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Artificial Intelligence-Enabled Wearable Biosensing Systems for Personalized Digital Healthcare

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Abstract. The fast progress of wearable biosensors and artificial intelligence (AI) is pushing modern medicine to change in a deep way, wearable biosensors let body signals be collected without entering the body and in a continuous way, while AI methods help people read these complex data in real time and also make predictive analysis of them, improved AI methods now give useful tools for reading complex, real-time biomedical data, so early disease finding and real-time health tracking become more accurate, the combination of wearable biosensors and AI has become a clear direction in digital healthcare, yet even with this fast progress, several problems still need to be solved, long-term, real-time wearable monitoring usually makes huge amounts of health data, and the need to remove noise efficiently and analyze large streams of dynamic monitoring data in real time puts much pressure on AI computing, this paper reviews recent developments in wearable biosensing and AI-driven real-time health monitoring technology, it mainly covers the main kinds of wearable biosensors used for human health monitoring, along with the data features, processing steps, and processing needs linked to long-term real-time monitoring, also, the paper sums up the main algorithms used for wearable health data analysis, finally, this paper discusses current problems and future directions of intelligent health monitoring based on AI and wearable devices.

Keywords: wearable biosensors, artificial intelligence, health monitoring, machine learning, digital healthcare, physiological sensing

1. Introduction

The growth of wearable sensing technology has opened new chances for health monitoring, AI can read real-time health data, and this also helps people understand their own health changes more accurately and quickly, a group of wearable biosensors, such as smartwatches, fitness bands, smart clothes, and some implantable devices, collect and analyze real-time body signals so that health tracking and detection can be done, unlike traditional medical practice, wearable devices can gather long-term, non-invasive, real-time data in a continuous way, this continuous health tracking and monitoring gives more convenient and fuller information about a person's real-time physical condition, health state, and early warning of disease, and it moves the medical model from treatment toward early warning and prevention.

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The fast growth of wearable sensing technology also asks more from AI and machine learning methods when they process human data in real time, real-time body signals recorded by wearable devices often show complex time patterns and nonlinear relations, as a result, these real-time data are hard to analyze with old AI algorithms, so new algorithms that fit better need to be developed, the coupling of AI with wearable sensing forms a strong link between new disease-monitoring ways and intelligent analysis of high-throughput real-time data, this combination makes it possible and practical to develop and improve intelligent health monitoring systems for early disease detection, personalized medical monitoring, and real-time risk tracking, and to deploy them at a large scale.

The fast rise of wearable Internet of Things (IoT) technology has further sped up the growth of digital healthcare systems, modern wearable devices collect many kinds of real-time body signals, connect the data relations between this physiological information and health status, and use machine learning to analyze these multimodal data streams, in this way, they mix real-time monitoring with predictive health assessment and build a full "monitoring–personalized assessment" framework, this has deeply changed the medical model and given a new way for services such as preventive medicine and telemedicine.

Even though AI-based wearable biosensing technology has made much progress in recent years, this new and fast-changing field still faces many challenges [1], because of body movement or outside environmental interference, body signals recorded by wearable biosensors often have noise, motion artifacts, and sometimes missing values, which puts high demands on AI algorithms for body data processing, second, continuous sensing makes large amounts of different, long-term data, and these data need efficient storage, synchronization, and accurate analysis algorithms, also, the small physical size of wearable biosensors limits their computing resources, and this, under hardware limits on computing power, raises the bar for integrating and developing higher-quality, more efficient algorithms.

Therefore, this paper first systematically reviews recent advances in AI-based wearable biosensors, with focus on sensing technology, data processing methods, and representative application examples of next-generation biosensing medical systems, on this basis, this paper also discusses, from another view, current limits of the field and issues that still need to be solved, by weighing these opportunities and challenges together, this paper further gives an outlook and forecast on future development trends and directions of wearable biomedical devices that integrate AI.

2. Wearable biosensors for health monitoring

Research on wearable biosensing devices is a hot topic in modern emerging digital healthcare systems, wearable biosensing devices are a new generation of convenient, intelligent devices that continuously monitor human body signals in a non-invasive way, compared with traditional medical testing and monitoring methods, wearable biosensing devices have many advantages, such as non-invasiveness, portability, and strong real-time and continuous monitoring ability, their development has greatly met the needs of preventive medicine, long-term real-time monitoring of chronic diseases, and personalized medicine.

With the fast development of biosensor technology, biomaterial science, and AI, wearable biosensors have also moved forward at a surprising speed in the past few years, early, basic wearable biosensing devices were mainly made for monitoring routine daily body signals and normal physical activity, as the field has grown, however, the new generation of wearable biosensors can monitor several more complex body signals at the same time and assess them in an integrated way, so a more complete, realistic, and holistic evaluation of a person's health status becomes possible.

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In addition, wearable biosensors are more and more combined with integrated mobile computing platforms and efficient AI algorithms, and this achieves continuous data transmission and accurate, efficient real-time health monitoring, the integration of IoT platforms, AI algorithms, and wearable biosensing devices forms the technical base for a new generation of intelligent health monitoring systems that link sensor-derived body data with efficient data analysis.

2.1. Wearable biosensors

The key point of a wearable biosensor lies in its wearability and its ability to monitor body physiological and biochemical signals in real time while it is worn, the basic parts of a wearable biosensing device usually include a sensing module, a signal acquisition and conversion module, a data processing module, and a wireless communication module.

Early wearable biosensors can be traced back to ambulatory monitoring devices used in clinical cardiology, such as wearable real-time electrocardiogram (ECG) monitors, with the fast development of microelectronics, biosensing, IoT, nanomaterial science, and AI, modern wearable biosensors have become smaller, more portable, and more intelligent, and because they are comfortable, they have quickly expanded into many health-monitoring areas, including cardiovascular monitoring, sleep analysis, exercise data monitoring, real-time stress monitoring, and chronic disease management [2], the wide use of wearable biosensing devices has given the general public a way to do routine, continuous health monitoring outside clinical settings, and this opens new chances for early disease detection and personalized medicine.

2.2. Types of wearable devices for health monitoring

Wearable biosensing devices can be set up to monitor different body signals according to the biomarkers of the disease being tracked, based on their sensing principles and monitoring scenarios, wearable biosensing devices can be divided into the following types.

2.2.1. Physiological signal types

Wearable biosensing devices can acquire, with high real-time sensitivity, many kinds of body signals that reflect the body's normal physiological state, these body signals usually include cardiovascular-related signals, neurophysiological signals, and metabolic physiological signals.

Cardiovascular signals are among the most often monitored and important body signals in both clinical and everyday health monitoring, the body signals most commonly monitored in the cardiovascular field include electrocardiogram (ECG) signals, photoplethysmography (PPG), and blood pressure, among them, ECG signals reflect the electrical activity of the heart, and related studies have shown a close link between these electrical signals and arrhythmias and other cardiac disorders, PPG, in contrast, tracks changes in blood volume in peripheral vessels that come with each heartbeat, it reflects cardiovascular function and circulatory status by measuring blood flow changes in microvessels under the skin surface [3], continuous, real-time blood pressure monitoring is also a very common monitoring target in wearable sensing devices.

Monitoring of neural signals is often used to show the start and progress of neurological diseases, and it mainly involves EEG and EMG, electroencephalography (EEG) records the electrical signals of the brain and is widely used in neuroscience research and brain–computer interface applications, electromyography (EMG) captures electrical signals produced by muscle contraction and is commonly used in monitoring exercise-related rehabilitation and in human–computer interaction.

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With the rise of basic medicine and the new generation of life sciences centered on human health, metabolic signals are increasingly put into the range that wearable biosensors can monitor, the most common example is the continuous glucose monitoring device, which is widely used to track blood glucose levels in diabetic patients and plays a clear role in glucose control and glucose alarms, in addition, some metabolism-related biochemical markers in sweat, such as cortisol, lactate, and electrolytes, are often monitored as another kind of indicator by wearable biosensing devices, their levels can give information on stress, exercise status, and other metabolism-related factors, and help describe a person's health level.

2.2.2. Mechanical signals

Beyond body signals, wearable biosensing devices are often used to recognize many kinds of mechanical signals, which are then processed together to give an integrated indication of movement and physiological state, mechanical and kinematic signals are usually acquired with inertial sensors, such as accelerometers and gyroscopes, and these are usually integrated into an inertial measurement unit (IMU).

Accelerometers are commonly used to measure the linear acceleration of body movement and can be used for activity-pattern recognition, step counting, and fall detection, gyroscopes, in turn, measure angular velocity and give information about the direction and pattern of body movement, by combining data from multiple inertial sensors, wearable biosensing devices can comprehensively assess gait features, postural stability, and overall physical activity level, and so give indicators of a person's movement attributes, movement information, motor ability, and related health metrics.

Wearable sensors of this kind, which capture movement-related mechanical signals, are commonly used in areas such as sports-rehabilitation monitoring, fall prevention for the elderly, comprehensive assessment of motor ability and performance, and health management.

2.3. Form factors of wearable devices

Depending on the type of signal being monitored and the needs of different application scenarios, wearable biosensing devices also come in many physical forms, the designs of these forms differ mainly in how they balance sensing and processing accuracy, wearing comfort, battery life, and long-term wearability for each detection scenario.

2.3.1. Smartwatches and wristbands

Smartwatches and wristbands are among the most commonly used and widely adopted wearable health-monitoring biosensor devices, these all-in-one health-monitoring devices usually integrate multiple sensors in one unit to meet the needs of collecting various monitoring data, they usually include PPG sensors for heart-rate monitoring, accelerometers for motion-data monitoring, and electrocardiogram sensors for cardiac monitoring.

Because of their outstanding convenience and real-time monitoring ability, health-monitoring devices such as smartwatches have become routine tools for daily health monitoring, at present, many commercial devices can track sleep patterns, exercise metrics, and cardiovascular indicators, their wide use has also helped form a new medical model of intelligent health management in the big-data context.

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2.3.2. Skin patches and smart textiles

Skin patches and smart textiles are another important kind of wearable biosensors, the development of these devices is closely tied to advances in materials science, such wearable biosensing devices usually use flexible and stretchable materials as their substrate, so they can stick closely to the body and make it easier to collect and monitor various body data.

Skin patches can continuously monitor body signals such as ECG, body temperature, and biochemical markers in sweat, smart textiles integrate sensing elements directly into the fabric, and this allows monitoring of various physiological, biochemical, and mechanical motion signals during daily activities, wearable biosensing devices based on skin patches and smart textiles hold much promise in continuous real-time health monitoring and clinical health monitoring.

2.3.3. Implantable and ingestible sensors

Another kind of wearable biosensing devices is implanted in, or swallowed into, the body to collect more accurate physiological and biochemical data that show relevant health levels, implantable sensors are often used for continuous monitoring of specific disease-related biomarkers, the most common application is the biosensor device for real-time monitoring of blood glucose levels in diabetic patients [4], ingestible sensors usually enter the body and then monitor physiological and biochemical information collected from the gastrointestinal tract.

However, although these biosensor devices can collect and provide deeper and more detailed data, their use is often accompanied by issues about security, privacy, invasiveness, and long-term biocompatibility.

2.4. Data challenges

Even with the fast development of wearable biosensing devices, a number of data-related problems and challenges still remain when they are used for health monitoring and management.

2.4.1. Noise, missing data, motion artifacts

Signals acquired by wearable biosensors are often disturbed by various kinds of noise, motion artifacts caused by body movement distort body signals, especially in optical sensing methods such as PPG, in addition, factors such as poor sensor contact or environmental interference can lead to data loss or corruption.

These inherent acquisition, transmission, and processing problems clearly affect the reliability of health-monitoring systems, and therefore put high demands on signal denoising, effective signal preprocessing, and artifact-removal techniques.

2.4.2. Multimodal longitudinal data streams

Another data challenge facing wearable biosensing devices is the complexity of processing multiple datasets in parallel, wearable biosensors usually acquire several types of body signals at the same time, these multimodal datasets may include various data types, such as cardiovascular signals, motion data, and biochemical indicators, recorded at different sampling rates.

Managing and analyzing such complex data streams brings significant challenges in data synchronization, storage, and efficient analysis, advanced AI and machine-learning algorithms are

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often needed to extract valuable information efficiently from these different data sources and to process the data accurately.

2.4.3. Energy and computational constraints

To meet their portability or flexible wearability needs, wearable biosensing devices are usually powered by small batteries, and this limits their endurance and computing power, as a result, many wearable health-monitoring systems rely on edge computing or cloud-based platforms for data processing, developing higher-performance algorithms and AI processing models is another important research direction that needs breakthroughs in wearable medical systems.

3. AI-enabled monitoring wearable health data

As noted above, the fast development of wearable biosensors comes with many data challenges, these data streams often contain complex time patterns and different signal types, and often carry significant signal noise, these data features make traditional data-analysis methods unable to support the data-processing needs of modern wearable biosensing devices, the strong growth of AI and machine learning has given powerful tools for analyzing and processing data from wearable biosensing devices, and this enables efficient automated feature extraction, pattern recognition, and predictive modeling.

Data processing in AI-based health-monitoring systems usually involves several modules, including data preprocessing (denoising), extraction of effective data features, and model training for classification or prediction tasks, it is especially worth noting that the core computing architecture used for data processing plays a very critical role in deciding the efficiency and scalability of wearable health-monitoring systems.

3.1. Preprocessing and signal enhancement

Multi-module data collected by wearable biosensing devices usually contain various types of noise and artifacts, motion artifacts distort optical signals such as photoplethysmography (PPG) pulse waves, while poor electrode contact can affect continuous recording of electrocardiogram (ECG) data and cause partial loss of data along the time series [5], therefore, signal preprocessing is a necessary step before efficient machine-learning algorithms are developed.

For the data types produced by wearable biosensing devices, common preprocessing techniques usually include signal filtering, normalization, and artifact removal, digital filtering methods, such as low-pass, high-pass, and band-pass filters, are often used to remove noise outside the valid data from body signals, adaptive filtering techniques and wavelet-based denoising methods are commonly used to improve signal quality and raise the signal-to-noise ratio in wearable monitoring systems.

Another important data challenge in the preprocessing stage is handling missing or corrupted data, data-imputation methods, interpolation techniques, and statistical estimation methods are commonly used to solve the problem of missing values in wearable datasets.

3.2. Feature engineering and representation learning

Feature extraction from effective data is a key step in wearable health-data analysis, traditional methods often rely on manually identifying and extracting features based on physiological prior knowledge, a common example is the heart-rate-variability index extracted by hand from ECG

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signals, which is often used for cardiovascular status assessment, another example is the extraction of statistical features, such as mean, variance, and spectral power, for activity-pattern recognition in the processing of motion and mechanical signals.

Traditional manual extraction of effective data features, however, is often inefficient and not well suited to recognizing complex patterns in large datasets, the rise of deep-learning-based AI algorithms can break through the limits of traditional methods and automatically learn hierarchical feature representations directly from raw sensor data.

Deep-learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are especially good at capturing the spatial and temporal dependencies in body signals, and these models usually deliver higher performance.

3.3. Computing architecture

In wearable health-monitoring systems, AI algorithms need an efficient computing architecture, and this is also central to data processing, depending on system design and resource availability, data processing may take place at different levels, including edge devices, mobile platforms, or cloud servers.

Edge computing allows some data-processing tasks to be run directly on the wearable device or a nearby gateway, this approach reduces latency and improves privacy by cutting down the transmission of data to remote servers, however, the limited computational resources of wearable devices call for lightweight algorithms and energy-efficient model architectures.

Cloud computing platforms provide powerful computational resources for large-scale data analysis and model training, wearable devices can send collected data to cloud servers, where advanced machine-learning models are used for efficient analysis, hybrid architectures that combine edge computing and cloud processing are currently the more widely adopted form.

4. Core AI/ML algorithms in healthcare

AI plays a central role in analyzing wearable biosensor data and in empowering intelligent health-monitoring systems, many machine-learning algorithms have been used for disease monitoring, motion-pattern analysis, and health assessment, classified by their underlying architecture, these algorithms can generally be put into traditional machine-learning methods, deep-learning architectures, and hybrid multimodal methods.

4.1. Traditional machine learning

Traditional machine-learning algorithms are widely used to analyze health data, given the features of data collected by biosensing devices, common algorithms include support vector machines (SVM), decision trees, random forests, and k-nearest neighbors (KNN).

These methods usually depend on manually extracted features from body signals for their analysis, in some scenarios, traditional machine-learning methods can give satisfactory analytical and processing performance, however, for datasets involving high-throughput and complex scenarios, more optimized methods are needed.

4.2. Deep learning architectures

Deep learning, with its clear advantage of automatically learning complex feature representations from raw sensor signals, has become the most important processing approach for analyzing health

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data collected by wearable biosensing devices [6].

Convolutional neural networks (CNNs) are often used to analyze physiological time-series signals such as ECGs and PPG, by using convolutional filters, CNNs can extract local temporal patterns and signal features that are useful for disease-detection and classification tasks.

Recurrent neural networks (RNNs), including long short-term memory (LSTM) networks and gated recurrent units (GRUs), are designed specifically for modeling sequential data, these models are especially well suited to analyzing the temporal dependencies in long-term physiological monitoring data.

Graph neural networks (GNNs) have recently been explored for modeling the relationships among multiple body signals or distributed sensor nodes, by representing multimodal health data as graphs, GNNs can capture the complex interactions between different physiological systems.

Transformer architectures have recently appeared as powerful approaches for analyzing wearable sensor data because they can capture long-range temporal dependencies through self-attention mechanisms, unlike recurrent neural networks that process sequential information step by step, Transformers can model relationships across entire physiological signal sequences at the same time, and this enables more efficient representation learning from long-term wearable monitoring data.

4.3. Hybrid and multimodal fusion

Wearable biosensing devices usually collect different types of real-time data from multiple sensors at the same time, so as to comprehensively assess the wearer's health status, multimodal data-fusion techniques can effectively integrate different types of body information, moreover, fusion can take place at different stages of the machine-learning pipeline, including data-level fusion, feature-level fusion, and decision-level fusion.

Combining multiple machine-learning algorithms and AI models is also gaining more advantage in health-data processing, convolutional neural networks are usually used to extract effective features from the data, and are combined with recurrent neural networks to capture temporal dependencies, so each algorithm's strengths can be brought into full play, these hybrid data-processing architectures can effectively improve the efficiency, accuracy, and robustness of the analysis of data from wearable biosensing devices.

5. Intelligent health monitoring applications

The close combination of wearable biosensing devices and AI has changed the healthcare model, continuous monitoring of body signals makes early detection of health abnormalities, personalized health management, and remote patient monitoring possible.

5.1. Disease detection and diagnosis

One of the most important applications of wearable biosensing devices is disease detection and diagnosis, by analyzing the body signals collected by wearable sensors, AI algorithms can accurately and quickly identify the possible presence of disease.

For example, wearable ECG monitors that include machine-learning algorithms can effectively detect arrhythmias such as atrial fibrillation and issue related disease warnings, other highly popular wearable biosensing devices include monitoring systems for detecting sleep disorders, respiratory abnormalities, and neurological diseases.

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These AI-assisted diagnostic tools, through continuous real-time monitoring, can help people detect diseases at an earlier stage and get timely treatment.

5.2. Continuous monitoring and early warning

Continuous real-time monitoring is very necessary for patients with chronic diseases, wearable biosensing devices are often used to continuously monitor physiological indicators such as heart rate, motor function, sleep status, and blood glucose levels over the long term, and this helps long-term health observation of patients with chronic diseases.

AI-based predictive models can analyze these real-time data streams to identify abnormal trends and give early warnings before serious health events occur, for instance, predictive algorithms can detect early signs of cardiovascular deterioration or abnormal blood-glucose fluctuations in diabetic patients.

Remote monitoring systems based on wearable sensors also let healthcare providers monitor patients outside the hospital setting, and this offers a more flexible model of medical care.

5.3. Mental health and affective computing

AI-based wearable biosensors are increasingly used to monitor and analyze people's emotional states and mental health, body signals such as heart-rate variability, skin conductance, and activity patterns can give useful indicators of stress, anxiety, and mood changes, and this also supports early warning of mental-health conditions such as depression and anxiety disorders [7], furthermore, affective-computing systems built on wearable devices have very promising market potential and application prospects in stress management, workplace health planning, and personalized mental-health intervention.

6. Conclusions

The integration of wearable biosensors and AI has greatly advanced the field of intelligent health monitoring, continuous real-time sensing of physiological, biochemical, and motion/mechanical signals enables real-time assessment of human health status, while AI-based analytical algorithms make it possible to extract meaningful information from complex biomedical data, these fast-changing technologies are gradually reshaping the traditional healthcare model and steering today's health management toward personalized, preventive, and remote healthcare services.

Nevertheless, even with the many advances and breakthroughs in this field, several challenges and hidden concerns remain, because wearable medical systems continuously collect and transmit sensitive personal health information, data privacy and information security are unavoidable and important privacy and ethical issues, another significant challenge is improving the reliability and robustness of wearable sensing technology, sensor noise, motion artifacts, and missing data can reduce the accuracy of health-monitoring systems, therefore, advances in signal-processing technology and robust machine-learning models will be indispensable for improving system performance.

Energy efficiency and computational limits remain key constraints on wearable devices, future research should focus on developing lighter yet more efficient AI models and energy-efficient hardware architectures, so as to enable real-time data analysis on resource-constrained devices.

Emerging technologies such as flexible electronics, bio-integrated sensors, edge computing, and privacy-preserving machine learning are expected to further enhance wearable health-monitoring

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systems, sustained interdisciplinary research spanning biomedical engineering, computer science, and clinical medicine will be crucial to fully unlocking the potential of intelligent health-monitoring technology.

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