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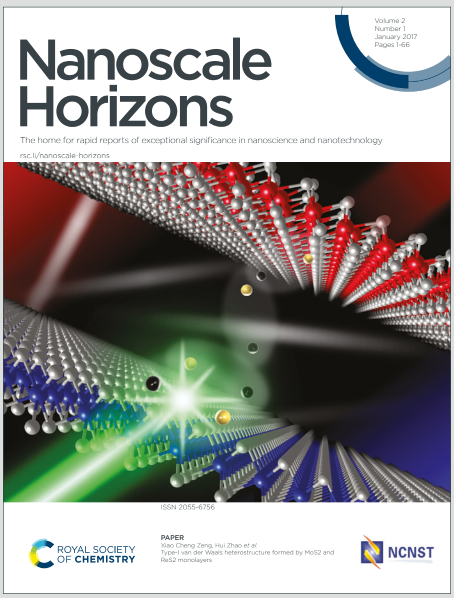

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REVIEW

Advances in Wearable Sensing Technologies and Intelligent Systems for Healthcare and Fitness

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Wearable sensing technologies and intelligent systems have gained significant attention due to their potential to revolutionize healthcare and fitness monitoring. These technologies enable the real-time continuous detection of various physiological and physical parameters, aiding in rehabilitation, fitness optimization, and personalized medicine. Recent advances show the integration of artificial intelligence with wearable sensors and electronics, offering clinical-grade home healthcare, accurate performance monitoring, and feedback-based health management. This review summarizes the latest progress in sensor technologies, device form factors, sensing modalities, data analysis algorithms, integrated electronics, and their applications to human health and fitness.

1. Introduction

In recent years, wearable devices have played a vital role in monitoring and analyzing human factors.[1-3] With key attributes of usability such as portability, miniaturization, and lightweight, as well as sensing performance in their sensitivity, rapid response time, and multifunctionality, wearable sensors have emerged as highly promising tools nowadays. Significant advancements have been made in developing adaptable and flexible wearable technologies that monitor body movements, detect applied pressure, and measure various physiological parameters.[4, 5] Over the past two decades, advancements in sensor and wireless technologies have made significant progress in wearable technologies, making these devices a common part of daily life. These innovations have enabled a wide range of practical applications in healthcare,[6, 7] robotics,[8, 9] the Internet of Things (IoT),[10, 11] and other fields.[12, 13]

In the fitness industry, wearable sensors are revolutionizing performance analysis by providing real-time data for users. This enables trainers, clinicians, or even users themselves to refine training strategies and enhance the overall experience.[14] Various conventional wearable garments, such as shirts, watches, and gloves, enable real-time monitoring of internal and external training loads in health and fitness. However, for these applications to be effective, wearable sensors must be capable of capturing multiple physical and physiological parameters, including strain, pressure, temperature, and bioelectrical signals.[15, 16] These bioelectrical signals, such as electrocardiography (ECG),[17, 18] electroencephalography (EEG),[19] electromyography (EMG),[20] and heart rate (HR)[21] serve as key indicators of physiological states and play a vital role in evaluating human activities. Traditional sensors based on rigid form factors have some disadvantages, including inaccurate signal measurement, which makes them unsuitable for use in large-strain and rough exercising conditions by introducing motion artifacts and even destroying the original signal. Recently, soft skin-like electronics with an intimate interface to the skin provide a wearing experience with increasing recording performance.[22-24] Combining wearable systems with machine learning (ML) algorithms can also enhance their performance. Traditionally, classical algorithms like random forest (RF) and linear discriminant analysis (LDA) have been used to classify physiological signals detected by wearable devices. More recently, neural networks, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have gained attention due to their robustness and ease of implementation.[25, 26] Large datasets improve the knowledge base of these algorithms, while high-quality signals enhance their learning accuracy. As a result, wearable systems integrated with ML have become a key area of research, enabling intelligent systems that not only detect human signals but also analyze and diagnose them.[27, 28]

In this review, we aim to discuss recent progress in wearable sensor development and emerging intelligent systems for advancing healthcare and fitness monitoring, a field with immense potential for further innovation. A particular focus will be on integrating ML models with wearable systems. This article explores the fundamentals of wearable sensors for signal measurement, sensor systems, form factors, the application of academic research trends, and the challenges and future directions of the field. Our review emphasizes the convergence of recent advances in wearable sensor development with emerging ML techniques, focusing on how this synergy is reshaping not only healthcare monitoring but also fitness tracking, including athletic performance, rehabilitation, and sleep monitoring, which is a domain with rapidly growing user engagement

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and substantial potential for further technological innovation. While previous works have primarily focused on health diagnostics and general applications like human-machine interface, our manuscript brings specific attention to fitness and daily well-being-oriented use cases, which are often underrepresented despite being one of the largest markets for wearable technologies. Furthermore, whereas existing reviews often present broad overviews of sensor materials, device structures, or general AI integration, our manuscript critically examines application-specific ML strategies with the most recently advanced frameworks. Finally, we have discussed current issues in the wearable intelligent system to bridge the gap between engineering progress and real-world applications, such as data scarcity, which often require large, diverse, and well-annotated datasets, and emerging solutions that are promising strategies to mitigate data limitations while preserving user privacy. Additionally, we focused on translational trends, including emerging commercial platforms and standards/policy frameworks, to bridge the gap between laboratory innovations and real-world deployment in healthcare and fitness technology. This perspective is not merely descriptive but aims to provide a forward-looking roadmap, with identified challenges and opportunities, particularly in fitness technology, where adaptive and individualized feedback is critical. Fig. 1 provides an overview of this review's structure, including discussions of wearable sensing methodologies, system-level form factors, key ML components, and their applications in sports training, health, rehabilitation, and sleep analysis. The review concludes by summarizing key insights, addressing challenges, and offering recommendations for future research.

2. Wearable Sensing System

The sensing process of a wearable intelligent system typically consists of four main steps: signal acquisition, data processing, data analysis, and assessment (Fig. 2). In this process, wearable sensors detect stimuli from body activities and convert them into electrical signals. A circuit board then records and processes these signals, translating them into meaningful parameters specific to the application. The processed data is either stored in memory or transmitted wirelessly, such as Bluetooth or Wi-Fi, for further analysis. Wearable devices are generally designed to be compact, not only to enhance user experience but also to improve overall performance. However, two major challenges in wearable sensing systems are the nonlinear and unstable sensing signals and signal noise. To address these issues, researchers have discovered improvements in sensor materials, structural designs, and signal processing techniques. Among these approaches, refining signal processing methods remains a widely adopted solution due to its cost-effectiveness and technical efficiency.[29] Following data processing, intelligent embedded ML models analyze the signals to facilitate decision-making. The growing integration of artificial intelligence (AI) with wearable electronics has led to the development of intelligent wearable sensing systems. By leveraging ML algorithms, these systems can conduct more in-depth data analysis, integrate multiple sensor inputs, and optimize algorithm parameters for more accurate predictions. Table 1 denotes the evolution of wearable sensing and learning frameworks over the past decade. The timeline synthesizes major milestones in sensor form factors, AI methods from classical ML to emerging deep learning (DL), and application maturity.

2.1. Target Signals

Physical Signals

Physical signals are essential for detecting both small movements, such as heart rate and respiration, and larger body movements. The most commonly used physical sensors are pressure, strain, and motion sensors, such as inertial measurement units (IMUs). Pressure sensors typically consist of multiple layers, including top and bottom electrode layers with an intermediate sensing layer such as piezoelectric[30] or triboelectric layer.[31, 32] These sensors are widely used in gait analysis and balance assessment, playing a crucial role in monitoring mobility for elderly individuals and patients recovering from injuries.[33] Strain sensors are commonly employed for motion recognition and tracking body, muscle, or chest movements.[34-36] By modifying material structures, these sensors can significantly enhance sensitivity, allowing for precise monitoring of body posture and movement. This capability is particularly valuable in applications such as fall detection, posture correction, and diagnosing movement disorders. IMU sensors integrate an accelerometer, gyroscope, and magnetometer to capture motion data.[37, 38] The accelerometer measures changes in acceleration due to applied forces, the gyroscope detects angular rotation, and the magnetometer determines orientation based on Earth's magnetic field. Additionally, environmental sensors monitor factors such as temperature, humidity, and air quality to assess external influences on health.[39-42]

Physiological Signals

Physiological signals are closely linked to the state of the human body and can be analyzed to quantitatively or qualitatively assess human intentions. These signals, generated by the activity of excitatory nerve or muscle cells, can be noninvasively recorded from the skin surface. Common physiological signals in health monitoring and fitness include ECG, EEG, EMG, photoplethysmography (PPG), and galvanic skin response (GSR).[43, 44] ECG and PPG are widely used for cardiac monitoring, allowing for continuous heart rhythm tracking and providing insights into heart rate variability (HRV).[45-47] ECG plays a crucial role in monitoring athletes' health and performance, optimizing training programs, and assessing overall heart function. EEG sensors measure brain waves by detecting electrical signals from neurons, offering valuable data on brain activity.[48] These sensors, placed at specific locations on the scalp, capture different brain wave frequencies that correspond to various mental states, including sleep, wakefulness, and cognitive focus. EEG data can be particularly useful in evaluating an athlete's concentration, sleep quality, and cognitive performance.[49, 50] EMG systems measure the electrical activity of muscles during contraction and relaxation.[51, 52] As muscle fibers are activated, neurons generate electrical signals that indicate movement or changes in muscle tone. EMG data, which provides insights into muscle contractions and strength, is widely used in rehabilitation therapy and athletic performance optimization. GSR sensors assess stress levels and cognitive states by measuring skin conductance, making them valuable for mental health monitoring and stress management.[53, 54] When an individual experiences cognitive or emotional stress, the sympathetic nervous system (SNS) triggers sweat secretion from the eccrine glands. GSR sensors detect variations in the ionic permeability of sweat gland membranes, providing a reliable measure of physiological arousal and stress responses.[55]

Biochemical Signals

Biochemical signals represent analytes and biomarkers secreted through non-invasive bodily fluids such as sweat and saliva, providing insights into athletic exertion, metabolic demands, and recovery status. Modern wearable biosensors have increasingly targeted key fitness-related biochemical markers, including lactate (as an indicator of anaerobic threshold), glucose (to monitor energy expenditure), electrolytes (to assess hydration), and cortisol (to gauge stress and overtraining risk). These signals are particularly relevant for performance monitoring in athletes and enable new modes of feedback beyond mechanical or physiological sensing alone. State-of-the-art systems leverage electrochemical sensors embedded in soft patches or garments to detect sweat metabolites during physical activity continuously. For example, lactate sensors have been coupled with DL to estimate effort level, while sweat glucose monitors paired with decision tree regression have tracked energy availability.[56, 57] Multi-modal patches can detect sweat rate, chloride concentration, and temperature, offering a holistic view of physiological strain.[58] ML models integrated into these systems enable predictive analytics, such as forecasting fatigue onset or alerting to dehydration.[59] As research progresses, such biochemical platforms are expected to bridge the gap between fitness tracking and clinical-grade metabolic insight.

2.2. Device Design and Form Factors

Wearable sensors are designed in various forms to enhance user comfort and functionality. In the fitness field, these devices are generally categorized into three types based on their materials and physical structure: rigid, textile-based, and soft. Rigid wearable devices, such as smartwatches, fitness trackers, and chest straps, feature solid structures with embedded sensors. While they offer high accuracy and reliable data collection, they may be less comfortable to use for prolonged periods. Textile-based sensors, integrated into garments like smart shirts, socks, and leggings, enable continuous and unobtrusive health monitoring.[60, 61] These sensors incorporate conductive fibers, flexible circuits, and microelectromechanical systems (MEMS) to enhance durability and data precision. They are widely used for applications such as posture monitoring, athletic performance tracking, respiratory assessment, and chronic disease management. Recent advancements have led to the development of soft, skin-like wearable devices.[62, 63] These ultra-thin sensors conform to the skin, providing high-quality signal detection and long-term usability. Beyond mechanical compliance and sensing performance, the translational potential of soft wearable sensors depends strongly on manufacturability. Material choice affects cost, yield, and scalability: natural and common synthetic polymers generally support more mature and scalable processing, whereas hydrogel-based and inorganic-integrated soft systems often face lower reproducibility and tighter manufacturing constraints. However, additive manufacturing methods such as direct ink writing, electrospinning, and 3D printing offer scalable patterning and microstructural control, cost-effective high-throughput production and batch consistency remain key challenges. Packaging reliability is equally critical for long-term use, as inadequate encapsulation under sweat, moisture, heat, and repeated deformation can cause signal drift, leakage, corrosion, delamination, and device failure, while also compromising skin compatibility. Therefore, encapsulation should be regarded as an integral design consideration rather than a secondary packaging step.

Rigid Device

Many wearable devices are designed with rigid structures to withstand impacts, falls, and compression that may occur during activities.[64, 65] In rigid sensor designs, a significant portion of the device is dedicated to protecting the system from mechanical damage while ensuring that the sensor remains securely positioned for accurate data collection. Fig. 3(A) illustrates a portable robotic glove developed to assist individuals with functional grasp impairments during rehabilitation.[66] The glove features soft actuators made of molded elastomeric chambers reinforced with fibers, enabling precise bending, twisting, and extending movements when pressurized with fluid. These actuators are mechanically programmed to align with the natural range of motion of individual fingers, allowing users to safely interact with everyday objects while providing qualitative evaluations of their rehabilitation progress. Fig. 3(B) shows 3D-printed, personalized, multifunctional electronic eyeglasses.[67] These wearable glasses are manufactured using fused deposition modeling with polylactic acid as the primary material, allowing for customization of shape and size to match individual facial features. Highly conductive, flexible electrodes composed of carbon nanotube/polydimethylsiloxane (CNT/PDMS) composites are integrated into the glasses, enabling wireless and continuous EEG signal monitoring near the ears and eyes. The device maintains stable and reliable contact with the skin through an adjustable spring-coupled mechanism, ensuring consistent performance across different facial structures.

Textile Device

Textile-based devices are typically created by embedding conductors, specialized fibers, and other electronic components into the fabric using techniques such as weaving, embroidery, or knitting.[60, 68, 69] Among these methods, the simplest and most common approach is attaching sensors directly to the textile surface.[70] This can be done by sewing or gluing conventional sensors onto the fabric. To enable functionality, transmission lines are integrated into the textile using conductive threads or a cable-drawing technique. Fig. 3(C) displays an example of a fabric-integrated garment capable of wirelessly sensing the wearer's movements.[71] This garment features a passive inductor-capacitor (LC) sensor made of electrically conductive textile elements that detect strain and communicate via inductive coupling. The passive LC textile sensor consists of an inductor sewn with conductive thread and a parallel-plate capacitor fabricated from stretchable conductive textiles, all interconnected through conductive haberdashery. A Colpitts oscillator-based frequency reader is placed in the garment's pocket to wirelessly detect these strain-induced capacitance variations. Another approach to integrating sensor properties into textiles involves modifying the textile surface itself. This can be achieved through chemical or mechanical alterations during the production of cationic yarns or fibers, making the fabric responsive to external stimuli. Alternatively, post-production techniques such as dyeing, coating, or lamination can transform textiles into functional sensors. Fig. 3(D) shows an example of this approach, featuring MXene-coated cellulose-based yarns for textile-based pressure sensing.[72] By coating cellulose yarns with Ti_3C_2Tx MXene, highly conductive and electroactive fibers are produced, which can be knitted into textiles using industrial knitting machines. These yarns exhibit high conductivity (up to 440 S cm^{-1}) and a specific capacitance of 759.5 mF cm^{-1}. Additionally, they offer a gauge factor of 6.02, a broad sensing range of up to 20% compression, and mechanical stability, making them highly suitable for wearable sensing applications.

Soft Device

Measurements in soft wearable technologies are based on the surface's deformation. Compared to traditional devices, soft sensors are more suitable for continuous motion tracking and physiological signal monitoring. Their close contact with the skin allows for real-time data collection without motion artifacts that could distort original signals.[73] Soft electronic-skin (E-skin) sensors are typically designed by integrating conductive elements into a soft, stretchable substrate, such as silicone.[74, 75] One common approach involves modifying conventional rigid metals (gold, silver, copper) into specific structures, such as serpentine/wavy patterns[76, 77] or island-bridge.[78, 79] These structural modifications enable the metal layers to accommodate mechanical strain while preserving or altering electrical conductivity. Fig. 3(E) shows a fully integrated, stretchable, and wireless skin-conformal bioelectronic system.[55] The design features mesh-patterned nanomembrane sensors that make direct contact with the skin, along with a stretchable wireless circuit incorporating miniaturized chips for portable stress monitoring through GSR signal measurements. A soft elastomer coats and permeates the device layers, ensuring natural adhesion to the skin while also providing structural support for the stretchable platform. Another approach leverages intrinsically stretchable conductive materials. Using advanced materials such as hydrogels,[24] nanocomposites, and stretchable polymers, these devices maintain their functionality while offering enhanced flexibility and durability. Fig. 3(F) presents piezoresistive strain sensors capable of detecting both strain and pressure by employing a laser patterning, graphite conversion, and polymeric transfer process.[80] The resulting sensors demonstrate a gauge factor of 37 and a pressure sensitivity of 0.088 kPa^{-1}, which can sustain strains of up to 70%. Additionally, the sensor films exhibit self-healing properties even under significant deformations. The strain sensors successfully measured human pulses, detected finger pressure and bending, and assisted a robotic arm in gripping and releasing operations. These findings suggest their potential integration into wearable electronics, including artificial skin and robotic systems.

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2.3. Discussion

While soft, skin-conformal electronics offer evident advantages in conformability and motion-artifact suppression, a critical assessment reveals important trade-offs. Rigid wearable platforms benefit from well-established manufacturing processes and robust mechanical protection; however, their limited skin contact and susceptibility to motion-induced signal artifacts under high-strain conditions represent fundamental limitations for electrophysiological monitoring during vigorous exercise.[81] In contrast, soft and stretchable systems achieve intimate skin coupling that minimizes motion artifacts and supports continuous wear, yet they remain challenged by fabrication scalability, susceptibility to sweat-induced delamination, and long-term electrochemical stability.[82] The selection of form factor is therefore not a matter of absolute superiority but one of application-specific optimization.

3. Intelligent Systems

3.1. Traditional Machine Learning Models

In the realm of wearable sensing technology, traditional ML models remain widely used due to their ease of implementation and effectiveness in tasks such as classification,[83] regression,[84] and dimensionality reduction.[85] These algorithms enable key functionalities in wearable fitness devices, including activity recognition, physiological signal analysis, and movement pattern classification, which are essential for applications in rehabilitation, bio-health monitoring, and real-time fitness tracking. Below, we provide an overview of widely used traditional ML algorithms relevant to wearable fitness sensing.

Decision Tree

A decision tree (DT) is a hierarchical model that sequentially splits data into subgroups based on feature values, forming a tree-like structure where decision nodes apply conditions, and leaf nodes provide final classifications or predictions. The tree is built using a recursive process called recursive partitioning,[86] where the dataset is divided based on a feature that maximizes class separation. Common splitting criteria include Gini impurity, which measures classification uncertainty, and entropy, which quantifies the dataset's disorder. DTs require minimal preprocessing and are highly interpretable since their structure reflects logical decision-making. However, they tend to overfit when the tree grows too deep, capturing noise rather than generalizable patterns. To prevent this, pruning techniques such as limiting tree depth or setting a minimum number of samples per split are applied.

Random Forest

To address overfitting in DTs, Random Forest (RF) enhances model robustness by employing an ensemble learning approach. Instead of relying on a single tree, RF generates multiple decision trees using bootstrap sampling (bagging), where each tree is trained on a randomly selected subset of the dataset. Additional randomness is introduced by selecting a random subset of features at each split, reducing the correlation between trees and improving generalization. As illustrated in Fig. 4(A), the final prediction is determined by majority voting for classification or averaging for regression.[87] This approach significantly improves stability and accuracy, making RF more resistant to noisy fitness data. However, it requires greater computational resources due to the large number of trees that must be trained and stored.

Support Vector Machine

Support vector machine (SVM) is a classification algorithm that constructs an optimal hyperplane to separate data points into distinct classes while maximizing the margin, or distance, between the hyperplane and the closest data points from each class, known as support vectors (Fig. 4(D) left). A wider margin improves generalization, making the model more robust to new data. When data is linearly separable, SVM finds a straightforward dividing hyperplane. However, for non-linearly separable data, SVM applies the kernel trick to transform input features into a higher-dimensional space where a linear separation exists (Fig. 4(D) right).[88] Common kernels include linear, polynomial, and radial basis functions (RBF), each suited for different data distributions. SVM performs well with structured, high-dimensional data, but it can be computationally expensive for large datasets and requires careful tuning of kernel parameters to achieve optimal performance.

K-Nearest Neighbors

Unlike parametric models, K-nearest neighbors (KNN) is a non-parametric, instance-based learning algorithm that classifies new data points based on their similarity to existing examples. Rather than building an explicit model, KNN stores all training instances and assigns a class label to new data based on the K closest neighbors (Fig. 4(B)),[89] determined using distance metrics such as Euclidean distance (for continuous data) or Manhattan distance (for grid-like data). KNN is simple, adaptable, and requires minimal training effort; however, it is computationally expensive during inference since it must calculate distances for all stored data points. Additionally, KNN is sensitive to noise and irrelevant features, making feature selection crucial for optimal performance. The choice of K (the number of neighbors considered) significantly affects accuracy; too small a K can lead to overfitting, while too large a K can smooth out important distinctions between classes.

Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a probabilistic classification model that is also widely used for dimensionality reduction. Unlike SVM, which relies on geometric margin-based separation, LDA models the probabilistic distribution of each class and computes decision boundaries based on statistical properties. This algorithm is illustrated in Fig. 4(C), which starts by calculating class means and the overall mean across all data points. It then computes two key matrices: within-class scatter, which measures data variability within each class, and between-class scatter, which captures how distinct the class distributions are. LDA optimizes a transformation that maximizes class separation while minimizing within-class variation.[90] Once data is projected into the lower-dimensional space, classification is performed based on the new feature representation. LDA is particularly useful when working with high-dimensional fitness data, as it reduces the number of input features while preserving classification accuracy. However, its effectiveness depends on the assumption that class distributions follow a Gaussian distribution with equal covariance matrices, which may not always hold in real-world fitness measurement scenarios.

Applications

Traditional ML algorithms are vastly used for their proven reliability and performance for a variety of tasks surrounding applications related to gesture classification, bio-health assessment, and many others. Fig. 5(A) demonstrates the application of LDA for real-time speech classification using a mechano-acoustic epidermal sensor.[91] This device simultaneously captures EMG signals from articulatory muscles and acoustic vibrations from the vocal cords, providing a multimodal approach to speech recognition. Prior research suggests that integrating multiple sensor modalities can enhance classification accuracy, especially for users with speech impairments. Unlike traditional microphones, which are susceptible to environmental noise, the epidermal sensor maintains performance even in loud settings due to its skin-mounted design. In this study, LDA is employed to classify four isolated speech commands: “left,” “right,” “up,” and “down” for controlling a Pac-Man game. This algorithm shows an overall classification accuracy of 90%, demonstrating LDA’s capability to effectively differentiate speech signals. Fig. 5(B) demonstrates the utilization of EOG sensors for the purpose of eye movement classification.[92] To classify nine distinct eye movement states for human-machine interaction, an SVM algorithm was implemented to train and classify signals collected from more than 50 cycles per movement state. As shown at the bottom of Fig. 5(B), the dataset was split evenly, with 50% of the data used for training and the remaining 50% for testing. Prior to classification, preprocessing steps such as peak detection and signal segmentation were applied to extract valid features from continuous periodic signals. A threshold-based approach was used to identify and cluster signal points corresponding to each eye movement, ensuring precise segmentation. Each segmented movement signal was then converted into a standardized single-cycle dataset to mitigate baseline drift and variations in signal intervals. The SVM classifier was trained on these processed signals and evaluated for performance. This classification method demonstrates an average classification accuracy of 92.6%, indicating the robustness of SVM in distinguishing between eye movement states. However, due to similarities in frequency between up-blinking and normal blinking, 27.3% of up-blinking signals were misclassified, slightly reducing overall accuracy. Despite this limitation, the SVM-based classification approach successfully enables accurate and contactless tracking of eye movements, showcasing its potential for seamless 2D (XY-axis) human-machine interaction in wearable electronic systems. Fig. 5(C) is from a study that presents an integrated system for decoding facial movements using conformable piezoelectric thin films, computational modeling, and real-time classification algorithms.[93] The system enables accurate strain mapping on soft, curvilinear surfaces, making it suitable for nonverbal communication and neuromuscular monitoring. A key component of this system is the creation of a customizable motion library where users can define distinct facial motions for communication. As illustrated in Fig. 5(C), different mapping strategies—including direct, tree-based, and conditional mapping—affect the number of possible expressions or actions that can be inferred from a set of seven facial motions. To classify these motions, the system employs a K-nearest neighbors with dynamic time warping (kNN–DTW) algorithm. Instead of relying on absolute voltage values or principal component analysis, kNN–DTW classifies facial motions by comparing the shape of voltage waveforms captured from multiple sensing elements on the device. The algorithm computes distances between detected voltage waveforms and those in the training set using a fast approximation of DTW, which coarsens the temporal resolution, computes a warped distance matrix, and refines it back to a finer resolution. This classifier was modified to calculate at k=3 nearest neighbors; these motion labels are used to compute weighted-average probabilities, ultimately assigning the most probable label to the detected motion. This approach enables real-time, user-customizable facial expression decoding, enhancing the system's potential for nonverbal communication and assistive technologies.

3.2. Deep Learning Models

Despite the increasing application of ML, particularly DL, in image processing, natural language processing (NLP), and audio analysis, research on DL for wearable healthcare devices remains relatively limited compared to traditional ML approaches.[94] In Fig. 6, we introduce major approaches of DL algorithms for wearable devices. Biosignals such as ECG, EEG, and EMG are inherently time-series data with complex temporal dependencies, non-stationarity, and inter-subject variability, making them more challenging to model using DL.[95] Unlike structured data in computer vision (CV) and NLP, biosignals lack fixed spatial structures and exhibit irregular patterns, requiring different methodological approaches. To address these challenges, various studies have explored ways to improve biosignal analysis using DL [95]. Some focus on developing models specifically designed for time-series data to better capture temporal dependencies, while others transform biosignals into alternative representations, enabling the use of DL models originally developed for other domains. These approaches aim to improve feature extraction, classification accuracy, and overall performance in healthcare applications. Another major limitation in this field is the availability of high-quality data and concerns over patient information security. Many studies highlight the difficulty of obtaining large, diverse datasets while ensuring compliance with privacy regulations. However, in recent years, an increasing amount of wearable healthcare data has been collected, along with efforts to improve data management efficiency.[95] This growth reflects the recognition of DL's potential in personalized medicine and real-time health monitoring. DL models, with their ability to extract hierarchical features directly from raw data, have demonstrated promising results in medical applications, particularly in classification, prediction, and anomaly detection. As research in this area continues to advance, DL-based approaches offer new opportunities to uncover complex patterns and enhance diagnostic and prognostic accuracy in healthcare. Below, we provide various DL algorithms relevant to wearable device applications.

Convolutional Neural Networks

Convolutional neural networks (CNNs) are widely used in biosignal analysis for wearable healthcare and sports applications due to their ability to automatically extract hierarchical features (Fig. 6(A)).[96] Their structure consists of convolutional layers that apply learnable filters to capture spatial and temporal dependencies, activation functions such as ReLU to introduce non-linearity, pooling layers for dimensionality reduction, and fully connected layers for classification. These components work together to enable efficient feature learning without requiring manual feature selection. In wearable device applications, 1D-CNNs process raw time-series biosignals such as ECG, EEG, EMG, and IMU signals, effectively capturing temporal patterns for real-time health monitoring and motion analysis. Meanwhile, 2D-CNNs operate on spectrogram representations of biosignals, enabling the use of image-based DL models to extract both temporal and frequency-domain features. This enhances classification accuracy in tasks such as sleep stage detection, seizure identification, and athlete performance tracking. CNNs offer advantages such as parameter sharing, reduced computational cost, and adaptability to various data formats, making them well-suited for wearable healthcare and sports monitoring applications.

Recurrent Neural Networks

Recurrent neural networks (RNNs) are designed to process sequential data by maintaining memory of previous inputs through recurrent connections (Fig. 6(B)).[97] They capture temporal dependencies by preserving information across time steps, making them effective for analyzing time-series data. However, traditional RNNs struggle with learning long-range dependencies due to the vanishing gradient problem, which can limit training stability and performance. To address this, Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have been introduced.[98, 99] LSTMs use input, forget, and output gates to regulate information flow, helping retain long-term dependencies, while GRUs offer a simplified structure with fewer parameters, making them computationally efficient for real-time healthcare monitoring applications. In wearable healthcare and sports applications, RNNs are widely used for time-resolution-dependent tasks due to their ability to model dynamic patterns over time. Recent studies have explored CNN-RNN hybrid models, which combine CNNs' ability to extract spatial features with RNNs' strength in sequential modeling. In these models, CNNs first process raw biosignals or spectrograms to identify spatial patterns, and the extracted features are then passed to RNN layers, such as LSTMs or GRUs, to capture temporal dependencies. This hybrid approach has been applied effectively in tasks where both spatial and temporal patterns are essential.

Transformers

Transformers are DL architectures designed to model sequential data using a self-attention mechanism instead of recurrent structures of RNN (Fig. 6(C)).[100] This approach enables transformers to process entire sequences in parallel, improving efficiency and scalability relative to RNNs and handling sequences sequentially. The self-attention mechanism allows the model to assign varying importance to different time steps, capturing both local and global dependencies without suffering from vanishing gradients. Positional encoding ensures that sequential relationships are preserved despite the parallel nature of the computations. Although transformers are still emerging in healthcare applications, transformer architectures have high potential for analysis in the healthcare and sports domains [101]. Their ability to model complex temporal relationships exploits high performance and efficiency for healthcare and sports domain data processing. However, their higher computational requirements pose challenges for deployment on resource-constrained devices, which is why transformers are not widely adopted in healthcare. Ongoing research focuses on developing efficient transformer architectures tailored for sequential data, improving biosignal adaptability while reducing computational demands. Advances in self-supervised learning and domain adaptation are also being explored to enhance transformer performance in data-limited environments. Advanced transformer models in the near future are expected to contribute to robust and scalable DL solutions for bio signal analysis, enhancing the accuracy and reliability of healthcare and sports applications.

Applications

In Fig. 7, DL has transformed wearable healthcare and sports monitoring by enabling automated feature extraction from sensor-based time-series data. Wearable devices equipped with accelerometers, gyroscopes, and biosensors generate vast amounts of data, requiring robust models for real-time processing. This paper explores DL applications in wearable systems, including activity recognition, sports performance analysis, and sensorimotor learning. Fig. 7(A) demonstrates the study of CNN with a waist-mounted wearable device for human activity recognition utilizing DL.[102] Unlike conventional wearable devices that are not designed for individuals with restricted arm movement, the proposed system enhances activity detection by leveraging a more stable placement. The proposed system enhances activity detection by leveraging a more stable placement. The device integrates an inertial sensor system, including a microcontroller, a three-axis accelerometer, and a three-axis gyroscope, to precisely capture motion signals. The HAR framework consists of motion signal acquisition, signal normalization, and automated feature extraction and classification using a 1D CNN. This DL model exploits the benefit of automatically customized features to individuals by learning representative patterns directly from raw sensor data. They trained and tested on a combination of the University of California (UCI) dataset and newly collected data from 21 participants performing six predefined activities: walking, walking upstairs, walking downstairs, sitting, standing, and lying. The proposed model achieved training accuracies of 98.93% (UCI) and 97.19% (recorded data) and test accuracies of 95.99% and 93.77%, respectively. The CNN-based algorithms show high classification accuracy, enabling real-time and reliable monitoring of human movement patterns. The results demonstrate the effectiveness of the CNN-based approach with real-time monitoring and precise classification. Fig. 7(B) demonstrates the application of DL models for analyzing badminton strokes using a multi-sensor dataset developed in consultation with coaches to ensure practical relevance.[103] The dataset consists of 7,763 stroke samples from 25 players across different skill levels, integrating eye tracking, body tracking, muscle signals, foot pressure, video recordings, and detailed annotations to capture biomechanical variations. DL models, including Conv-LSTM, Long Short-Term Memory (LSTM), and Transformers, were applied to extract sequential patterns from sensor data and evaluate the dataset's effectiveness. These models classify stroke types and player proficiency directly from raw motion data, eliminating the need for handcrafted features. Model performance was assessed using accuracy, balanced accuracy, and F1-score, with validation conducted through 10-fold cross-validation and leave-three-out (LTO) cross-validation to ensure generalizability across skill levels. The study presents the LTO cross-validation results for stroke type and skill-level classification, demonstrating the effectiveness of DL models in capturing complex movement patterns. Among the models tested, Conv-LSTM outperformed other architectures in stroke type classification, achieving the highest accuracy (90.03%), balanced accuracy (90.07%), and F1-score (89.99%). For skill-level classification, LSTM demonstrated superior performance, with the highest accuracy (46.56% for clear, 46.98% for drive), balanced accuracy (48.35% for clear, 47.02% for drive), and F1-score (44.92% for clear, 44.56% for drive). These results show that DL enables precise motion classification and real-time performance assessment, making it a valuable tool for data-driven training in sports science. Fig. 7(C) demonstrates the study of substrate-less nano-mesh receptors integrated with a DL framework to enable user-independent, data-efficient motion recognition.[104] Advanced electronic gloves and skins without bulky devices leverage biocompatible nano-mesh sensors that conform to the skin, mimicking cutaneous receptors by detecting electrical resistance changes from fine skin movements. The nano-mesh sensor enables precise finger and hand gesture tracking, and the DL approaches enable gesture recognition, keyboard typing, and object classification. A transformer-based DL model was performed as a contrastive learning algorithm to distinguish between unlabeled motion sequences. The transformer approach utilizes few-shot learning, allowing the model to adapt to new gestures and users without additional training. The study demonstrates that even with a limited number of labeled samples, DL effectively generalizes across tasks, achieving 85% accuracy within 20 transfer epochs in numpad typing recognition. Additionally, the model was capable of full QWERTY keyboard typing, accurately differentiating left- and right-hand signals. The transformer-based inference mechanism refined its predictions over multiple interactions. The model classified objects with 82.1% accuracy within 20 transfer epochs, significantly reducing the need for extensive labeled datasets compared to supervised methods. These results highlight the effectiveness of advanced DL in this study. The transformer-based approach in wearable devices efficiently extracts motion features, adapting with minimal labeled data, and improves classification accuracy across tasks. As a result of applying transformer-based DL with contrastive embeddings, the model overcomes the limitations of conventional sensor-based systems and plays a critical role in significantly enhancing motion recognition with efficient training. Table 2 summarizes the comparison of traditional ML and DL models utilized in intelligent sensing systems, highlighting their strengths and limitations.

3.3. Recent Advances in ML Models

Despite their demonstrated performance on benchmark datasets, the deployment of deep learning architectures in real-world wearable contexts is constrained by challenges that have received insufficient attention. CNNs and LSTMs exhibit substantial performance degradation under distribution shift, when evaluated on individuals or environments not represented in the training set, a concern acutely relevant for personalized fitness and clinical applications.[105] Transformer-based architectures introduce prohibitive computational overhead for direct deployment on wearable MCUs without aggressive compression, but with measurable accuracy trade-offs. Furthermore, the near-universal lack of explainability in deployed wearable AI represents a critical barrier to regulatory approval and clinician trust.[106] Explainable AI (XAI) methods such as Grad-CAM, SHAP, and attention visualization are beginning to be applied in this domain,[107] but rigorous clinical validation of their explanations remains limited. To illustrate the practical role of XAI in wearable sensing, we added two representative case studies. First, in sleep apnea detection, attention heatmaps on Flow and SpO_2 signals highlight clinically relevant respiratory events, improving interpretability and clinician confidence in AI-assisted diagnosis.[108] Second, in wearable human activity recognition, SHAP analysis identifies the most informative sensor locations, supporting optimized sensor placement and more interpretable movement analysis in fitness and rehabilitation applications.[109] In practical terms, this type of XAI output can support system-level decision-making by identifying the most informative sensor placements, reducing hardware redundancy, and improving the interpretability of movement analysis in fitness coaching, rehabilitation monitoring, and assistive human–machine interaction.

Advanced machine learning models in wearable sensor domains have progressed slowly compared to fields like computer vision and natural language processing. This lag is primarily due to the complexities of bio signal data, such as inter-subject variability and scarcity of large, labeled datasets. However, increased access to annotated datasets, improved sensor technologies, and novel algorithms specifically tailored for bio signal data have accelerated the adoption of sophisticated models. Recently, in soft wearable bio signal studies, advanced ML models such as ConvLSTM, Graph neural networks (GNNs), and various generative models, including Autoencoders, Generative adversarial networks (GANs), and diffusion-based models, are increasingly adopted to capture complex temporal dynamics, achieving high performance to monitor and translate the bio signal. Table 3 summarizes recent advances in ML models utilized in intelligent sensing systems.

ConvLSTM

ConvLSTM architecture combines convolutional feature extraction with LSTM-based temporal modeling, effectively preserving localized signal patterns while managing long sequential dependencies. They have been applied to tasks such as cuffless blood pressure estimation, using fused PPG and ECG inputs to capture both spatial and temporal dynamics.[110] ConvLSTM models are also effective in activity recognition from wearable motion sensors by capturing rich spatiotemporal features.[111]

Graph Neural Networks

GNNs explicitly model spatial relationships among bio signal channels, enabling effective spatiotemporal learning. Recent approaches, such as GraphS4mer, have combined GNNs with structured sequence modeling to improve performance across EEG, ECG, and sleep-stage classification tasks.[112] Additionally, graph attention networks enhanced by feature selection and residual learning have shown improvements in activity recognition.[113] A key limitation is the requirement for predefined graph structures or sensor topology, which may not generalize across datasets or applications.

Autoencoders

Autoencoders efficiently encode bio signals into latent representations, supporting anomaly detection and signal reconstruction, yet might neglect essential temporal contexts. For instance, convolutional autoencoders have been applied to ECG for morphological analysis.[114] In another study, autoencoders have enabled disentangled learning for detecting abnormalities in single-lead ECG.[115] However, autoencoders have limitations that underutilize temporal dependencies in sequential signals.

Generative Adversarial Networks

GANs generate synthetic biosignals to address data imbalance and enhance model training. Conditional GANs have successfully synthesized IMU sequences for therapeutic activity recognition and augmented the Human Action Recognition (HAR) dataset using spatiotemporal features.[116, 117] However, training remains sensitive to instability, especially in bio signal domain.

Diffusion Models

Diffusion models iteratively refine noise into realistic bio signals, offering potential for augmentation, denoising, and imputation. For example, diffusion-generated inertial sensor data improved HAR accuracy under scarce data conditions, and synthetic biosignals have shown promise in enhancing classification robustness.[118, 119]

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Nonetheless, their high computational cost limits current on-device or real-time applications.

Foundation Models

Foundation models have emerged as a promising solution in biosignal analysis, enabling large-scale pretraining on diverse physiological signals to learn generalized representations. These models, often Transformer-based, can be fine-tuned for wearable tasks, significantly reducing the need for labeled data and improving cross-subject generalization. For example, NormWear, a foundation model trained on multimodal signals, including ECG, EEG, GSR, and IMU, demonstrated enhanced performance across several health-related applications.[120] Similarly, Pulse-PPG, an open-source PPG foundation model, achieves strong results in cardiovascular health monitoring and sleep disorder detection.[121]

4. Recent Studies of Wearable Devices and Intelligent Systems for Fitness Monitoring

4.1. Athletic Performance Analysis

Table 4 summarizes wearable systems used for athlete performance analysis, detailing sensor types, device forms, measurement locations, ML models, and learning objectives. Wearables range from soft patches, wristbands, gloves, and watches to motion capture systems, integrating IMU, ECG, PPG, strain sensors, and electrochemical biosensors. DL models (CNN, LSTM) and traditional ML methods (SVM, RF, LightGBM) enhance motion classification, injury detection, and physiological monitoring, demonstrating data-driven advancements in athletic performance analysis. Fig. 8(A)-(D) demonstrates wearable devices, including soft devices, designed for athlete monitoring by capturing biomechanical, physiological, and biochemical data.[103, 122] Fig. 8(A) presents a liquid-metal-based stretchable sensor that measures strain and pressure during movements like punching and bending, providing real-time biomechanical feedback and feeding these signals into a CNN model trained on 150 labeled punch sequences, enabling 90.5 % accurate recognition of jabs, swings, uppercuts, and combination punches.[123] Fig. 8(B) introduces a saliva-based biosensor embedded in a mouth guard, with non-invasive tracking of hydration, stress, and fatigue biomarkers. Chronoamperometric signals show a correlation with laboratory lactate assays (r = 0.988). Also, the study demonstrates that time-series biochemical data can be modeled using regression and SVM to learn athlete-specific dehydration or predict over-training risk. [122]. Fig. 8(C) illustrates IMU-based badminton stroke motion tracking to analyze their movements, leveraging the publicly released 7,700 strokes data involved MultiSenseBadminton dataset. Various ML model (Transformer, ConvLSTM, LSTM) was exploited to classify into three categories (Stroke type, Clear skill level, and Drive skill level) and achieved more than 90% accuracy in classifying for strike types by the ConvLSTM model.[103] Fig. 8(D) demonstrates a piezoresistive wearable sensor applied to joint-motion tracking, detecting strain variations to support injury prevention, with raw resistance waveforms processed by an LSTM-based model. The proposed ML model achieved 99.25% action-classification accuracy and 98.75% posture-correction accuracy across push-up, shoulder press, fly, and curl exercises.[124] Fig. 8(E)–(F) demonstrates DL models applied to athlete monitoring.[124, 125] Fig. 8(E) outlines a 4-layer CNN architecture for an activity recognition pipeline, using 6-IMU sensors (chest, hand, and foot) effectively distinguishing movement patterns such as squats, dips, and pull-ups, and achieved the best accuracy as 92% in its best configuration with an overlapping window and raw data setting. The study highlights the MLmethods outperforms all traditional baselines.[125] Fig. 8(F) presents an LSTM-based DL model, which processes sequential biomechanical data, enhancing motion recognition for training optimization.[126] Also, the training curve in the same figure shows the ML models' classification accuracy during training, illustrating a steady rise in accuracy and rapid network convergence with no sign of overfitting. The integration of DL models with wearable devices enhances real-time performance monitoring and precise movement classification, without bulky, wired devices that can potentially distract professional athletes during training. By leveraging CNNs and LSTMs, these systems provide data-driven training optimization, injury prevention with real-time monitoring, and personalized athlete development for training.

4.2. Rehabilitation and Assistive Technologies

In Table 5, we introduce a comparative list of studies in the field of wearable sensing technology for rehabilitation; these include the types of sensors that were used, device form factor, ML models used, and others. In Fig 9, we introduce three studies in particular to discuss in a little more depth. Fig. 9(A) highlights a study that introduces a remote quantitative Fugl-Meyer assessment (FMA) framework for stroke patients, leveraging wearable sensor networks to facilitate rehabilitation outside traditional clinical settings.[127] This framework utilizes two accelerometers and seven flex sensors to monitor upper limb, wrist, and finger movements, aiming to quantify motor function impairments more efficiently. A key innovation in this study is the application of an extreme learning machine (ELM) based ensemble regression model to map sensor data to clinical FMA scores. By incorporating the RRelief algorithm, the system identifies optimal feature subsets, enhancing prediction accuracy. Given the complexity and time-consuming nature of traditional FMA assessments, the researchers designed seven training exercises as a streamlined alternative to the full 33-item upper limb FMA scale. The study involved 24 stroke inpatients in a clinical setting and was later extended to 5 patients in home settings (demonstrating the feasibility of remote rehabilitation). Experimental results showed a high correlation (R^2 = 0.917) between predicted and actual FMA scores, displaying the reliability of this approach. While the Remote Quantitative FMA framework represents a meaningful step toward objective, home-based stroke rehabilitation monitoring, a balanced appraisal reveals several challenges. First, the system inherits the ceiling effects and limited sensitivity of the original FMA scale. Second, ML models trained under controlled laboratory conditions raise concerns about robustness to real-world variability. Third, no large-scale prospective validation has been performed in clinically diverse post-stroke populations.[128, 129] These limitations underscore the need for rigorous clinical validation studies before remote FMA systems can be responsibly deployed as clinical assessment tools. This study is an example of how machine learning-enabled wearable rehabilitation systems can enhance the accessibility and efficiency of

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stroke recovery monitoring. By reducing the need for in-person assessments while maintaining clinical accuracy, this type of framework can play a crucial role in the future of telerehabilitation. Fig. 9(B) presents a study that introduces a smart-shoe-based, long-term Center of Pressure (CoP) monitoring system designed to overcome the limitations of conventional CoP evaluation methods.[130] CoP is a critical metric for assessing postural stability, particularly in individuals with neurological diseases and movement disorders such as Alzheimer's disease, Parkinson's disease, and chronic ankle instability. However, traditional CoP assessment methods rely on lab-based equipment or clinical evaluation procedures that are often expensive, complicated, and impractical for long-term use. To address these challenges, the researchers developed a wearable smart insole system that offers continuous CoP monitoring with minimal setup requirements. The thin and flexible smart insole was designed with optimized sensor placement, allowing for accurate CoP estimation while maintaining a compact and energy-efficient design for all-day wear. The system also integrates a smartphone app with cloud-based data management, allowing real-time monitoring and facilitating usage in both clinical and home settings. This study addresses a major barrier in existing wearable sensor-based approaches and develops a calibration-free CoP estimation model. Additionally, a machine learning-based human activity recognition (HAR) method was incorporated to automate the CoP detection process. This research is a significant step forward in wearable rehabilitation technology, enabling continuous CoP tracking for patients undergoing extended recovery processes or those at risk of stability-related disorders. Fig. 9(C) highlights a study that introduces a smart, non-invasive throat sensor designed for oropharyngeal treatment applications, addressing the limitations of conventional videofluoroscopy (VFS) techniques.[131] While VFS remains a standard for assessing throat muscle movement, it exposes patients to radiation, requires costly specialized equipment, and depends on highly trained speech-language pathologists for interpretation. The proposed wearable throat sensor offers an alternative by leveraging ionic polymer–metal composite (IPMC) material to detect muscle movements in a non-invasive and cost-effective manner. The sensor operates based on the movement of cations inside the IPMC material, allowing it to self-generate signals in response to throat muscle activity. The researchers applied a corrosive-resistant gold coating to enhance performance and durability, improving the sensor's output response and longevity. A support vector machine (SVM) algorithm was employed to classify throat movement patterns, achieving an impressive accuracy of 95%. By eliminating the need for radiation exposure and complex clinical procedures, this machine learning-enabled throat sensor is a major step forward for smart healthcare devices.

4.3. Sleep Analysis

Table 6 summarizes wearable systems for sleep analysis, highlighting sensor types, device forms, measurement locations, and ML models applied for tasks such as sleep apnea detection, sleep staging, and insomnia assessment. Wearables range from soft patches and rings to chest-worn and rigid sensors, integrating EEG, EOG, EMG, PPG, ECG, and IMU. DL models (CNN, RNN, LSTM, MTL) and traditional ML methods (SVM, KNN, XGBoost) enhance classification and real-time monitoring, demonstrating advancements in portable, data-driven sleep health analysis. Fig. 10(A)–(D) demonstrates the development of soft wearable sensors designed for non-intrusive sleep monitoring. These devices are strategically placed at different body locations, optimizing signal acquisition for diverse physiological parameters. The sternal bio-patch captures seismocardiogram (SCG), electrocardiogram (ECG), and photoplethysmogram (PPG) signals, enabling the detection of cardiac and respiratory activity during sleep (Fig. 10(A)).[126] The finger-worn device integrates a microcontroller, battery, and sensor system, collecting continuous blood oxygen and pulse wave monitoring through PPG-based apnea detection (Fig. 10(B)).[132] Additionally, wrist-worn wearables track at-home sleep monitoring (Fig. 10(C))[133] while forehead patches collect EEG, EOG, and EMG signals, monitoring brain activity and muscle movements for sleep staging and sleep apnea classification (Fig. 10(D)).[134] These devices provide an alternative to traditional polysomnography (PSG), enhancing accessibility and user comfort in sleep studies. ML models are applied to process and classify the collected biosignals, as illustrated in Fig. 10(E)–(G).[126, 132, 133] DL architectures, including CNN and bidirectional LSTM, are exploited to extract and classify sleep-related features and diseases. Fig. 10(E) demonstrates a residual CNN model, which mitigates the vanishing gradient problem, ensuring deep feature learning for apnea and hypopnea detection. Fig. 10(F) introduces a bidirectional LSTM-based model for sleep stage classification, where hierarchical embeddings capture sequential dependencies in HRV signals.[133] Additionally, (Fig. 10(G)) models sequential relationships in biosignals, enhancing predictive accuracy across different sleep stages. These models enable automated feature extraction and classification, improving diagnostic efficiency.[132] Fig. 10(H) is an example of the effectiveness of DL approaches in sleep-related studies.[135] The effectiveness of these machine learning-enhanced wearables. This study compares the wearable system's sleep stage classification to gold-standard PSG data. The results show high sleep-scoring accuracy (87.50% and 88.19%), confirming the wearable system's high performance. These applications highlight the potential of soft wearables integrated with DL for accessible and accurate sleep monitoring.

5. Conclusions

Future advancements in intelligent wearable sensors will revolutionize health and fitness monitoring by improving materials, enabling automated assessment with AI algorithms, and enhancing energy efficiency.[136] The development of ultra-thin, stretchable, and self-healing materials, along with the integration of nanomaterials, will enhance sensor durability, flexibility, and sensitivity. AI-driven wearables will enable real-time analysis of measured signals, offering personalized health insights and improving predictive analytics for early disease detection and performance optimization. Non-invasive, continuous monitoring will allow tracking not only physiological signals but also analytes in the body, such as glucose and hydration levels. At the same time, multi-modal sensor fusion will enhance diagnostic capabilities. Personalized healthcare and fitness applications will expand, with AI-driven sensors facilitating remote patient monitoring, injury prevention, and rehabilitation. However, multiple challenges remain, including

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accuracy and reliability issues caused by motion artifacts and physiological variability among users.

5.1. Energy Sustainability

Energy efficiency can be improved by integrating energy-harvesting technologies such as triboelectric nanogenerators[137] and biofuel cells,[138] enabling self-sustaining wearable devices with low-power electronics and wireless energy transfer. A critical bottleneck in translating wearable sensing systems from laboratory to real-world deployment is energy sustainability. Self-powered systems that harvest energy from the body's own mechanical, thermal, or biochemical outputs represent a compelling solution. Piezoelectric nanogenerators (PENGs) based on PVDF, $BaTiO_3$, or ZnO nanostructures transduce mechanical strain from joint flexion or footfall into electrical energy, achieving power densities of 1–10 μW cm^{-2} under physiological loading.[139] However, PVDF-based PENGs exhibit fatigue-induced coefficient degradation under prolonged cyclic strain. Triboelectric nanogenerators (TENGs) leverage contact electrification between dissimilar materials and are particularly amenable to textile integration, achieving peak power outputs exceeding 1 mW cm^{-2} during vigorous motion, but exhibit strong frequency- and amplitude-dependent behavior. Thermoelectric generators (TEGs) exploit the Seebeck effect to convert the skin-to-ambient temperature gradient into continuous power, with wearable TEG arrays achieving 1–40 μW cm^{-2} under indoor conditions.[140, 141] Biofuel cells (BFCs) enzymatically oxidize sweat-borne metabolites (lactate, glucose) to generate power densities of 100–200 μW cm^{-2},[142, 143] enabling fully autonomous sweat biochemical sensing patches. Electronic tattoo platforms are uniquely positioned to leverage these modalities: the intimate epidermal coupling of e-tattoo systems maximizes thermoelectric and triboelectric harvesting while enabling enzymatic BFC electrodes to interface directly with the sweat microenvironment.[144, 145]

5.2. Data Security, Privacy Frameworks, and Regulatory Standards

The continuous collection of sensitive physiological and behavioral data introduces security and privacy challenges that are both technically complex and ethically consequential. Wearable devices present multiple potential attack surfaces spanning on-device storage, wireless transmission (BLE, Wi-Fi, NFC), cloud processing, and EHR integration. From a technical standpoint, hardware-level secure enclaves (e.g., ARM TrustZone)[146] and lightweight cryptographic protocols (AES-256, TLS 1.3) are increasingly incorporated into wearable SoCs. Federated learning (FL) has emerged as a principled framework for training shared ML models without centralizing raw personal data.[147, 148] Differential privacy (DP)-guaranteed FL allows quantifiable bounds on privacy leakage,[149] and secure multi-party computation (SMPC) enables collaborative inference. From a regulatory standpoint, in the US, HIPAA requirements govern data encryption, access control, and breach notification.[150] FDA 510(k)/De Novo clearance and the Digital Health Center of Excellence provide guidance on AI/ML-based SaMD.[151] In the EU, the AI Act (Regulation 2024/1689) classifies medical AI as high-risk.[152] CE marking is required under EU MDR (2017/745). Internationally, ISO 13485 governs QMS for medical device manufacturing,[153] and the IEEE 11073 (X73) standard specifically addresses personal health device communication.[154]

5.3. Ethical Considerations and Clinical Adoption Barriers

The translation of wearable sensing technologies to clinical deployment involves not only technical readiness but also ethical, regulatory, and sociotechnical barriers. Algorithmic fairness and dataset representativeness present a fundamental ethical challenge: most wearable ML studies have been conducted on demographically homogeneous populations, yet physiological signal properties vary significantly with age, sex, body composition, and skin melanin content. PPG-based SpO_2 monitoring has been shown to exhibit significantly lower accuracy in patients with dark skin tones, a form of algorithmic bias with direct clinical consequences.[155, 156] Prospective validation studies must mandate reporting of disaggregated performance metrics across demographic subgroups. Informed consent and data autonomy represent a second dimension of ethical complexity. The continuous, passive nature of wearable data collection raises concerns about meaningful informed consent. The emerging concept of dynamic consent frameworks, which allow individuals to granularly control data sharing permissions, offers a promising but operationally immature solution.[157, 158] Clinical validation and regulatory pathways constitute perhaps the most significant practical barrier to adoption. The FDA's Predetermined Change Control Plan (PCCP) framework for adaptive AI/ML medical devices[159] represents a potentially enabling mechanism that allows planned modifications to approved AI models without requiring full re-submission, and its application to wearable SaMD is an important area for future regulatory development.

Data privacy concerns regarding sensitive health data storage and ethical questions about data ownership and third-party access require strict regulatory compliance. Data security can be strengthened through blockchain technology and encrypted data transmission, reducing risks associated with cloud-based storage.[160] As standardizing data formats and communication protocols is crucial for interoperability, seamless integration with healthcare systems remains a challenge. It is also critical issue of data scarcity, especially for training DL models, which often require large, diverse, and well-annotated datasets. Emerging solutions such as Federated learning (FL) and synthetic data generation as promising strategies to mitigate data limitations while preserving user privacy. For example, FL enables collaborative model training across users' devices without centralizing data.[161] Nurse-stress prediction using FL on wearable biomechanical data achieved >90% accuracy while preserving privacy. In activity and stress monitoring, FL has been shown to offer comparable performance to centralized models while upholding data privacy. To supplement limited real data, synthetic data techniques such as GANs and other differential privacy methods generate plausible synthetic wearable sensor data. One recent study produced synthetic multi-sensor smartwatch stress data, improving F1-scores by 11.9-15.5% under privacy constraints.[162]

5.4. Commercial and Industrial Aspects

While academic research in wearable sensing has rapidly expanded the frontier of sensing modalities and machine

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learning applications, a critical dimension for widespread adoption lies in understanding how these innovations translate into real-world consumer products. Emerging commercial platforms such as the Apple Vision Pro, WHOOP 4.0, and Samsung's Bio-Processor, which offer practical case studies on successful deployment and signal the direction of industry standards, usability, and regulatory readiness. Commercial wearables prioritize user comfort, battery life, data robustness, and reliability. For example, WHOOP 4.0 integrates multi-wavelength PPG sensors, skin temperature, and accelerometry to continuously track cardiovascular strain, recovery, and stress.[163] Apple's Vision Pro and Watch series incorporate advanced AI processors and on-device ML for real-time spatial tracking or cardiac arrhythmia detection, representing edge-computing use cases not often seen in academic prototypes.[164] Samsung's Bio-Processor exemplifies the miniaturization of multiple biosensors (ECG, PPG, temperature, GSR) onto a single chip, setting a precedent for sensor fusion hardware design in commercial products.[165] Despite these advancements, commercial devices typically rely on validated physiological sensors and avoid more experimental modalities, such as biochemical sweat sensing or multi-lead electrophysiology, due to challenges in calibration, form factor, or regulation. Academic prototypes continue to explore these frontiers, often producing higher-fidelity data in controlled environments and proposing novel machine learning architectures like hybrid edge-cloud pipelines or explainable AI. A consistent limitation in academia is translational readiness: devices are often bulky, power-inefficient, or lack a mature user interface, and models are seldom validated across diverse user populations. In contrast, commercial platforms benefit from large-scale usability testing, iterative feedback loops, and integration with consumer ecosystems.

5.5. Interoperability and Standardization in Wearable Health Ecosystems

The clinical and commercial realization of multisensor wearable health ecosystems requires systemic interoperability—the capacity for heterogeneous devices, data platforms, and clinical information systems to communicate and exchange data coherently. At the wireless communication level, the coexistence of BLE, ANT+, Zigbee, and proprietary protocols creates fragmentation in multisensor deployments. The evolution of BLE toward standardized Health Device Profiles represents progress toward protocol harmonization. At the data format and semantic level, HL7 FHIR (Fast Healthcare Interoperability Resources) defines a RESTful API and modular data resources for representing clinical observations, including wearable-derived vital signs, in a format compatible with major EHR systems.[166, 167] The IEEE 11073 (X73) standard family governs the nomenclature and information models for point-of-care medical device data, with its PHD profile (ISO/IEEE 11073-20601) directly applicable to wearable biometric sensors.[168] The Open mHealth schema provides a complementary framework for representing consumer-grade wearable data in a machine-readable format compatible with clinical research infrastructure.[169] At the organizational level, the development of shared, well-annotated, and demographically representative benchmark datasets, analogous to PhysioNet for ECG data, is urgently needed to enable reproducible ML benchmarking. The current fragmentation of evaluation datasets makes cross-study comparison nearly impossible and significantly impedes scientific progress.[170]

Moreover, industry-led efforts increasingly align with standards and anticipate evolving policy frameworks, enabling regulated deployment and cross-platform interoperability. To bridge the gap between laboratory innovations and real-world deployment, it is critical to consider not only the technical advancements in wearable sensing and machine learning but also the regulatory interoperability and standardization frameworks that enable safe and scalable adoption. Notably, the HL7 FHIR (Fast Healthcare Interoperability Resources) standard has become a widely accepted protocol for enabling seamless integration of wearable sensor data into Electronic Health Record (EHR) systems. This is essential for aligning wearable-derived insights with clinical workflows and facilitating longitudinal patient monitoring. Similarly, the ISO/IEEE 11073 Personal Health Device (PHD) communication standards define protocols for the secure and interoperable exchange of data between personal health devices and external systems. These standards ensure that data from wearables can be interpreted and utilized consistently across platforms. In addition to data standards, emerging policy frameworks such as the EU Artificial Intelligence Act (AI Act) introduce critical considerations for AI-enabled wearable technologies, particularly those that support or automate health-related decision-making. The AI Act classifies such systems as high-risk and mandates transparency, traceability, and accountability in algorithm development and deployment. These requirements are particularly relevant for machine learning models embedded in wearable devices, which may need to meet strict compliance for clinical validation, bias mitigation, and post-deployment monitoring. Incorporating these standards and regulatory considerations is vital for ensuring market readiness, cross-platform data compatibility, and ethical implementation of intelligent wearable systems. By acknowledging these frameworks, researchers and developers can better align technological innovations with the real-world constraints and expectations of the healthcare and fitness industries. In summary, a meaningful bridge between academic innovation and commercial viability must address miniaturization, power efficiency, UI/UX design, real-world validation, and regulatory foresight. Strengthening collaborations between academic labs and industry stakeholders, through joint validation trials, shared datasets, or open platforms, could accelerate the path from concept to deployment. Continuous advancements in materials, algorithms, data policy, and energy technologies will drive innovation, making wearable sensors more accurate, reliable, and accessible for widespread adoption in daily human life.

5.6. Limitations of This Review

This review has several limitations that should be acknowledged. First, the article is intended as a critical and forward-looking synthesis of representative advances rather than an exhaustive catalog of all wearable sensing platforms and intelligent systems reported to date. Second, direct quantitative comparisons across studies remain inherently limited because published works differ substantially in sensor modality, body placement, dataset size, subject demographics, acquisition environment, validation protocol, and evaluation metric. Third, although we discuss emerging translational issues including

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regulation, privacy, and commercialization, these domains are evolving rapidly and may change on a shorter timescale than core sensor or algorithmic development. Finally, recent progress in highly dynamic areas such as multimodal foundation models, edge AI optimization, and interoperable digital health infrastructures is advancing rapidly, such that some developments may postdate the scope of the literature covered in this review.

Author contributions

H. K. and W. -H. Y. conceptualized the review. H. K., D. C., and I. S. wrote an original draft. H. K., D. C., and W. -H. Y. reviewed and edited the manuscript.

Conflicts of interest

There are no conflicts to declare.

Data availability

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

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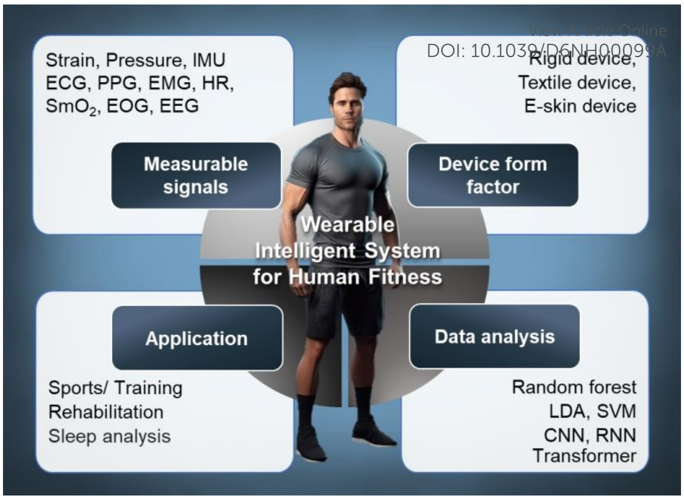

Fig. 1 Overview of the review that summarizes recent advances in wearable sensing methodologies, system-level form factors, key machine learning components, and their applications in sports training, health, rehabilitation, and sleep analysis.

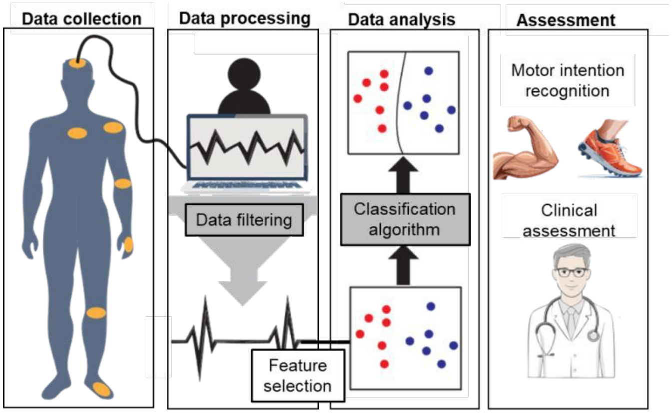

Fig. 2 Processing flow of wearable intelligent systems.

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Table 1 Development trends in wearable sensing technology and intelligent systems.

Time period	Sensor platform evolution	ML/DL methodologies evolution	Remarks/trends
Pre-2015	Rigid, bulky devices (watches, chest straps)	Classical ML (DT, SVM, RF, KNN, LDA)	Focused on basic activity classification and physiological signal monitoring.
2015-2018	Textile-based sensors (garments, bands)	Early DL adoption (CNN, RNN, LSTM for biosignals)	Textile integration improves comfort; DL begins to automate feature extraction.
2018-2020	Soft, skin-conformal, stretchable devices	CNN-RNN hybrid models; multimodal fusion begins to emerge	Fusion of multimodal signals (ECG, IMU, EEG) with DL for better activity and health state classification.
2020-2023	Stretchable, self-healing, wireless skin electronics	Transformer-based models (contrastive learning, attention mechanisms)	Data-efficient DL models appear; unsupervised/self-supervised learning gains attention for scarce labeled data in wearables.
2023-2025	Next-gen e-skin, self-powered (triboelectric, biofuel) & biochemical sensors (e.g., sweat, saliva analytes)	Self-supervised, federated, and personalized ML models; lightweight Transformers for on-device AI	Integration of biochemical sensing with ML; domain adaptation and self-supervised models address personalization and data scarcity. Also, toward autonomous, explainable, and privacy-preserving AI.

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Fig. 3 Sensor system design and form factors. (A) Rigid platform-based device design. Reproduced from ref. 66 with permission from Elsevier, P. Polygerinos *et al.*, *Robotics and Autonomous Systems*, 2015, 73, 135–143, copyright 2015. (B) Rigid platform-based device design. Reproduced from ref. 67 with permission from American Chemical Society, J. H. Lee *et al.*, *ACS Applied Materials & Interfaces*, 2020, 12, 21424–21432, copyright 2020. (C) Textile-based device design. Reproduced from ref. 71 with permission from Wiley-VCH GmbH, V. Galli *et al.*, *Advanced Science*, 2023, 10, 2206665, copyright 2023. (D) Textile-based device design. Reproduced from ref. 72 with permission from Wiley-VCH GmbH, S. Uzun *et al.*, *Advanced Functional Materials*, 2019, 29, 1905015, copyright 2019. (E) Soft electronic-skin device design. Reproduced from ref. 55 with permission from Wiley-VCH GmbH, H. Kim *et al.*, *Advanced Science*, 2020, 7, 2000810, copyright 2020. (F) Soft electronic-skin device design. Reproduced from ref. 80 with permission from Elsevier B.V., Y. Wu *et al.*, *Sensors and Actuators A: Physical*, 2018, 279, 46–52, copyright 2018.

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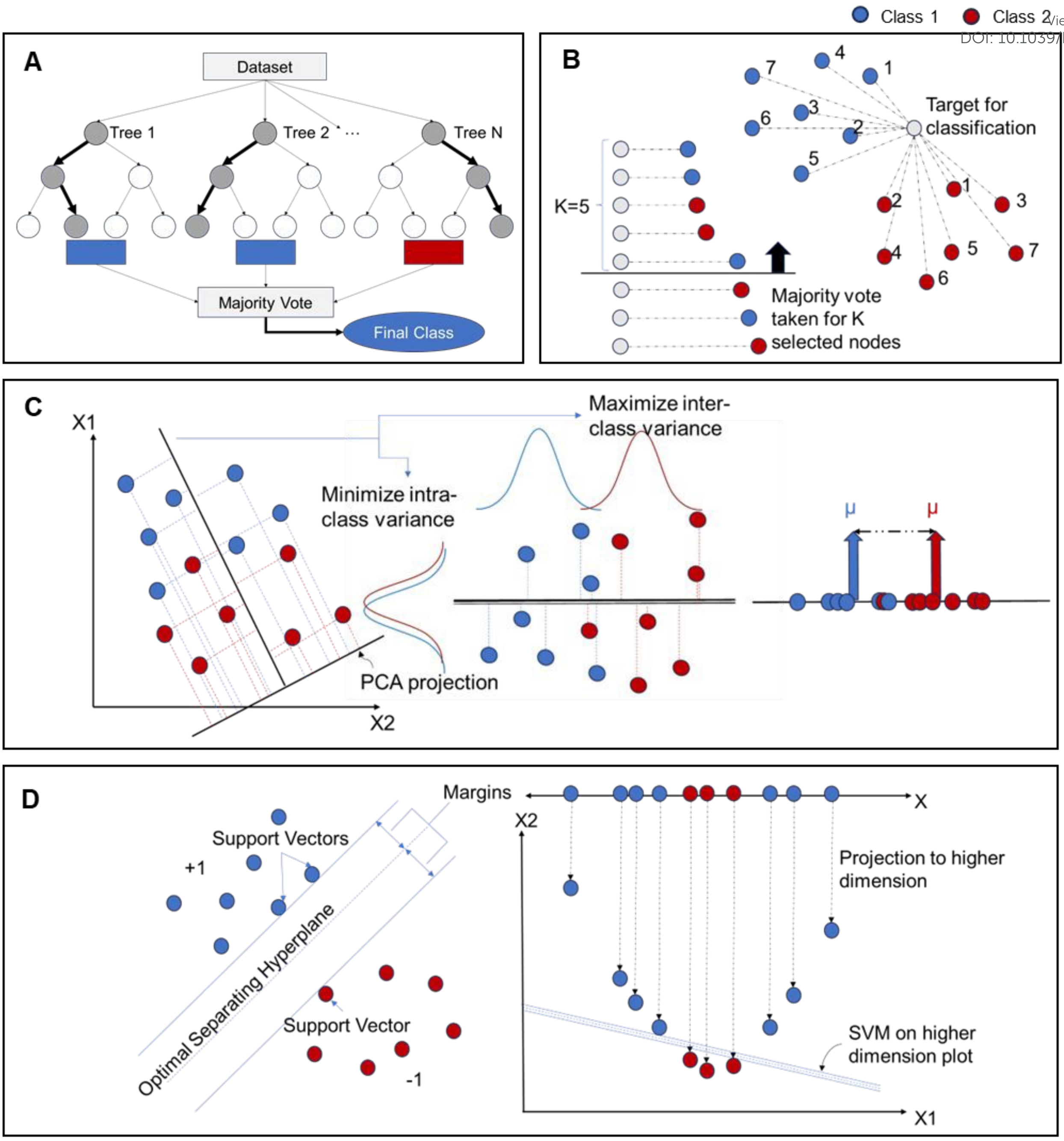

Fig. 4 Intelligent sensing system: Traditional machine learning models. (A) Random forest (RF). (B) Support vector machine (SVM). (C) K-nearest neighbors (KNN). (D) Linear discriminant analysis (LDA).

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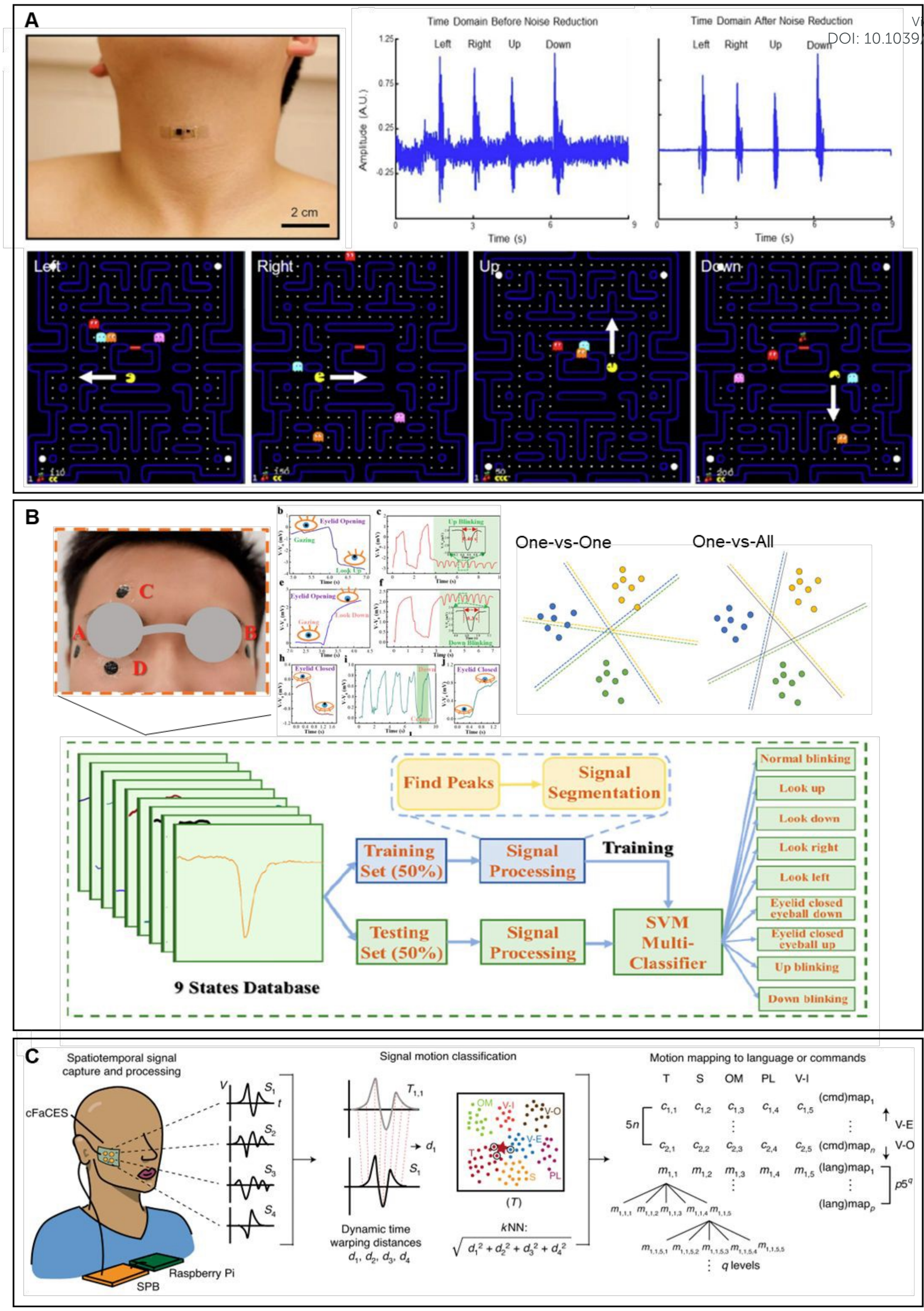

Fig. 5 Applications of ML-enabled models. (A) Application of LDA for real-time speech classification using a mechano-acoustic epidermal sensor. Reproduced from ref. 91 with permission from AAAS, Y. Liu *et al.*, *Science Advances*, 2016, 2, e1601185, copyright 2016. (B) EOG sensors for eye movement classification using SVM. Reproduced from ref. 92 with permission from the American Chemical Society, J. Xu *et al.*, *ACS Nano*, 2022, 16, 6687–6699, copyright 2022. (C) Integrated system for decoding facial movements using conformable piezoelectric thin films, computational modeling, and real-time classification algorithms. Reproduced from ref. 93 with permission from Springer Nature, T. Sun *et al.*, *Nature Biomedical Engineering*, 2020, 4, 954–972, copyright 2020.

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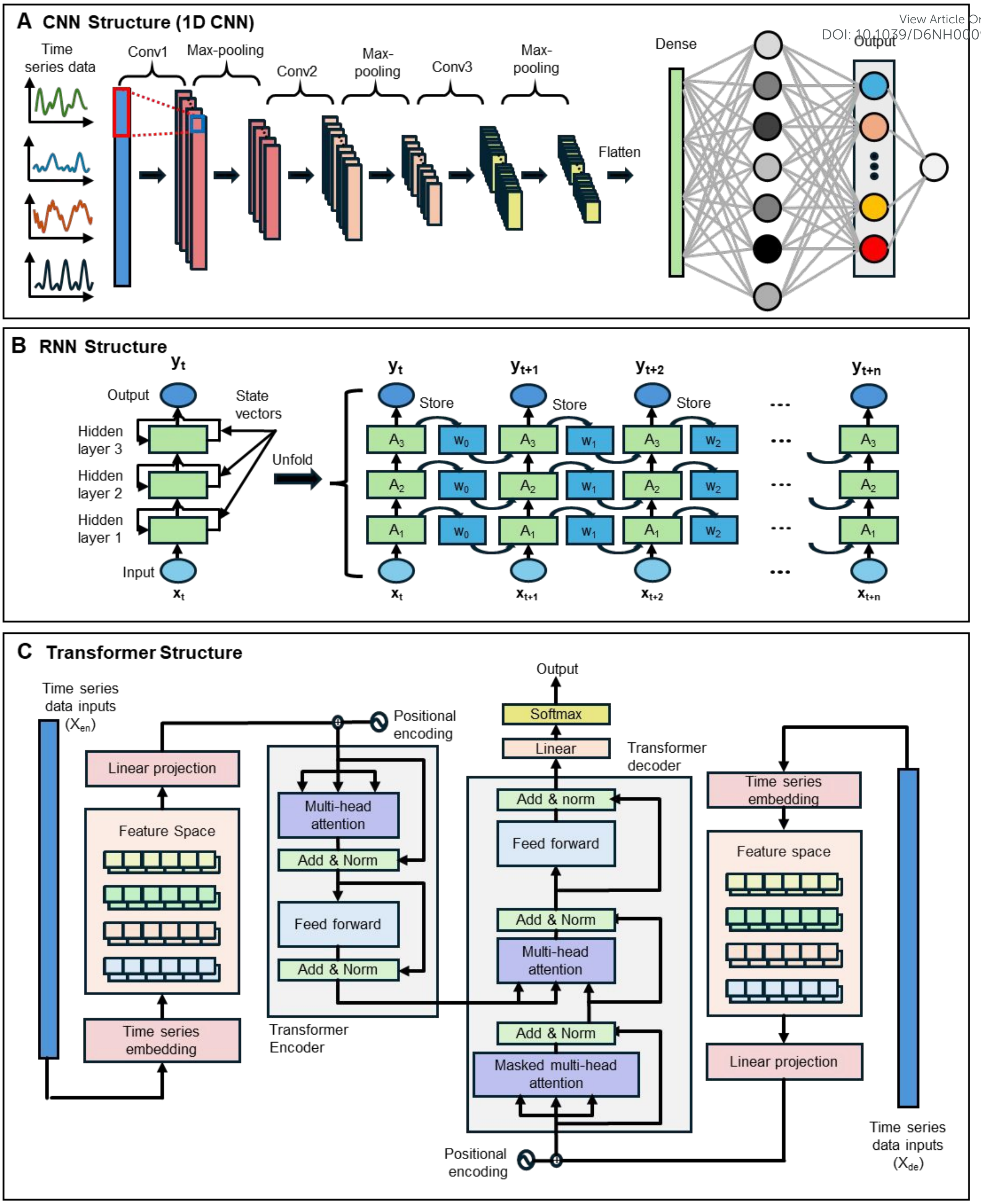

Fig. 6 Intelligent sensing system: Deep learning-enabled models. (A) Convolutional Neural Networks (CNN). (B) Recurrent Neural Networks (RNN). (C) Transformer structure.

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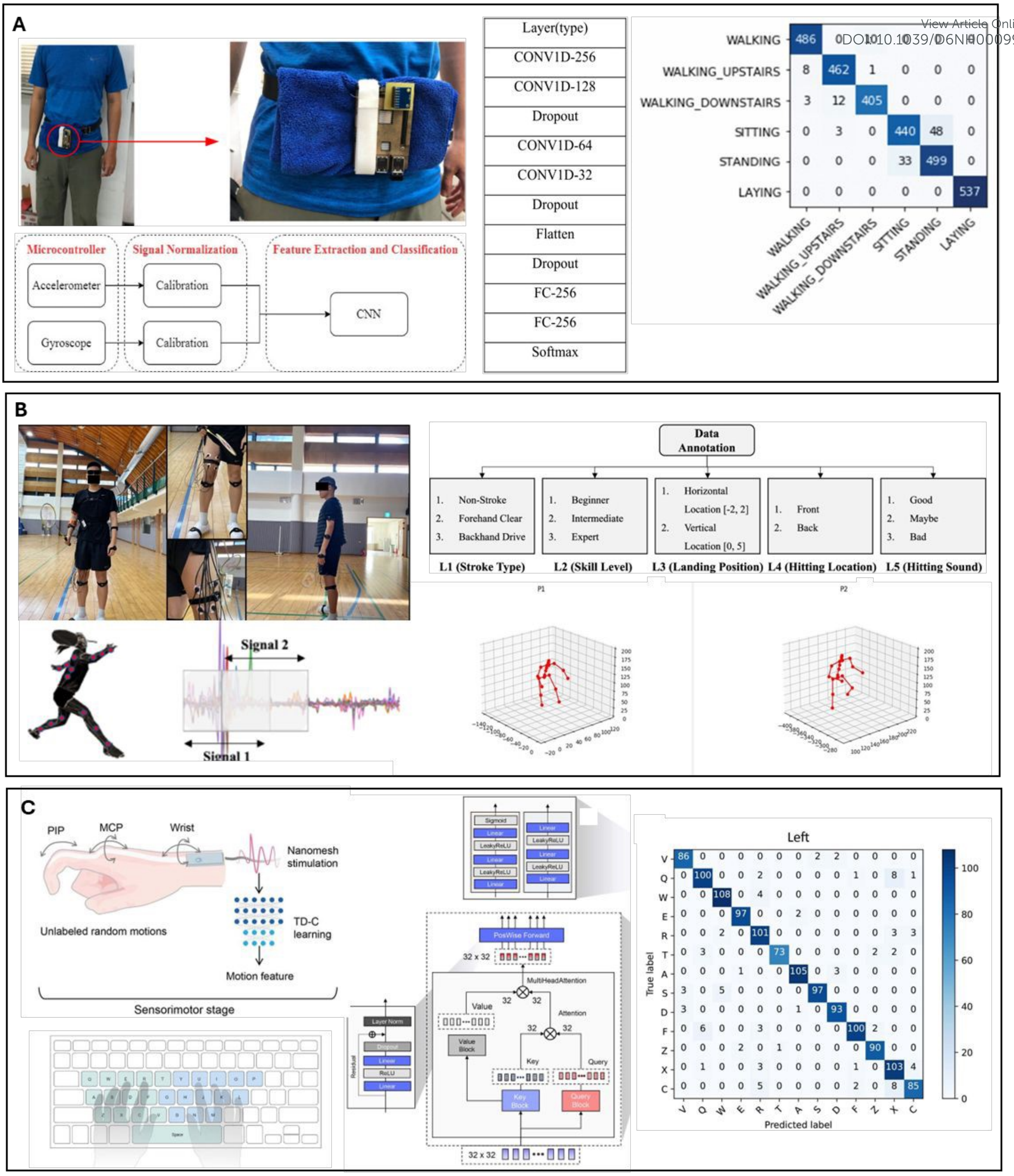

Fig. 7 Applications of DL-enabled models. (A) CNN model-based a waist-mounted wearable device for human activity recognition. Reproduced from ref. 102 with permission from IEEE, C.-T. Yen *et al.*, *IEEE Access*, 2020, 8, 174105–174114, copyright 2020. (B) Analyzing badminton strokes using a multi-sensor dataset developed in consultation with coaches to ensure practical relevance. Reproduced from ref. 103 with permission from Springer Nature, M. Seong *et al.*, *Scientific Data*, 2024, 11, 343, copyright 2024. (C) Substrate-less nano-mesh receptor integrated with a deep learning framework to enable user-independent, data-efficient motion recognition. Reproduced from ref. 104 with permission from Springer Nature, K. K. Kim *et al.*, *Nature Electronics*, 2023, 6, 64–75, copyright 2023.

Table 2 Comparison of traditional machine learning and deep learning models utilized in wearable intelligent sensing systems.

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Model	Sensor data	Strengths	Limitations
Decision tree (DT)	ECG, EMG, IMU	Easy interpretation, fast computation	Overfitting risk with deep trees, unstable splits under data variation
Random forest (RF)	ECG, EMG, IMU	Robust to overfitting, handles noisy data well	Higher computation, less interpretable than DT, memory and inference cost increase with tree number
Support vector machine (SVM)	Eye-tracking (EOG), EMG, IMU	High accuracy, good for small datasets	Training and inference cost increase with dataset size and support vector count
K-nearest neighbors (KNN)	EMG, facial motion	Simple, non-parametric, works well with a few classes	Inference and memory scale with dataset size
Linear discriminant analysis (LDA)	Mechano-acoustic signals	Efficient, low computational cost	Limited under nonlinear boundaries and violated covariance assumptions
Convolutional neural networks (CNN)	ECG, EMG, EEG, IMU, spectrograms	Hierarchical feature extraction, robust to noise	~1.2M params / 68.48 MFLOPs, performance can be dataset-dependent
Recurrent neural networks (RNN)	ECG, EMG, EEG	Captures temporal dependencies, suitable for dynamic data	Sensitive to domain shift, F1 may drop from 87.6% to 70.2% in real-world deployment
CNN-RNN hybrid models	ECG, EMG, EEG	Combines spatial & temporal pattern learning	Computationally demanding, complex model tuning
Transformer Models	Time-series biosignals, complex sequences	Models global dependencies efficiently, scalable	High computation, even lightweight models require optimization, ~0.62M params / 2.45 MB / 11.3 MFLOPs; real-world F1 drop possible

Table 3 Comparison of recent advances in ML models utilized in wearable intelligent sensing systems.

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Model	Sensor Data	Strengths	Limitations
ConvLSTM	EEG, EOG, ECG, IMU, PPG	Captures localized spatial features and long temporal dependencies	Computationally heavy, risk of overfitting on small datasets
Transformer	ECG, IMU, multimodal streams	Excels at modeling long-range and cross-modal dependencies	Requires large, labeled datasets and computationally heavy
Graph Neural Network (GNN)	EEG, IMU (structured/multi-channel)	Learns spatial and temporal relationships in structured signals	Depends on predefined graph structure; limited generalizability
Autoencoder (VAE)	ECG, EEG, PPG (anomaly detection, reconstruction)	Compresses signals for reconstruction and unsupervised tasks	Neglects temporal dynamics; limited performance on sequential data
Generative Adversarial Network (GAN)	IMU, EEG (synthetic data generation)	Augments data under imbalance with synthetic signals	Unstable training, prone to mode collapse
Diffusion Model	IMU, ECG, EEG (synthetic augmentation, denoising)	Produces high-quality, denoised synthetic data from noise	High inference cost, less suited for edge deployment
Foundation Model	EEG, ECG, GSR, IMU, PPG	Learns generalized representations for diverse downstream tasks	Still emerging

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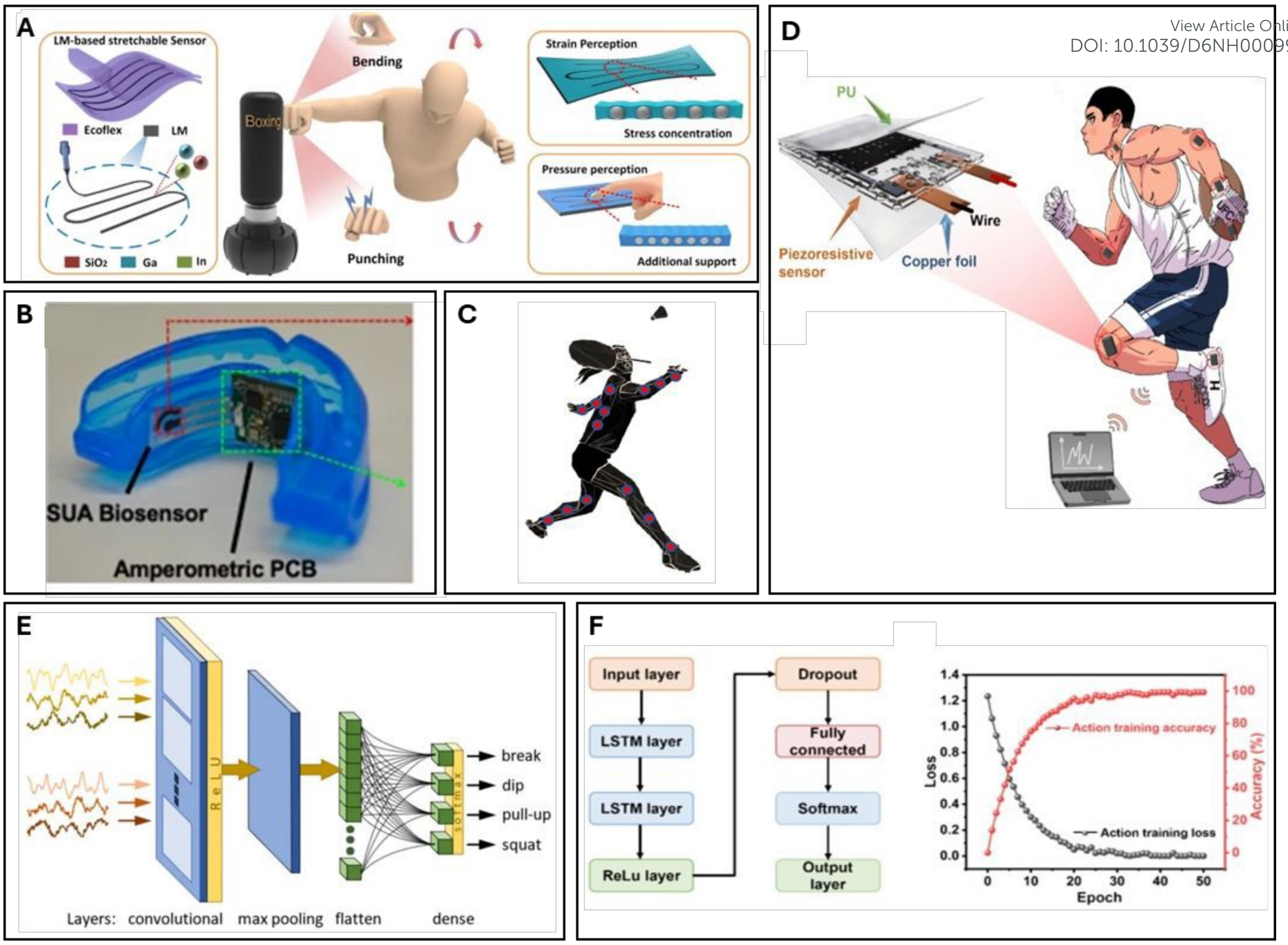

Fig. 8 Intelligent wearable sensing system for athletic performance analysis. (A) A liquid metal-based stretchable sensor that measures strain and pressure during movements like punching and bending. Reproduced from ref. 123 with permission from Springer Nature, Y. Qiu *et al.*, *npj Flexible Electronics*, 2023, 7, 37, copyright 2023. (B) Saliva-based biosensor embedded in a mouthguard with non-invasive tracking of hydration, stress, and fatigue biomarkers. Reproduced from ref. 122 with permission from Springer Nature, D. R. Seshadri *et al.*, *npj Digital Medicine*, 2019, 2, 72, copyright 2019. (C) IMU-based badminton strokes motion tracking to analyze sports movements. Reproduced from ref. 103 with permission from Springer Nature, M. Seong *et al.*, *Scientific Data*, 2024, 11, 343, copyright 2024. (D) Piezoresistive wearable sensor applied to joint motion tracking, detecting strain variations to support injury prevention. Reproduced from ref. 124 with permission from Elsevier, W. He *et al.*, *Chemical Engineering Journal*, 2024, 495, 153362, copyright 2024. (E) CNN-based exercise classification, effectively distinguishing movement patterns such as squats, dips, and pull-ups. Reproduced from ref. 125 with permission from MDPI, J. Patalas-Maliszewska *et al.*, *Sensors*, 2023, 23, 1137, copyright 2023. (F) LSTM-based DL model, enhancing motion recognition for training optimization. Reproduced from ref. 126 with permission from AAAS, N. Zavanelli *et al.*, *Science Advances*, 2021, 7, eabl4146, copyright 2021.

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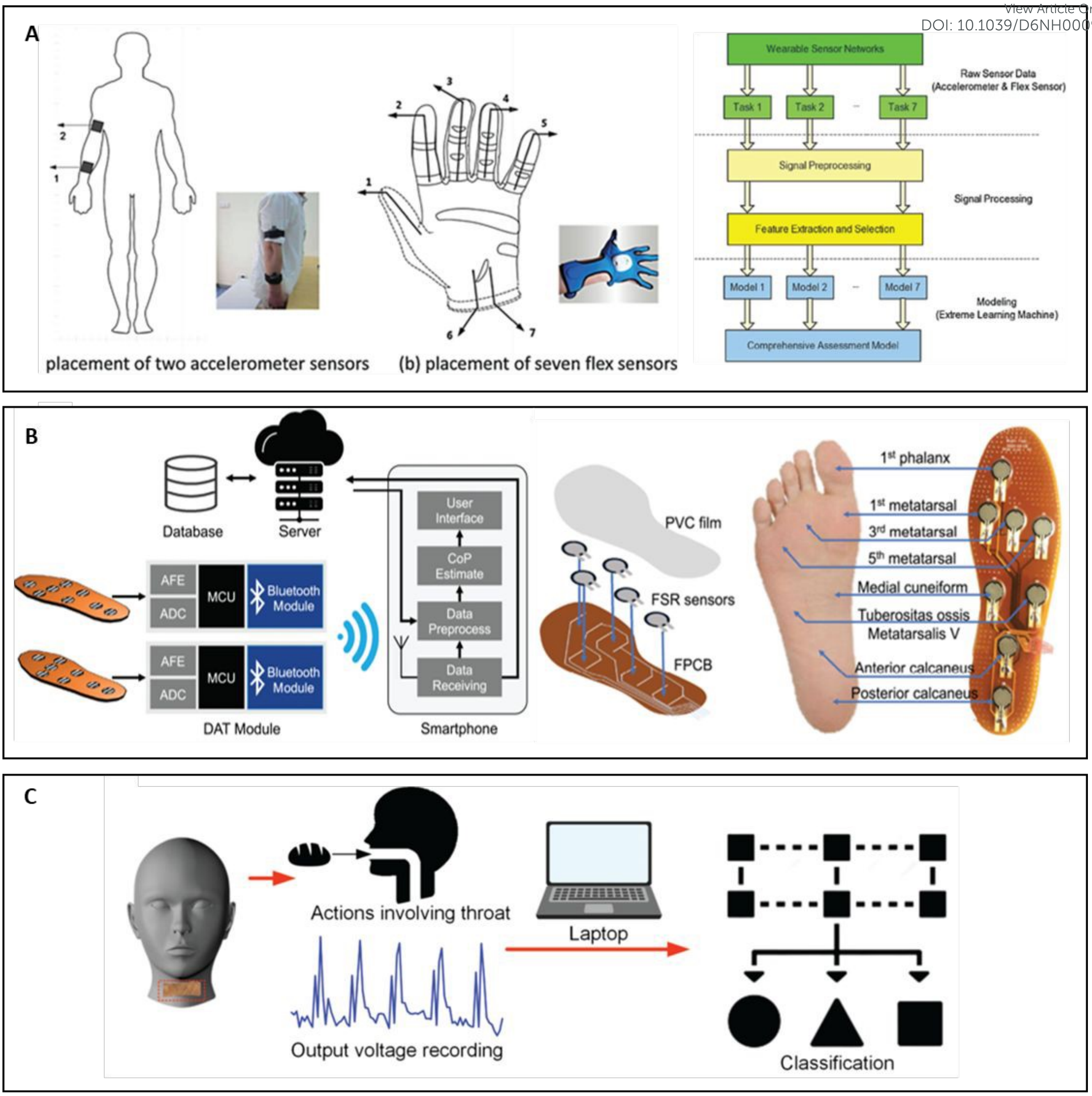

Fig. 9 Intelligent wearable sensing system for rehabilitation and assistive technologies. (A) Remote quantitative Fugl-Meyer assessment (FMA) framework for stroke patients. Reproduced from ref. 127 with permission from Elsevier B.V., L. Yu *et al.*, *Computer Methods and Programs in Biomedicine*, 2016, 128, 100–110, copyright 2016. (B) Smart-shoe-based long-term center of pressure (CoP) monitoring system. Reproduced from ref. 130 with permission from IEEE, R. Guo *et al.*, *IEEE Sensors Journal*, 2021, 21, 27037–27044, copyright 2021. (C) Smart, non-invasive throat sensor designed for oropharyngeal treatment applications, addressing the limitations of conventional videofluoroscopy (VFS) techniques. Reproduced from ref. 131 with permission from MDPI, J.-H. Lee *et al.*, *Polymers*, 2021, 13, 3041, copyright 2021.

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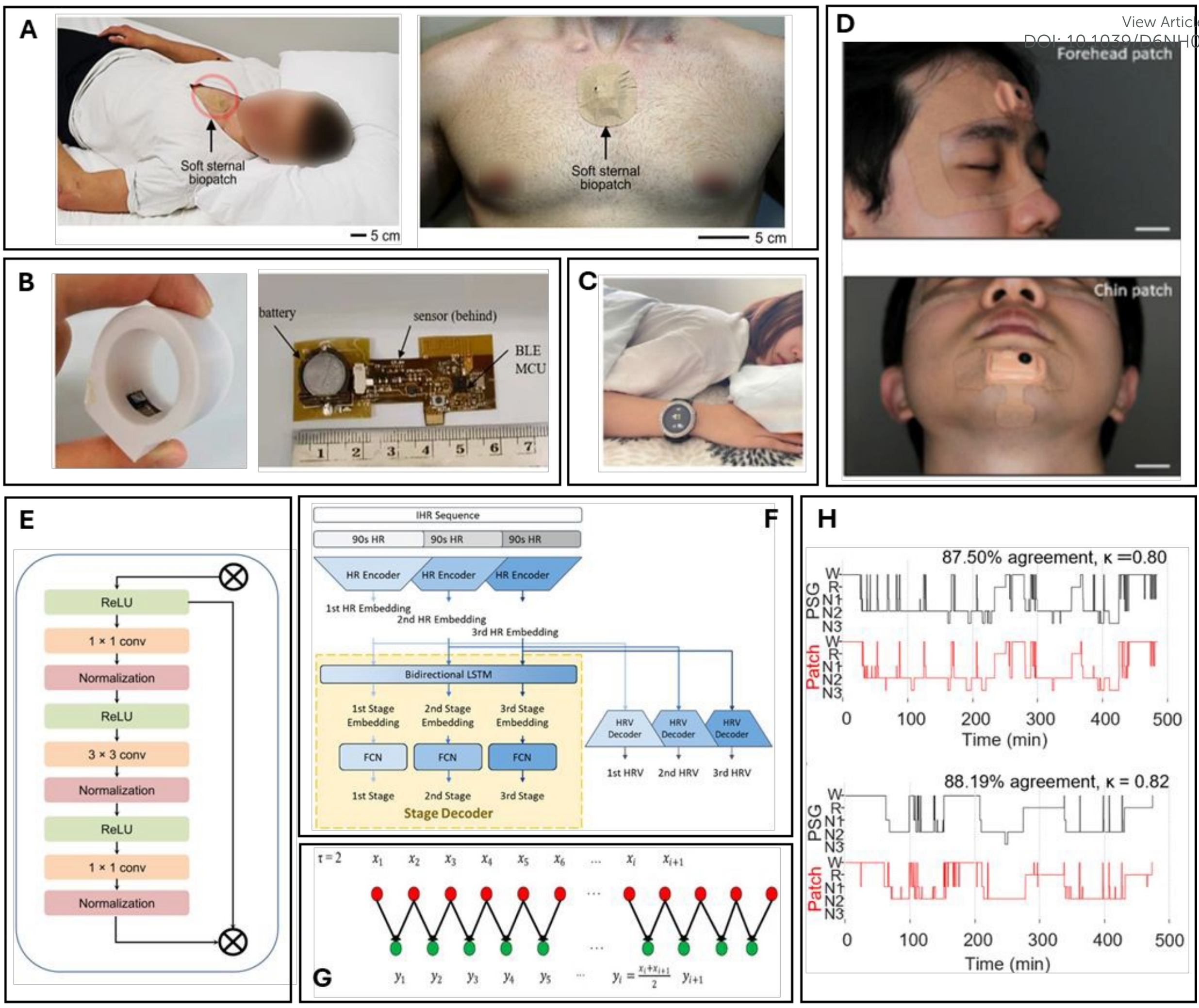

Fig. 10 Intelligent wearable sensing system for sleep analysis. (A) The sternal bio-patch captures SCG, ECG, and PPG signals, enabling the detection of cardiac and respiratory activity during sleep. Reproduced from ref. 126 with permission from AAAS, N. Zavanelli *et al.*, *Science Advances*, 2021, 7, eabl4146, copyright 2021. (B) Microcontroller, battery, and sensor system, collecting continuous blood oxygen and pulse wave monitoring through PPG-based apnea detection. Reproduced from ref. 132 with permission from MDPI, S. Wang *et al.*, *Biosensors*, 2023, 13, 483, copyright 2023. (C) Wrist-worn wearables tracking at-home sleep monitoring. Reproduced from ref. 133 with permission from Wiley-VCH, H.-Y. Chih *et al.*, *Advanced Intelligent Systems*, 2024, 6, 2300270, copyright 2024. (D) EEG, EOG, and EMG monitors for brain activity and muscle movements for sleep staging and sleep apnea classification. Reproduced from ref. 134 with permission from AAAS, S. Kwon *et al.*, *Science Advances*, 2023, 9, eadg9671, copyright 2023. (E) Residual CNN model, which mitigates the vanishing gradient problem, ensuring deep feature learning for apnea and hypopnea detection. Reproduced from ref. 126 with permission from AAAS, N. Zavanelli *et al.*, *Science Advances*, 2021, 7, eabl4146, copyright 2021. (F) Bidirectional LSTM-based model for sleep stage classification, where hierarchical embeddings capture sequential dependencies in HRV signals. Reproduced from ref. 133 with permission from Wiley-VCH, H.-Y. Chih *et al.*, *Advanced Intelligent Systems*, 2024, 6, 2300270, copyright 2024. (G) Model sequential relationships in biosignals, enhancing predictive accuracy across different sleep stages. Reproduced from ref. 132 with permission from MDPI, S. Wang *et al.*, *Biosensors*, 2023, 13, 483, copyright 2023. (H) DL-enabled sleep staging results. Reproduced from ref. 134 with permission from AAAS, S. Kwon *et al.*, *Science Advances*, 2023, 9, eadg9671, copyright 2023.

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Table 4 Machine-learning-enabled wearable system for athletic performance analysis.

Ref. (Year)	Sensors	Device foam factor	Measurement location	ML models	Learning objectives
[124] (2024)	Piezoelectric, piezoresistive, and capacitance	Soft patch	Knee, neck, and wrist	LSTM	Fitness motion classification
[171] (2022)	PPG	Bracelet	Wrist	CNN- LSTM	Fitness motion classification
[172] (2018)	IMU	Wristband	Wrist	RF	Gait pattern classification
[125] (2023)	Inertial sensor	Tactile wristband	Foot, hand, and chest	CNN	Climbing strategies analysis
[25, 173] (2019)	6-axis intertial sensor	Tactile wristband	Wrist and ankle	CNN	Sport activity classification
[28, 174] (2021)	9 DOF IMU	Rigid device	Back	LR,SVM,LSVM, and MLP	Running Surface classification
[123] (2023)	LM strain and pressure	Tactile glove	Hand	CNN	Boxing punch analysis
[175] (2020)	Motion capture	Whole body	N/A	BLR, LDA, and SVM	Motion states classification
[122] (2019)	ECG, EMG, EEG, and electrochemical	mouthguard	Wrist and mouth	Gradient Boost, KNN, and NLP	Physiological and biochemmical profile monitoring
[176] (2023)	PPG	Watch	Wrist	lightGBM	Skin hydration and body sweat loss monitoring
[177] (2023)	3D-gyroscope and digital compass	Rigid ankle watch	Ankle	SVM, LR, KNN, and DT	Injury detection for soccer players
[178] (2022)	3 WSN nodes, 3 IMU	Pocket, Wrist	Smartphone, and smartwatch	SVM, KNN, EC, and DT	Athlete states classification

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Table 5 Machine-learning-enabled wearable system for rehabilitation and assistive technologies.

Ref. (Year)	Sensors	Device foam factor	Measurement location	ML models	Learning objectives
179 (2018)	9-axis IMU	Wristband	Wrist	KNN, Random forest, Bayesian classifier, and SVM	Post-stroke hemiplegia
131 (2021)	IPMC	Soft-patch	Throat	SVM	Oropharyngeal dysphagia
180 (2015)	EMG	Sensor nodes	Lower leg	SVM	Stroke/multiple sclerosis
181 (2018)	IMU and EMG	Rigid arm-band	Arm	Decision tree, Discriminant analysis, Ensemble, KNN, Naïve bayes, and SVM	Stroke
26, 182 (2015)	IMU	Smart leggings	Right knee	Random forest	Knee osteoarthritis
183 (2020)	Force and flex sensor	Soft glove	Knuckle/fingertips/palm	Decision tree	Hand paralysis

Table 6 Machine-learning-enabled wearable system for sleep analysis.

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Ref. (Year)	Sensors	Device form factor	Measurement location	ML models	Learning objectives
[135] (2023)	EEG,EOG, and EMG	Soft patch	Forehead and chin	CNN	Sleep apnea
[123] (2023)	EEG,EOG,EMG, PPG, and IMU	Headband	Forehead	CNN+RNN, RNN	Insomnia
[132] (2023)	PPG	Ring	Finger	SVM, KNN, and Xgboost	Sleep apnea
[133] (2024)	PSG, EEG,EOG,EMG, and ECG	Watch	Finger	Multi-Task Learning (MTL)	Sleep stages
[184] (2023)	PPG, EEG,EMG, and ECG	Chest worn	Chest	Sleep-See-Through(SST) Architecture	Sleep apnea, irregular, breathlessness, and snoring
[126] (2021)	ECG, PPG, SCG, and ACC	Chest worn	Chest	RCNN	Sleep apnea and sleep stages
[185] (2020)	Respiration, 3-axis acceleration, PPG, HR, PPG	Nasal Tube, Rigid wristwatch, finger clip	Nose, wrist, finger	KNN and ANN	Sleep apnea
[186] (2023)	MRI	N/A	N/A	LightGBM, Xgboost, and RF	ADHD and sleep quality
[187] (2022)	ECG	N/A	N/A	RF, DT, and LDA	Insomnia and sleep stages
[188] (2022)	EEG and PSG	Rigid Patch	Forehead	Deep Sleep Net	Sleep stages
[189] (2022)	IMU	Rigid Sensors	Chest, leg, and ankle	SVM	Sleep posture detection

Data availability

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