing mask fit, further enhancing the monitoring quality of cMaSK. This work provides a modular, customizable research tool for studying environmental and health technologies in real-world environments where human behavior may affect performance, broadening the understanding of key factors affecting mask-wearing behavior and their impact on human health and well-being.

The integration of ML algorithms and wearable sensors has the potential to transform health monitoring, enabling clinicians to better track and manage the health of their patients. By improving the accuracy, efficiency, and predictive capabilities of health monitoring systems, this approach has the potential to enhance the quality of care provided to patients in a variety of settings, including hospitals, clinics, and home care environments. As such, research in this area is crucial for advancing the field of health monitoring and realizing its complete potential in improving patient outcomes.

One area where ML algorithms exhibit practicality is disease tracking and prediction, particularly in the early detection of chronic diseases. By analyzing data from wearable sensors, ML algorithms can detect subtle changes in health patterns that may indicate the early onset of chronic diseases such as diabetes or heart disease. Early detection enables clinicians to intervene before the disease progresses, potentially improving patient outcomes and reducing healthcare costs. For example, one in every 17 people suffers from rare diseases, and drug development progresses slowly due to the limited number of patients. Clinical scales commonly adopted to measure the progression of rare diseases are often slow and subjective, necessitating objective methods.[122] For Friedreich's ataxia (FA), researchers captured the whole-body kinematic characteristics of test subjects using wearable sensors (Figure 3a), defining digital behavioral features based on their 8-m walk (8-MW) test and 9-hole peg test (9 HPT) (Figure 3b). Employing ML to longitudinally predict clinical scores in FA patients, results showed that digital behavioral features could accurately predict individual components of the Scale for the Assessment and Rating of Ataxia (SARA) and Spinocerebellar Ataxia Functional Index (SCAFI) scores and forecast future FA gene expression levels. In this study, effective predictions for early disease progression were shaped by analyzing these digital behavioral features through ML. The advantage of this approach lies in its ability to substantially reduce the duration or scale of clinical trials for testing disease-modifying therapies while providing more accurate predictive results. Physicians can detect and diagnose diseases earlier, thereby offering more effective treatment and management strategies and resulting in better healthcare services and treatment outcomes for patients.

ML algorithms are instrumental in predicting disease progression and assessing treatment effectiveness. By analyzing data from wearable sensors over time, ML algorithms can detect trends and patterns that may indicate disease progression or a response to treatment. Clinicians can leverage

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this information to adjust treatment plans and monitor patient's progress, ultimately improving the overall quality of care. For instance, the fusion of wearable sensors and ML algorithms to analyze behavioral data holds great potential in improving the prediction of disease progression and the assessment of treatment outcomes. Ricotti et al. developed a KineDMD ethic behavioral biomarker based on daily living activity data, using ML algorithms to predict and assess the progression and treatment efficacy of Duchenne muscular dystrophy (DMD).[123] Specifically, a wearable sensor suite was designed to quantitatively test the differences in joint motion between healthy control subjects and DMD patients during daily living activities, particularly the distinct manifestations of DMD patients compared to healthy controls in terms of joint angles and posture (Figure 3c). Subsequently, a whole-body motion behavior analysis method was employed, extracting ethomic fingerprints from participants' digital twins and deriving digital biomarkers using the Gaussian process (GP) regression ML algorithm (Figure 3d). Compared with current clinical assessments, this biomarker demonstrates exceptional performance in predicting disease progression and may revolutionize the conduct of clinical trials for neurological disorders. This approach holds the potential to provide more personalized and effective treatment strategies for patients with neuromuscular diseases. Furthermore, the utilization of multisensor systems and ML algorithms can provide a more comprehensive, objective, and detailed disease assessment for clinical monitoring, aligning more effectively with clinical rehabilitation needs. Recently, Li et al. developed a multimodal sensor glove for hand function assessment in Parkinson's Disease (PD) patients with hand dysfunction (Figure 3e).[93] The built-in flexible sensor network can comprehensively capture patients' hand-related motion signs, such as rigidity, muscle weakness, and tremors. By employing filtering, normalization, clustering analysis, and neural network evaluation, the data glove based on hand kinematics can quantitatively assess finger flexibility, hand muscle strength, and hand stability (Figure 3f). The generated hand function impairment assessment grading results can be used to assist in evaluating disease progression stages. In addition to helping devise rehabilitation therapies, the multisensor data glove can objectively assess patients' progress following hand rehabilitation training, assist physicians in formulating disease rehabilitation treatment plans, and bring breakthroughs in evaluating hand function in PD patients.

Another area where ML algorithms find utility is in the development of personalized disease tracking and prediction systems. By analyzing data from multiple sensors, ML algorithms can identify individual differences in health patterns and risk factors, enabling clinicians to tailor disease prevention and management strategies to the specific needs of each patient. Quer et al. explored the possibility of using personal sensor data to identify COVID-19-positive and negative individuals.[124] They developed a smartphone application that collects data from individuals' smartwatches and activity trackers, as well as self-reported symptoms and diagnostic test results. The study results indicate that an ML model combining symptom and sensor data effectively distinguishes between COVID-19 positive and negative individuals (AUC = 0.80, $P < 0.01$), outperforming models that consider symptoms alone (AUC = 0.71). This continuous, passively captured data may serve as a complement to virus testing, aiding in more accurately identifying COVID-19 infection risks and facilitating the development of personalized prevention and management strategies.

The integration of ML algorithms and wearable sensors possesses the promise of revolutionizing disease tracking and prediction, affording clinicians the ability to detect and respond to health risks in real time. By improving the accuracy and predictive capabilities of disease tracking and prediction systems, this approach bears the prospect of enhancing the quality of care provided to patients and reducing healthcare costs.[125−128] In essence, ongoing and dedicated research in this area is crucial for advancing the field of pushing the boundaries of disease management and prevention, ultimately unlocking its full spectrum of possibilities in improving patient outcomes.

HUMAN−MACHINE INTERACTION

HMI is an essential part of wearable sensors research that aims to create a seamless interface between humans and machines.[28,129−132] It involves integrating various technologies such as sensors, feedback mechanisms, and AI to enhance communication and collaboration between humans and machines.[133−138] HMI plays a crucial role in various industries, including aviation, healthcare, gaming, and robotics, among others.[139−142] However, traditional HMI approaches often rely on predefined rules and models to facilitate the interaction between humans and machines, constraining their adaptability and responsiveness to individual differences, ultimately producing a suboptimal experience. Additionally, predefined rules and models may fall short of accommodating changes in the environment, further diminishing their effectiveness.

The integration of wearable sensors and ML algorithms is reshaping the HMI landscape, offering an approach capable of adapting to the needs and preferences of each individual.[143,144] Wearable sensors, such as body motion sensors and fitness trackers, can provide real-time feedback on the user's behavioral and physiological states, which can be used to inform ML algorithms. These algorithms, in turn, leverage this information to personalize the interaction between humans and machines, establishing a more adaptive and responsive interface. This innovative approach to HMI enhances the user experience by improving the effectiveness of machines in comprehending and responding to human behavior.

Gesture recognition, which is rapidly evolving in the field of HMI, aims to bridge the gap between machines and humans by allowing machines to interpret and respond to human gestures with reliability and precision. This critical area of research contributes to enhancing the efficiency and usability of human−machine interfaces. The integration of ML algorithms and wearable sensors holds promise to improve the accuracy and robustness of gesture recognition systems. The applications of ML algorithms in gesture recognition are vast and varied.[145,146] One key application is the development of real-time gesture recognition systems. By analyzing data from multiple wearable sensors, ML algorithms can detect and correct errors in gesture recognition, improving the reliability and accuracy of these systems. This approach allows machines to recognize complex gestures accurately, even in the presence of significant data noise. Researchers at the University of California, Los Angeles designed a smart wearable glove based on the triboelectric nanogenerator (TENG) for real-time translation of sign language movements into audio speech.[86] By continuously monitoring individuals' finger movement, the smart glove could successfully detect and collect signals of different American Sign Language (ASL) gestures. With the

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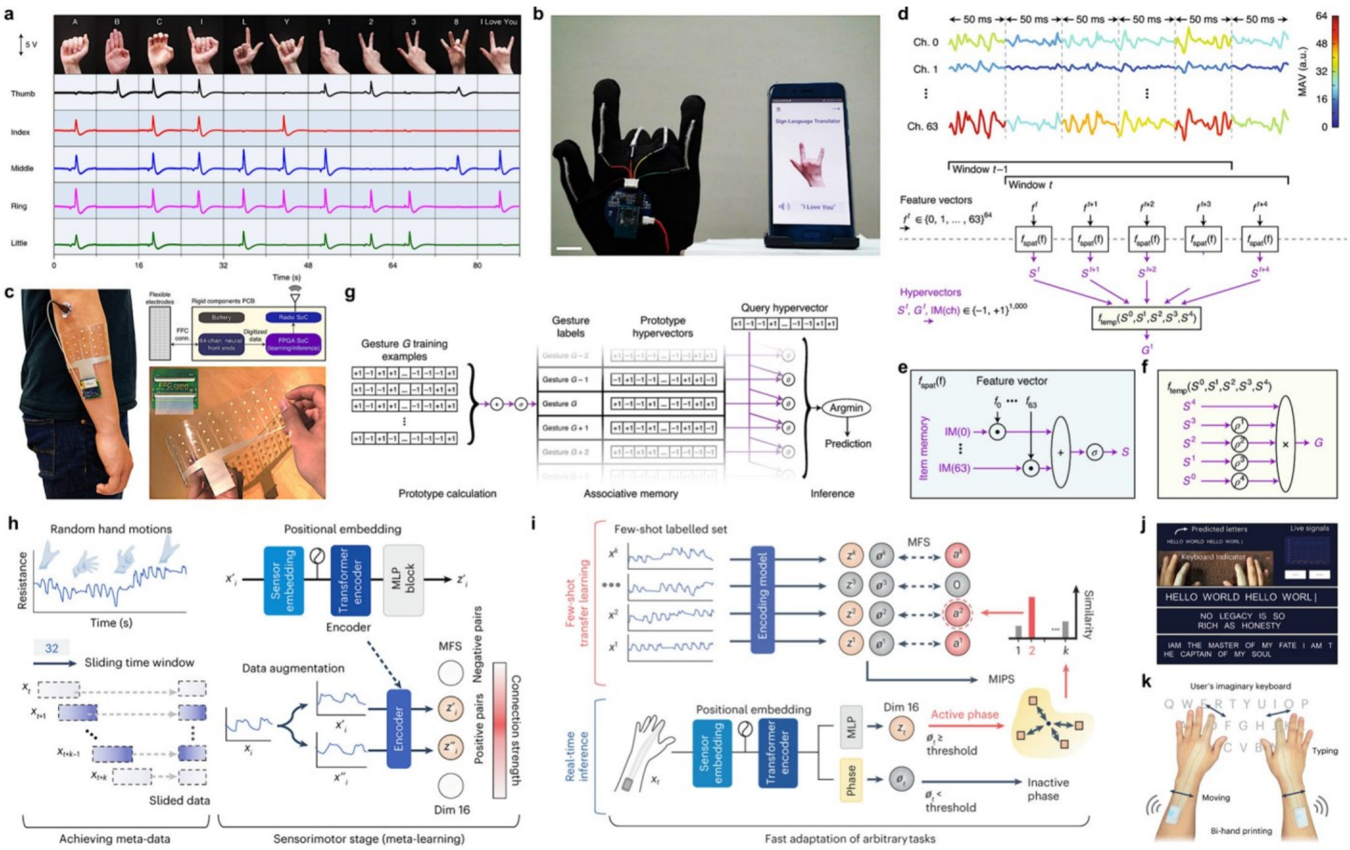

Figure 4. ML algorithms for wearable gesture recognition. a, Photographs of the gestures and the corresponding TENG wearable glove-generated voltage signals used for sign language recognition with the assistance of ML. b, Photograph showing the wearable sign-to-speech translation system translating the sign-to-speech and real-time display on a commercial mobile phone application interface. Scale bar, 2 cm. Reproduced with permission from ref 86. Copyright 2020 Springer Nature. c, Custom-designed 16 × 4 array of electrodes with a miniaturized printed circuit board (PCB) that conforms to the forearm of a participant for surface electromyography (sEMG) recordings. d, Using hyperdimensional (HD) computing algorithm to implement in-sensor adaptive learning and real-time inference for hand gesture classification. e,f, Projecting sEMG data into hyper-vectors through (e) spatial encoding and (f) temporal encoding. g, Usage of the associative memory (AM) from prototype calculation and storage for training (left) to Hamming distance calculation for inference (right). Reproduced with permission from ref 149. Copyright 2020 Springer Nature. h, Principles of sensor signal processing and unsupervised time-dependent contrastive (TD-C) learning with unlabeled signals. MFS stands for motion feature space. i, Transfer learning and real-time inference mechanism with the provided few-shot labeled data set. Dim 16 and MIPS stand for a dimension of 16 and maximum inner product search, respectively. j,k, Demonstration of two-handed keyboard typing recognition with nanomesh printed on both hands via (j) a picture of the user interface and (k) illustration. Reproduced with permission from ref 102. Copyright 2022 Springer Nature.

assistance of ML, the collected signals were merged into a matrix and analyzed by using principal component analysis (PCA) to extract the main features of each gesture and eliminate redundant information (Figure 4a). The extracted features were then classified using a multiclass support vector machine (SVM) algorithm to create a real-time sign-to-speech translation system. To demonstrate the efficacy of the device, 11 sign language hand gestures were selected from ASL to represent numbers, words, and phrases (Figure 4b). Four deaf signers repeated each gesture 15 times, resulting in 660 gesture recognition patterns that were randomly split into a training set of 440 and a test set of 220. The confusion matrix showed an overall accuracy of 98.63% and an average recognition time of less than 1 s. To enhance the user experience, a mobile application was developed to convert the translated text to speech via a third-party platform. The study underscores the transformative impact of ML algorithms on the ability of wearable sensors for more accurate detection and recognition. The result is a real-time interpretation of human gestures, fostering enhanced communication not only between humans and machines but also among individuals.

Another area where ML algorithms find valuable applications is in the development of personalized gesture recognition systems. By analyzing data from sensors, ML algorithms can identify individual differences in gesture patterns, enabling machines to respond to the distinct gestures of each user. This approach offers a noteworthy advantage. ensuring machines can quickly and accurately interpret human input. While the indisputable power of ML in wearable technology has been demonstrated in numerous studies, most commercialized devices cannot update their ML models during usage, leading to lower performance under practical conditions.[147,148] Addressing this challenge, recent research has introduced a wearable biosensing system incorporating hyperdimensional computing for in-sensor adaptive learning and real-time hand gesture classification.[149] The proposed wearable biosensing system features a screen-printed electrode array affixed on the human arm to continuously monitor muscle activity for hand gesture recognition (Figure 4c). Hyperdimensional computing

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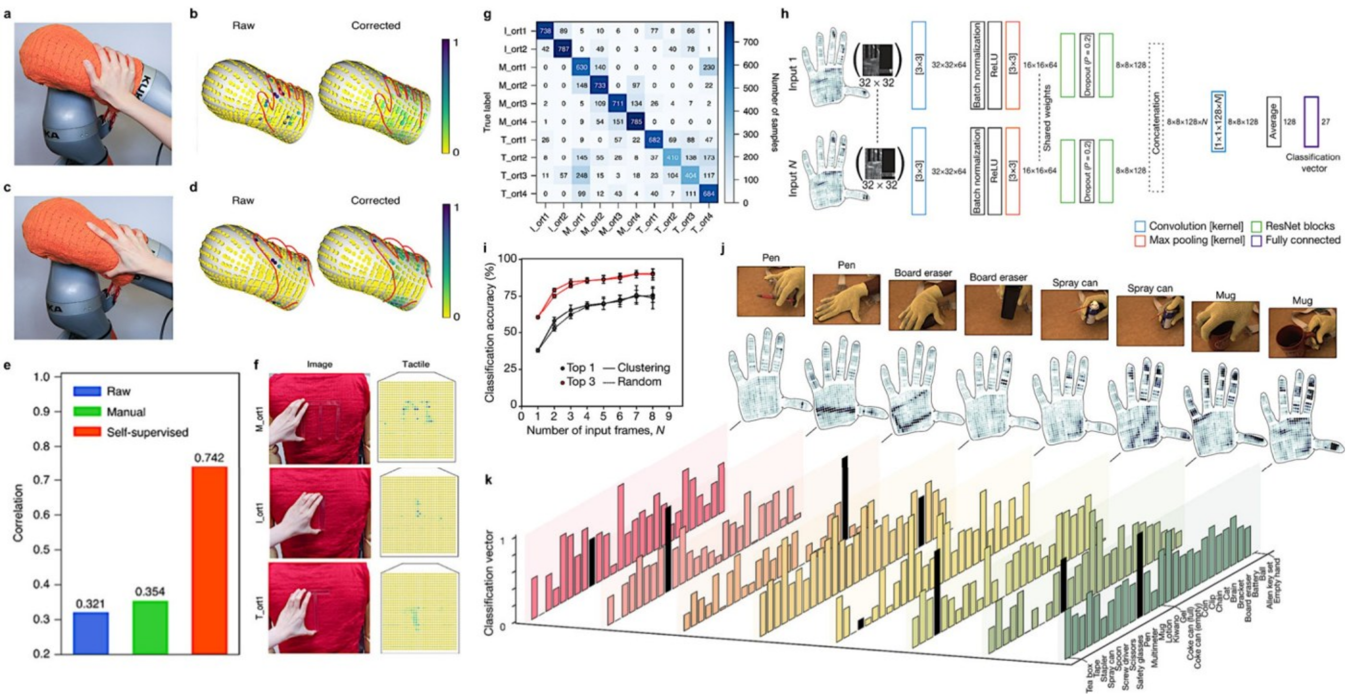

Figure 5. ML-assisted wearable sensors for environment perception. a−d, The self-supervised calibration network removes artifacts and enhances the smoothness of the sensors. The color bar indicates the relative pressure in each sensing point. e, Correlations between the tactile response and the scale reading: "Raw" indicates the correction of the original, unprocessed tactile signal; "Manual" indicates the correlation of manual-adjusted data where all saturated tactile signals were clipped; and "Self-supervised" indicates the correlation obtained after self-supervised correction. f, Photographs and tactile frames of pressing letters "M", "I", and "T" on the tactile vest. g, Confusion matrix of the letters and the orientation classification. Reproduced with permission from ref 150. Copyright 2021 Springer Nature. h, Convolutional neural network (CNN) architecture used for identifying and weighing objects from tactile information. "ReLU" stands for rectified linear units. i, Accuracy of object identification when using a diverse set of tactile maps from N distinct clusters as input and a random choice of inputs. The results are averaged over ten training runs (mean ± s.d.). j,k, A representative set of tactile maps during single-hand manipulation of objects. Tactile maps, (j) corresponding visual images, and (k) the classification vectors from single tactile map inputs are shown□the ground-truth object labels are marked in black. Reproduced with permission from ref 151. Copyright 2019 Springer Nature.

is an inventive computational approach known for its quick learning and resistance to noise and errors. This method processes high-dimensional hyper-vectors and simplifies complex tasks like classification and reasoning (Figure 4e). Consequently, it permits the reuse of the same hardware modules for both sensor training and classification. The process involves the sliding window approach, extracting five feature segments in total (each being 50 ms long), with the mean absolute value of the feature calculated for each channel in each segment. The feature vector for each segment is projected into a hyper-vector representing spatial information by scaling and summing unique, pseudorandom bipolar hyper-vectors representing electrode channels. The resultant spatial hyper-vector is transformed into a spatiotemporal hyper-vector by encoding the order in which the five vectors occur through a bitwise rotation (Figure 4f). The rotated hyper-vectors are multiplied together elementwise, resulting in a single 1,000D bipolar hyper-vector that represents the entire 250 ms window (Figure 4g). The encoded hyper-vectors that represent both space and time can serve as either training examples or search queries. This research introduced a prototype hyper-vector i for each category, calculated by determining the centroid of that category. These prototypes were then saved in associative memory for subsequent use in classification. In contrast to other neural network methods, this process is simple and one-pass, helping the studied wearable sensor to improve sensing accuracy and reliability by updating the ML model in response to changing conditions in real time without needing an external device.

Besides updating and simplifying the process of ML algorithms, an alternative approach to improve the functionality of ML in wearable sensors involves optimizing the data volume or calibration processes. Researchers at Stanford University described the creation of a nanomesh artificial mechanoreceptor capable of recognizing different hand tasks without the need for extensive data or individual calibration.[102] The system could analyze signal patterns from skin stretches by extracting proprioception information similar to that from cutaneous receptors. The system required only a single sensor to decode complex proprioceptive signals and could reconstruct multijoint proprioceptive information from low-dimensional data (Figure 4h). The authors developed a time-dependent contrastive learning framework that uses unlabeled random finger motions to furnish prior motion representation knowledge, which allows the system to learn task-specific signal patterns from unlabeled signals collected from multiple users (Figure 4i). The pre-trained model exhibited quick adaptation to different daily tasks using minimal hand signals, exemplified by its proficiency in recognizing two-handed keyboard typing (Figure 4j,k).

Environment perception is a critical research area that enables machines to interpret and understand their surroundings. It concentrates on recognizing hand posture and delving into touch-based environmental interpretation rather than

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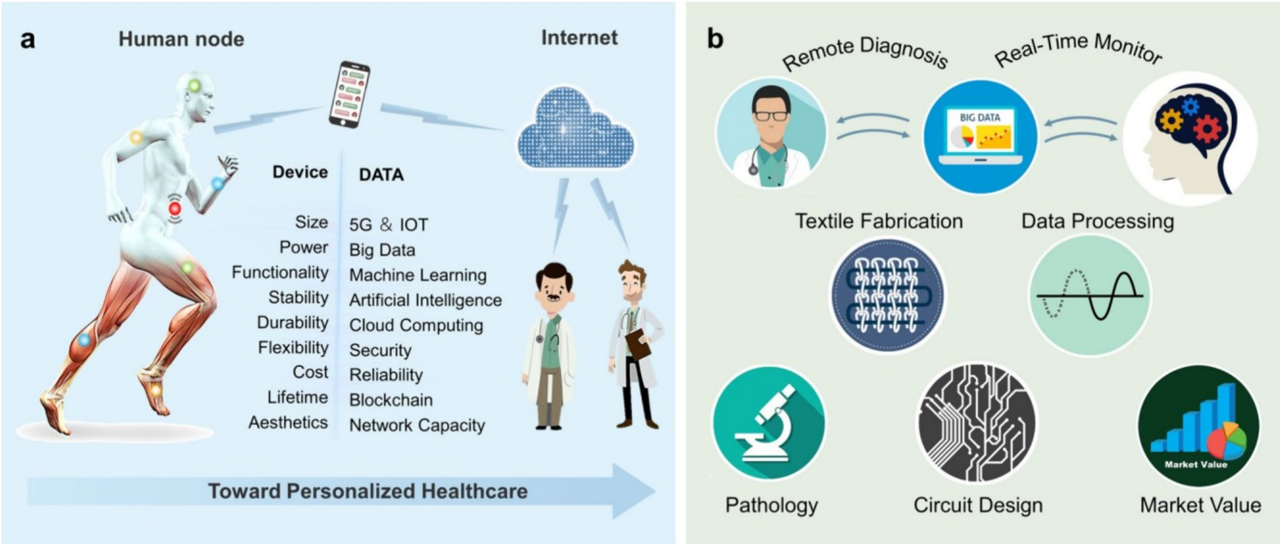

Figure 6. Perspective toward future development of ML-aided wearable sensors. a, Integration of ML in personalized healthcare. b, Future developments in ML for wearable sensors, including the integration with next-generation wearable devices, existing biomonitoring technologies, and personalized health interventions.

simply analyzing finger movements. The combined help of ML algorithms and wearable sensors has led to innovative methodologies in environment perception, promising improved accuracy, and robustness. One of the key areas of research in environmental perception is the development of tactile sensors that can simulate the sense of touch. This is achieved by integrating a variety of sensors onto the surface of a wearable sensor that can detect different types of pressure, friction, and temperature. These sensors can then provide information about the texture, shape, and material properties of an object upon touch, promoting a more profound understanding of the object and its environment. Exploiting ML algorithms to analyze the data generated by these sensors is a common practice, allowing the devices to undergo a learning process in which they become adept at recognizing and interpreting different types of objects and environments. The model is trained on an extensive data set, enabling it to distinguish between different types of objects and environments and to precisely predict the properties of encountered objects.

Researchers at the Massachusetts Institute of Technology developed a tactile learning platform employing textile materials crafted from piezoresistive fibers to record and learn human−environment interactions (Figure 5a,b).[150] To ensure its sensing accuracy, ML techniques were equipped for correction and calibration (Figure 5c,d). By utilization of a self-supervised learning framework, the correlation between responses significantly increased, ensuring more uniform and continuous responses that were robust against variation and disruption among individual elements. Moreover, the data set was collected by pressing three letter cutouts against the back of a manikin dressed in a vest made of functional fibers in various orientations. The type and orientation of the letter were predicted using a classification network that took a small window of tactile responses. The accuracy of prediction was 63.76%, and the effective resolution influenced the accuracy, as depicted by the decrease in accuracy as resolution decreases (Figure 5e). The platform successfully captured diverse human−environment interactions and showcased promising results for classifying various poses and motions. The results underscore the possibility of the proposed self-supervised sensing correction to normalize sensor responses and correct malfunctioning sensors in the array. The demonstrated applications highlight the value of the developed system for various human−environment interaction learning scenarios.

Another work introduced a cost-effective method of constructing a tactile glove with 548 sensors that cover the entire hand.[151] The glove not only generates tactile maps with high resolution but also measures normal forces ranging from 30 mN to 0.5 N with a quantization of approximately 150 levels and a peak hysteresis of about 17.5%. It also captured tactile videos with a frame rate of about 7.3 Hz. Furthermore, the authors also introduced a large data set of tactile maps consisting of 135,000 frames recorded using the tactile glove while manipulating objects with a single hand. The tactile maps' spatial correlations and finger regions' correspondence revealed the human grasping strategy's tactile signatures. A convolutional neural network (CNN) was trained to identify objects using filtered frames, which were 32 × 32 arrays in sensor coordinates (Figure 5f). The classification accuracy of the CNN improved with the number of input frames and reached its maximal performance with about seven random input frames, as shown in Figure 5g. Along with the corresponding tactile frames shown in Figure 5h, the output classification vectors of eight example tactile frames are shown in Figure 5i.

CONCLUSION AND PERSPECTIVE

Wearable sensors have witnessed significant advances in recent years, prominently marked by the integration of ML playing a crucial role in enhancing its capabilities (Figure 6a). This includes the ability to make accurate predictions and detect patterns in large and complex sets of biometric data, leading to a better understanding of human physiology and providing insights into various health conditions. The application of supervised learning algorithms has notably resulted in the development of personalized health models, enabling wearable sensors to forecast the likelihood of certain health conditions based on individual data. In parallel, unsupervised learning

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Table 1. Comparison of Different Machine-Learning Algorithms

Algorithm	Advantages	Effects on Wearable Sensors
Decision Trees	- Simple to understand and interpret	- Can handle large feature spaces, useful for multisensor data
	- Requires little data preprocessing	- Prone to overfitting, affecting sensor data reliability
Random Forest	- Reduces overfitting	- Enhances sensor data accuracy through ensemble learning
	- Handles large data sets well	- Requires more computational resources
Support Vector Machines (SVMs)	- Effective in high-dimensional spaces	- High accuracy for sensor data classification
	- Robust to overfitting (especially in high-dimensional space)	- Computationally intensive, may affect real-time processing
K-Nearest Neighbors (KNNs)	- Simple and easy to implement	- Effective for real-time applications with wearable sensors
	- No training phase	- Performance decreases with large data sets
Naive Bayes	- Fast and efficient	- Quick to adapt to new data
	- Performs well with small data sets	- Assumes independence of features, which may not always be the case
Neural Networks	- High accuracy	- Suitable for complex, multisensor data integration
	- Can model complex relationships	- Requires significant computational power and large training data sets
Convolutional Neural Networks (CNNs)	- Excellent for image and spatial data	- Highly effective for sensor data with spatial dependencies (e.g., motion sensors)
		- High computational cost
Recurrent Neural Networks (RNNs)	- Good for sequential data	- Ideal for time-series sensor data (e.g., heart rate, temperature)
		- Computationally expensive and can suffer from vanishing gradients

algorithms have been employed to detect hidden patterns in biometric data, providing a more holistic comprehension of underlying biological processes. The increasing availability of large and diverse data sets propelled the adoption of deep learning techniques in the field of wearable biomonitoring. CNNs and Recurrent Neural Networks (RNNs) have proven effective in extracting features from raw biometric signals and classifying different physiological states, thereby leading to improved accuracy in detecting physiological states and predicting health outcomes. Table 1 provides an overview of how different machine-learning algorithms can be applied to wearable sensor data, highlighting their advantages and potential effects on the performance and reliability of the sensors. The integration of ML in wearable biomonitoring has also enabled the development of real-time monitoring systems. Wearable sensors can now provide continuous monitoring of critical health parameters and alert the user in the case of any deviations, promoting timely interventions and reducing the risk of adverse health outcomes.

The wearable sensor market is expected to continue to expand, driven by an aging population, increasing chronic disease burden, and a growing focus on preventative healthcare.[152−156] As wearable sensors become more widespread, ML algorithms will play a critical role in analyzing the vast amounts of data generated by these sensors. One of the prominent trends in the field of ML for wearable biomonitoring involves the development of personalized health algorithms. These algorithms leverage ML to analyze data from wearable sensors and other sources to generate personalized health profiles, which can help guide health decision-making and treatment planning.[157] Another area of growth for ML in wearable biomonitoring is the development of predictive models. These models harness ML algorithms to analyze data from wearable sensors and other sources to predict future health outcomes such as disease progression or hospitalization. Such models stand poised to transform healthcare management by enabling early identification of health risks and interventions to prevent negative outcomes. Finally, ML is assuming an increasingly important role in advancing our understanding of complex health conditions such as mental illness and sleep disorders. By analyzing data from wearable sensors and other sources, ML algorithms can help identify patterns and correlations in health data that may be missed by traditional methods, advancing our understanding of these conditions and treatments.

The future of ML for wearable sensors holds significant promise, with several areas of development being envisioned on the horizon. One such area is the integration of ML with next-generation wearable sensors.[158,159] These sensors will likely be smaller, thinner, more flexible, and capable of capturing a wider range of physiological data. Another promising avenue for development is the integration of ML with existing wearable biomonitoring technologies, such as electrocardiograms and sleep monitoring sensors, to provide more accurate and comprehensive health assessments. For example, AI algorithms can be used to optimize the power consumption of wearable sensors, by reducing the amount of data transmitted and stored and by improving the efficiency of the algorithms that process the data. This can help extend the battery life in wearable sensors and make them more convenient and user-friendly.

Personalized healthcare is a growing expanding field dedicated to delivering individualized medical treatment based on an individual's unique health profile.[160−168] This approach recognizes that each person's health is influenced by a variety of factors, including genetics, lifestyle, and environmental factors.[169−176] Wearable sensors offer a powerful tool for collecting data on these factors, supplying healthcare providers with a more comprehensive understanding of an individual's health status.[177−185] In tandem, ML algorithms serve as a robust means for analyzing this data, identifying patterns and relationships that may not be immediately apparent to human analysts. By combining wearable sensors with ML algorithms, personalized healthcare providers can develop tailored treatment plans that consider an individual's unique health profile.

Disease tracking and prediction is an important area of research in healthcare, as it can help clinicians identify and respond to health risks before they become more serious.[186−188] By combining ML algorithms with wearable sensors, researchers have developed approaches for disease tracking and prediction that hold significant potential to

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improve the accuracy and effectiveness of these systems.[189−191] Additionally, an increasing interest centers on using ML to personalize health interventions based on an individual's unique physiological profile (Figure 6b). Fiber bioelectronics is a compelling platform for developing advanced wearable sensors, as it enables the integration of sensors into textiles, enhancing flexibility, comfort, and wearability.[192−200] VR interactions represent a cutting-edge application area where wearable sensors can significantly enhance user experience and provide immersive, real-time data visualization and analysis.[201,202] Combining ML and wearable sensors encompasses tailoring recommendations for physical activity, nutrition, and stress management based on real-time data derived from wearable sensors.[203−208] ML algorithms may also be used to detect early signs of disease and predict future health outcomes, helping to inform preventative strategies and improve health outcomes.[123,209−211] Finally, there exists a need to enhance the interpretability and transparency of ML models in the wearable biomonitoring domain. This undertaking will help ensure the reliability of predictions and decisions made by these models, garnering trust from medical professionals and patients alike.

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Notes

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VOCABULARY

Machine Learning (ML):A subset of artificial intelligence that involves the use of statistical models and algorithms to enable computers to perform specific tasks without explicit programming, focusing on making predictions or decisions based on data.

Wearable Sensors:Devices worn on the body that continuously measure and transmit information about bodily functions and external environment, commonly used in healthcare and fitness monitoring.

Supervised Learning:A type of machine learning where the model is trained on labeled data, i.e., data that includes the correct answer, to predict outcomes for new, unseen data.

Unsupervised Learning:A machine-learning technique used to find hidden patterns or intrinsic structures in input data that is not labeled, often used for clustering or association tasks.

Human−Machine Interaction (HMI):The study and design of systems and environments that involve interaction between humans and machines, enhancing user interface and experience through responsive technology.

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