International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 8, Number 6, Year 2026
DOI: https://doi.org/10.62051/ijcsit.v8n6.06
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Application of AI Products in Wearable Health Monitoring Devices

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ABSTRACT

Review of the application of artificial intelligence (AI) in wearable health-monitoring devices and analysis of their development from basic activity monitors to clinical diagnostic instruments. Wearable sensors can collect continuous health data now; therefore, machine learning algorithms need to be introduced to process this complex, high-dimensional data. Analyze the particular algorithmic structures in wearable ecosystems for this study, including supervised learning for anomaly detection and deep learning for time-series forecasting. Review of practical clinical applications: cardiovascular continuous monitoring, management of metabolic disorders and early diagnosis of neurological diseases. In addition, this paper will also investigate the technical and regulatory problems of wearable artificial intelligence, such as data privacy, system interoperability and algorithmic bias. Optimisation strategies are proposed in the paper, such as edge computing and federated learning, to process data locally and reduce privacy risks while maintaining model accuracy. Based on the above analysis, a unified regulatory system and transparent machine-learning protocols need to be established for the incorporation of wearable AI into official medical institutions.

KEYWORDS

Artificial Intelligence; Wearable Health Devices; Machine Learning; Remote Patient Monitoring; Cardiovascular Monitoring; Federated Learning

1. INTRODUCTION

With the development of new healthcare facilities in recent years, they have gradually introduced digital technology to move away from traditional treatment models and build proactive disease management platforms. Most of the traditional clinical practice is based on periodic patient visits and is conducted in a controlled environment. It is suitable for managing acute illnesses, but a long-term, continuous observation of chronic diseases cannot be conducted under this episodic model. Wearable health-monitoring devices have emerged as a technological solution to extend the time of continuous monitoring for patients. The first wearable fitness devices focused on gathering basic health data for the general public, such as a person's steps and estimated calories burned; now, many advanced biosensors in these devices are capable of acquiring clinical-grade physiological signals.

Continuously collect physiological data to generate a large volume of unstructured information. Raw telemetry data from continuous glucose monitors and smartwatches of electrocardiograms cannot be manually analysed by clinicians in real time due to the large volume of generated data. Computational systems will be used to extract practical medical information from this data. AI technology in the field of wearable health devices can be used to analyse the collected data at any time. Machine learning algorithms in artificial intelligence are used to learn about the normal body functions of people from data and detect any changes that may be related to illness in wearable devices.

Thus, the function of the wearable device is no longer to record data passively but to diagnose actively. Embedded software is used to perform risk stratification in wearables, alert users of any health problems that may have occurred, and send an organised list of relevant data to doctors. Although technology has advanced, many problems in the actual application of these devices have not been solved. Given that it will be used by patients, a lower-risk device has been selected. Currently, with the rise of remote monitoring, new problems have emerged regarding data security and the right to privacy for patients, as well as fairness in the application of diagnostic algorithms to different groups.

The purpose of this paper is to examine the current applications, supporting technologies and system-level problems of artificial intelligence in wearable health monitoring. Section 2 shows the development of wearable sensors and the particular machine learning algorithms applied to physiological data. Section 3 reports on the application of clinical practice in cardiology and endocrinology. Section 4 describes the structural and regulatory problems preventing clinical application. Section 5 puts forward the technological optimisation path, and Section 6 is the conclusion. Based on the present research, this paper will examine the application of computational intelligence in continuous remote monitoring systems safely.

2. EVOLUTION OF BIOSENSORS AND MACHINE LEARNING ARCHITECTURES

Small-scale sensors and complex algorithms have been developed for software that now help to expand the range of wearability for health-monitoring devices [1]. The first type of wearable device used micro-electromechanical systems (MEMS) for motion detection and was only an accelerometer. Over the past ten years, materials science has enabled the construction of complex biosensors that are flexible and wearable [2]. At present, many devices have added optical pulse-oximetry sensors for heart rate monitoring, galvanic skin response (GSR) sensors to gauge stress levels, and continuous subcutaneous glucose monitoring systems [2-3]. These sensors produce high-frequency, continuous time-series data of changes in the body. Steinhubl et al. [3] were the first to propose in their early research on mobile health that the specific applications of biometric data would depend on the analysis method used.

Extract clinical knowledge from the initial data of a sensor using machine learning. Train a machine-learning algorithm to recognise various physiological features of a disease. Support vector machines and random forests are typical examples of supervised learning models applied in wearable device classification tasks [4]. Train these models with a large amount of labelled physiological data and then classify new data. For example, a random forest algorithm can be trained to distinguish between the gait variations of a healthy person and the specific asymmetrical gait patterns of early-stage Parkinson's disease [5].

Recently, deep learning has been applied in many ways to improve the analysis performance of wearable health-monitoring systems. Deep learning models are better at handling complex, high-dimensional sensor data without the need for manual feature engineering compared with traditional machine learning [4-6]. Convolutional neural networks are often used to extract spatial or morphological features of physiological signals, and recurrent neural networks are more suitable for dealing with sequential time-series data to detect changes in health indicators over time [4]. Ravi et al. [6] have shown that deep learning methods can be used to analyze data from on-node sensors in the context of mobile and wearable devices, and they are suitable for real-time activity recognition and anomaly detection. Development will be particularly useful for wearable health management to reduce delay and promptly respond to any abnormalities in a person's body.

In the past, to run a large-scale deep-learning model, one had to send all the raw data to a central cloud server. This transmission process has a relatively large power consumption and some delay [6, 8]. Edge computing is being employed to boost performance in recent years [8]. Edge computing is used to run machine-learning algorithms directly on the microprocessors inside wearable devices. Process the data locally on the wearable device to issue an immediate clinical alarm without an internet connection and save energy and data transmission risks [7-8].

3. CLINICAL APPLICATIONS IN REMOTE PATIENT MONITORING

Machine learning algorithms are now used in wearable biosensors to address problems in long-term health monitoring for chronic diseases. A typical application area is cardiovascular monitoring; otherwise, some irregular heartbeats that do not occur at the time of a general ECG examination may go unnoticed. Photoplethysmography (PPG)-sensor-enabled wearable devices are used to acquire data on alterations in blood circulation across different areas of the body over extended periods of time through daily life. Perez et al. have conducted a large-scale smartwatch-based study to determine that an algorithm for irregular pulse notification can identify individuals who may have atrial fibrillation requiring additional medical attention and are therefore suitable for combining with traditional cardiovascular screening methods [9].

Artificial intelligence (AI)-enabled wearable devices can also be used to monitor metabolic health. To monitor fluctuations in blood sugar for diabetes management, it is necessary to repeatedly take blood samples; thus, the previous method of single measurements may no longer be reliable. Continuous Glucose Monitoring (CGM) devices are worn under the skin to measure blood glucose levels in the interstitial space continuously and provide more comprehensive information on daily changes in blood sugar. Machine learning can be employed to process data, and at the same time, an alarm will be issued immediately upon any abnormal fluctuations in blood sugar to enable people with diabetes to promptly modify their diet, exercise and medication [5,8].

Wearable technology is also being applied to monitor the lungs and other diseases. Collect all kinds of physiological data over time, such as resting heart rate, breathing rhythm, sleep duration and physical exercise, using a wearable device to build an individual's normal pattern; then, any deviation from this normal pattern can be detected. Although these systems should not be regarded as replacements for formal clinical diagnosis, they can serve as early warning devices for acute physiological stress and provide support for earlier medical examination [1, 2].

4. TECHNICAL, ETHICAL, AND REGULATORY CHALLENGES

Although the application scope of AI-driven wearable devices in clinical practice is expanding, serious structural problems still exist. The first reason for regulation by authorities and hospitals is to protect the security of medical data. Older people have better accuracy and diagnostic capabilities for machine-learning algorithms, but a substantial volume of data is still needed. Telemetric data collected by wearable devices in a typical architecture is uploaded to a private cloud service provided by the technology company [11]. Centralisation of the sensitive health data will lead to problems of unauthorised access and commercial exploitation of data, as well as failure to meet medical privacy laws such as the US Health Insurance Portability and Accountability Act [8, 11].

The other problem is that the data from wearables cannot be conveniently integrated with the old electronic health record (EHR) system. The institutional hospital has a unified database for patient data. Data generated by consumer-grade wearable devices are currently in silos and proprietary formats. A standard Application Programming Interface for safely transmitting algorithmic knowledge from a patient's device to an electronic health record has not yet been established [3].

Without this integration, physicians will be unable to use the continuous monitoring data from wearables in their work efficiently and will face limitations in practice [3, 8].

In addition, the medical community has pointed out some problems with algorithmic bias and the general applicability of machine-learning models. The accuracy of a diagnostic algorithm depends on the diversity of the training data to some extent [6-11]. If the training data of an AI model is mainly composed of physiological data from a specific, homogeneous group, its accuracy will likely be reduced when used on people of different ages, ethnicities or with various underlying diseases. Changes in skin colour will affect the accuracy of the optical photoplethysmography sensor in cardiovascular observation, and thus, there will be errors in the algorithm's output [4, 9]. Biased algorithms will further widen the health gap by issuing incorrect diagnostic warnings for underrepresented groups in actual practice [11].

The final regulatory division of AI-powered wearables is also unclear. When the software in a consumer wearable provides diagnostic information, it may be classified as a medical device. The authorities will determine if the Algorithms are safe and effective. However, the adaptive machine-learning model continuously modifies its parameters based on new data and thus poses a regulatory problem. The previous regulatory system was designed for fixed-function devices; now, autonomous-adjustment algorithms in diagnostics have emerged, requiring new regulatory paths for continuous audit [5].

5. OPTIMIZATION STRATEGIES AND FUTURE DIRECTIONS

To address the obstacles to clinical application, developers and researchers have proposed some optimisation strategies, such as strengthening data privacy and algorithm transparency. One of the first practical applications of a solution to the data-privacy problem is a federated-learning framework. Traditional machine learning needs to centralise the data in one place for model training. Federated learning will be used to distribute the training process on the wearable devices. The central server sends a global machine learning model to the user's wearable device in a federated architecture. A model is trained locally with the patient's own data [8, 10]. Only the updated model parameters, which do not contain identifiable patient data, are encrypted and sent back to the central server after training. The server collects the above parameters to enhance the global model, and then distributes it to all devices [10]. This way, the algorithm can learn from a wide range of data across the globe, and at the same time, the raw biometric data will never leave the user's device; thus, privacy and data sovereignty are protected.

In addition to protecting privacy, all parts of the industry are also seeking to enhance the explainability of AI algorithms. In medicine, it is necessary for doctors to know why a deep learning model has reached a particular conclusion in diagnosing a patient. 'Black-box' deep learning models can provide a diagnosis but generally do not explain the reasons behind this decision in terms of physiological factors, and are thus not widely used by the medical community [4]. Research is increasingly being done on explainable AI (XAI) to understand how algorithms make decisions. Visually mark the parts of the electrocardiogram waveform or specific glucose fluctuations that triggered an alarm to provide clinicians with the context necessary to trust and verify the results of explainable AI [4, 11].

Optimisation of wearable technology in practice requires the construction of a standardised data-formatting protocol. Develop open-source data standards to help connect wearable telemetry data with electronic health records (EHRs). The two will help doctors observe long-term changes in a person's body and, in conjunction with traditional laboratory tests, obtain a more complete picture of their health [3]. Regulatory authorities have established particular systems for 'Software as a medical devices' and issued explicit instructions on the clinical verification of adaptive algorithms [5]. The above new standards will help ensure that AI-powered wearable devices meet the safety and effectiveness requirements for broad application in clinical practice [5, 11].

6. CONCLUSION

At present, many wearable devices for monitoring health remotely are now powered by artificial intelligence. Passively collect data and actively analyze diagnostic information to continuously monitor the progress of chronic diseases, such as heart and metabolic diseases. Machine learning algorithms and edge computing architectures provide sufficient computing power for the real-time processing of large volumes of physiological data, abnormal change detection, and disease development prediction. Continuously monitor for any health problems in a person's life and take timely countermeasures if they occur.

However, due to some technical and regulatory problems, these technologies have not been widely used in clinical practice yet. Ensuring the security of continuous biometric data transmission, achieving interoperability between wearable data and hospital record systems, and addressing bias in algorithm training datasets are also problems to be solved. The approval process for continuously evolving software models will also need to be modified to ensure patient safety.

The future applications of wearable health technology will be promoted by structural optimisation. A feasible technical path has been proposed to address privacy issues by means of a federated learning framework that decentralizes the machine-learning training process. Similarly, by advancing the construction of transparent algorithms, more doctors will learn why the system reached that conclusion. Through the construction of a standard protocol and the establishment of transparent engineering practices, these system-wide problems can be solved; thus, artificial intelligence will be applied to wearable biosensors for more accurate and continuous health data collection in a data-driven manner. At present, many wearable devices for monitoring health remotely are now powered by artificial intelligence. Passively collect data and actively analyze diagnostic information to continuously monitor the progress of chronic diseases, such as heart and metabolic diseases. Machine learning algorithms and edge computing architectures provide sufficient computing power for the real-time processing of large volumes of physiological data, abnormal change detection, and disease development prediction. Continuously monitor for any health problems in a person's life and take timely countermeasures if they occur.

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