Editorial

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Integration of wearable devices and deep learning: New possibilities for health management and disease prevention

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SUMMARY In recent years, the market for wearable devices has been rapidly growing, with much of the demand for health management. These devices are equipped with numerous sensors that detect inertial measurements, electrocardiograms, photoplethysmography signals, and more. Utilizing the collected data enables the monitoring and analysis of the user's health status in real time. With the proliferation of wearable devices, research on applications such as human activity recognition, anomaly detection, and disease prediction has advanced by combining these devices with deep learning technology. Analyzing heart rate variability and activity data, for example, enables the early detection of an abnormal health status and prompt, appropriate medical interventions. Much of the current research focuses on short-term predictions, but adopting a long-term perspective is essential for further development of wearable devices and deep learning. Continuously recording user behavior, anomalies, and physical information and collecting and analyzing data over an extended period will enable more accurate disease predictions and lifestyle guidance based on individual habits and physical conditions. Achieving this requires the integration of wearable devices with medical records. A system needs to be created to integrate data collected by wearable devices with medical records such as electronic health records in collaboration with medical facilities like hospitals and clinics. Overcoming this challenge will enable optimal health management and disease prediction for each user, leading to a higher quality of life.

Keywords wearable device, deep learning, healthcare

1. Introduction

In recent years, the demand for health management has been increasing, leading to rapid growth in the market for wearable devices such as smartwatches and fitness trackers. These devices, equipped with sensors that measure heart rate, sleep patterns, and physical activity, serve as tools to help users record their activity levels and manage their health. The wearable technology market size is projected to grow from $157.94 billion in 2024 to $1.41526 trillion by 2032, with an average annual growth rate of 31.5% (*1*).

The applications of wearable devices are not limited to health management and fitness; they also extend to gaming, entertainment, fashion, and education, among others. The health and fitness sector has the largest market share of these devices. The use of wearable devices has made people increasingly aware of the importance of fitness and health. In particular, wearable devices are expected to encourage users to take an active approach to their health by providing critical health indicators in real time. Moreover, these devices are increasingly being used to share information with medical facilities and monitor patients' health remotely. This allows patients to check their condition and progress without visiting a medical facility, which is beneficial for those with chronic diseases.

As the wearable device market grows, research using deep learning to effectively utilize the information obtained from these devices is garnering attention. A type of machine learning, deep learning has seen significant advances in fields like image recognition and natural language processing with methods such as convolutional neural networks (CNN) (*2-4*) and Transformers (*5*). Deep learning can also be applied to time-series data obtained from sensors. When estimating a user's level of activity (such as walking or running) from measured sensor information, for example, deep learning requires actual sensor data and corresponding information on the level of activity. By collecting accurate data on sensor information and the level of activity and training deep learning models with this data, the models themselves acquire methods with which to extract the necessary information for task estimation from sensor data. The sensors equipped on wearable devices are diverse, including inertial measurement unit (IMU) that measure acceleration, gyroscope, and magnetic force, electrocardiograms (ECG), heart rate sensors, photoplethysmography (PPG) sensors that can measure blood oxygen saturation, electromyography (EMG) sensors, and mechanomyography (MMG) sensors (*6-8*). There are a wide range of research applications for these sensor data, including activity estimation, anomaly detection, and disease prediction. The combination of wearable devices and deep learning enables the recording of daily activities and is expected to lead to the early detection and prevention of diseases.

2. Predictions using deep learning

Research utilizing deep learning is advancing to support healthcare in areas such as health management, anomaly detection, and early disease detection, as shown in Table 1. Wearable devices can continuously record dynamic information from users through inertial sensors, but they cannot identify user activities directly. User activities need to be estimated based on sensor information. This task is called human activity recognition (HAR),

Table 1. Overview of studies related to wearable devices and deep learning

Task/Research	Sensors/Signals used	Dataset
Human activity recognition		
Wang K, *et al*. (*9*)	• Inertial measurement unit (IMU)	• Human Activity Recognition Using Smartphones (*35*)
Jiang W, *et al*. (*10*)	• IMU	• Human Activity Recognition Using Smartphones (*35*), USC-HAD (*36,37*)
Chen Y, *et al*. (*11*)	• IMU	• Dataset containing 31688 samples with 8 activities
Zeng M, *et al*. (*12*)	• IMU	• OPPORTUNITY (*16*), Skoda (*38*), Actitracker (*39*)
Yen CT, *et al*. (*13*)	• IMU	• Human Activity Recognition Using Smartphones (*35*)
Stress detection		
Patlar Akbulut F, *et al*. (*17*)	• Electrocardiogram (ECG), electrical conductivity of the skin, oxygen saturation, and blood pressure	• Dataset of 312 records from 30 participants
Arrhythmias detection		
Lee KS, *et al*. (*18*)	• ECG	• Dataset of 28,308 unique patients (15,412 normal and 12,896 with arrhythmia)
Shashikumar SP, *et al*. (*19*)	• ECG, photoplethysmography (PPG), IMU	• Dataset of 98 patients (45 with atrial fibrillation and 53 with other rhythms)
Seizures detection		
Meisel C, *et al*. (*20*)	• Electrodermal activity, body temperature, blood volume pulse, and actigraphy	• Dataset of 69 patients with epilepsy (total duration > 2,311 hours, 452 seizures)
Stirling RE, *et al*. (*21*)	• Heart rate, sleep, and step counts	• Dataset of 11 epilepsy patients followed for more than 6 months
Parkinson's disease detection		
Camps J, *et al*. (*23*)	• IMU	• Dataset of 21 Parkinson's disease patients who manifested freezing of gait episodes
Zia J, *et al*. (*24*)	• IMU	• Daphnet Freezing of Gait (*40*)
Assessment of sleep state		
Cho T, *et al*. (*25*)	• IMU	• Dataset of 10 subjects sleeping for 8 hours
Sleep disorders detection		
Wang T, *et al*. (*26*)	• ECG	• PhysioNet Apnea-ECG dataset (*34*), University College Dublin Sleep Apnea Database (*41*)
Ye G, *et al*. (*27*)	• PPG	• PhysioNet Apnea-ECG dataset (*34*), University College Dublin Sleep Apnea Database (*41*), Apnea Interventions for Research (*42*)
Dementia detection		
Lim J, *et al*. (*30*)	• Electrical conductivity of the skin, body temperature, and IMU	• Dataset of 18 elderly subjects (5 males, 13 females) age 65 years or older
Saif N, *et al*.(*31*)	• Sleep cycle, heart rate variability, and IMU	• Dataset of 33 subjects recruited at the Alzheimer's Prevention Clinic
Lee H, *et al*.(*32*)	• IMU	• Dataset of 60 subjects (30 cognitively normal and 30 with mild cognitive impairment)
Jeon Y, *et al*.(*33*)	• IMU	• Gait data from 145 subjects

which can predict and record activities such as sitting, walking, lying down, climbing stairs, jogging, running, and falling. HAR research is important as it allows users to reflect on their actions and habits and consider their lifestyle. Various deep learning models have been proposed to achieve HAR (*9-13*). These studies mainly use deep learning models based on CNNs. Commonly used in image recognition, CNNs are also suitable for signal processing. CNNs excel in extracting features from short-term signal information and are well-suited for regular human activities of a brief duration. One reason why HAR is actively researched is the availability of abundant datasets. Large amounts of quality data are required to make estimates using deep learning. There are extensive datasets for HAR, such as the University of California Riverside-Time Series Classification (UCR-TSC) archive (*14*), the University of East Anglia multivariate time series classification (UEA-MTSC) archive (*15*), and the OPPORTUNITY dataset (*16*). Each dataset includes time-series signals measured by various sensors: UCR-TSC has 128 datasets, UEA-MTSC has 30 datasets, and the OPPORTUNITY dataset includes data collected from 12 subjects that consists of 18 types of activity information and measurements from 7 IMU and 12 3D accelerometers.

In addition to HAR, anomaly detection is also being researched. For instance, detecting stress states (*17*), arrhythmias (*18,19*), and seizures (*20,21*) are some of the approaches being researched to detect abnormal states in users. In stress detection research, for example, models evaluating stress levels using ECG, skin conductance, oxygen saturation, and blood pressure measurements have been developed for patients with metabolic syndrome. Early intervention is crucial because chronic symptoms worsen when these patients are exposed to stress. In arrhythmia detection, techniques utilizing CNN-based deep learning models to detect arrhythmias in PPG and ECG data with a high level of accuracy have been proposed. For example, atrial fibrillation is asymptomatic in about 10% of cases (*22*) and it increases the risk of stroke and myocardial infarction, so early detection is important. Arrhythmia detection research has proposed CNN-based deep learning models using PPG and ECG data collected from wearable devices to detect arrhythmias with an accuracy of over 95%. Epilepsy is a neurological disorder affecting the central nervous system, causing seizures, limb spasms, and loss of consciousness. Research predicts high-risk states of seizures using information such as skin conductance, body temperature, heart rate, sleep, and steps. Predicting seizures allows patients to avoid high-risk periods and prepare a safe environment. These studies showcase significant technological advances in the early detection and rapid response to abnormal states, ensuring user safety and health.

Constantly worn in daily life, wearable devices are suitable for monitoring signs of disease. Diagnostic models are being developed for various diseases (*e.g.*, Parkinson's disease, sleep disorders, and dementia). Parkinson's disease is a neurodegenerative disorder affecting movement and speech, with symptoms such as uncontrollable tremors, muscle rigidity, and slowed movements. As an example, studies have proposed deep learning models that predict freezing of gait and tremors using acceleration and rotational motion information measured by IMU (*23,24*). Sleep quality is crucial for health, but identifying problems on one's own is difficult. Wearable devices help monitor, measure, and provide feedback on sleep states. For example, studies on sleep stage identification enable the detection of sleep and wake states and quality assessment (*25*). Sleep apnea syndrome, a common breathing disorder, is also detected using wearable devices by analyzing ECG and PPG signals (*26,27*). In an aging society, early detection of dementia is a crucial issue. Indirect methods are effective for early detection and intervention in signs of dementia. Research is underway to estimate cognitive decline using blood, gait patterns, and voice as indirect information to allow inference (*28,29*). Studies using wearable devices have similarly attempted to predict cognitive decline using a combination of information from IMU, skin conductance, and body temperature to ascertain the indirect effects of cognitive decline on the body (*30-33*).

Obtaining datasets for predictions related to such diseases is a significant challenge. Unlike HAR, the difficulty of data collection results in limited available data. An open dataset that is beneficial for prediction tasks involving clinical data and wearable device measurement data is PhysioNet (*34*). PhysioNet has helped to develop wearable devices and deep learning by providing physiological and clinical data in many areas, including arrhythmias, Parkinson's disease, and cognitive decline.

3. Possible applications of wearable devices and deep learning from a long-term perspective

Thus far, we have described various areas of predictive research using deep learning with information obtained from wearable devices. Many studies focus on estimating the user's state at a specific time from short-term signal information, primarily using CNN-based algorithms. While CNNs excel at extracting local patterns and features from input signals, they may not be suitable for long-term predictions.

From a long-term perspective, the information recorded by wearable devices may contain abnormal data with features and patterns related to the user's behavior, lifestyle, and disease predictions. Utilizing this information can enable predictions of diseases related to future lifestyle habits, allowing recommendations to improve those habits. Models based on Transformers are effective for long-term predictions. Initially proposed for natural language processing, Transformers divide text into meaningful chunks called tokens and learn the relationships between these tokens. When Transformers is applied to long-term predictions from sensor data, meaningful token information needs to be extracted from the signals. CNN models built for HAR or anomaly detection are effective at extracting these tokens. HAR estimation converts signal information into user activity data, giving meaning to the signals. Converting sensor information into event data for individuals through existing HAR and anomaly detection will enable the early detection of diseases and the provision of personalized lifestyle guidance based on long-term event histories. For long-term prediction models to become a reality, long-term wearable device data and clinical data are necessary, making data collection a significant challenge. With the growth of the wearable device market, the hope is that new mechanisms will be created to collect and record sensor information linked to medical and health data. In addition, wearable devices will presumably be increasingly used in research that guides users' lives from a long-term perspective.

4. Conclusion

The combination of wearable devices and deep learning holds great potential for health management and disease prevention. These technologies are useful for health monitoring, anomaly detection, and even early disease detection. As a long-term perspective on data collection and analysis is adopted, providing personalized health management tailored to individual users will become possible. In addition, the accuracy and applicability of deep learning models will increase as datasets become more comprehensive. Wearable devices will continue to increase in predictive value as specific applications such as HAR, anomaly detection, and disease prediction progress. In the future, balancing efficient data collection with privacy protection will be a crucial challenge. Overcoming this challenge will allow wearable devices to further integrate into daily life, where they will serve as essential tools to encourage the health of more people.

Ultimately, the fusion of wearable devices and deep learning provides innovative means to more accurately understand individual health conditions and promote preventive medicine. This will enable us to lead healthier and more fulfilling lives, and it is expected to significantly change the nature of healthcare.

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