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Survey on Smart Wearable Devices: What Can AI Affect

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Abstract: In the modern era, as smartphone penetration is approaching saturation, wearable mobile devices have emerged as a significant technological trend. This article focuses on smart wearable devices and explores the critical role of artificial intelligence (AI) in their evolution. It analyzes their development history, technical characteristics, application scenarios, and future directions. By reviewing relevant research, it summarizes the application achievements and challenges of AI in smart wearable devices, such as in the fields of healthcare and education, as well as the data collection and algorithm issues they face. The article also looks forward to the future, emphasizes trends in device integration and multifunctionality. For example, new wristband devices will integrate multiple functions. It also points out that data sharing and database construction are crucial for promoting the development of smart wearable devices, providing forward-looking guidance for research in related fields.

Keywords: wearable devices, artificial intelligence, machine learning

1. Introduction

In today's era, the penetration rate of smart phones is gradually reaching saturation state. With the continuous progress and development of science and technology, wearable mobile devices have become a new trend. More and more users have shown a strong interest in this type of wearable mobile devices, and it is growing day by day. Because wearable mobile devices enhance quality of life in ways that smartphones cannot. In the broad market, a variety of wearable devices have emerged. In Seneviratne et al. and Gao et al., smart wearable devices are classified [1,2]. There are powerful smart watches, which can not only display time, but also realize many functions such as health monitoring and information reminder. A convenient and practical wristband that can monitor movement data and physical condition in real time; There are also smart glasses full of technology, which bring users a new visual experience and interaction.

At the same time, many advanced artificial intelligence technologies have emerged, which play a crucial role in smart wearable devices. You know, although smart wearable devices can collect a lot of data, but if there is no active participation of artificial intelligence technology, then these data remain meaningless without the analytical power of AI, and cannot be applied to in-depth analysis and mining. Only with the help of the powerful computing power and data analysis ability of artificial intelligence technology can these data be analyzed in detail and valuable information and laws can be extracted from them. Then, based on these information and laws, we can form suggestions with practical guiding significance for people's lives, help people better understand their physical

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conditions, living habits, etc., to make more scientific and reasonable decisions, improve the quality of life and happiness.

This review focus on wearable devices and their wide application fields, through in-depth analysis of the development history, technical characteristics, application scenarios and other aspects of wearable devices, the key role of artificial intelligence methods in wearable devices is discussed. It aims to provide a forward-looking and guiding direction for the research of wearable devices in the future, leading the field towards a more intelligent, efficient and humane direction.

2. Related works

A wearable device is a computer that integrates into the user's personal space, is controlled by the user, has continuous operation and interaction (that is, it is always on and accessible at any time), has the same computing power as mobile phones and tablets, and in some cases is more capable of specific tasks because of its portability.

Jiang et al. detailed the historical evolution of wearable devices. During the 1960s - 1970s, wearable devices were created for special purposes, such as MIT's cheating shoes, Hamilton's calculator watches, and CC Collins' device for the blind [3]. However, their adoption was limited due to unclear roles and niche applications. In the 1980s - 1990s, these devices attracted more attention but were impractical and unfriendly for consumers, like Steve Mann's head-mounted cameras and backpack computers. Since 2000s, wearable devices have made significant advances, with complex designs based on user/market needs. Many companies launched products such as Fitbit in 2007, Google Glasses in 2013, and Apple smart watches. A boom with increased shipments is expected, and they'll increasingly enter people's lives and attract more users.

In Ba et al.'s explored the combined use of machine learning and wearable devices for measuring emotional states in educational settings [4]. Through 15 studies, machine learning employs traditional classifiers to model data-emotion relations, an important way to infer the correlation between physiological signals and educational emotions. However, it has challenges like data volume and ground truth value difficulties and poor model interpretation. Future efforts should focus on building datasets and improving advanced models. Wearable devices can detect physiological signals for emotion measurement. Some portable ones aid natural context data collection and those measuring multi-channel signals have advantages. But analyzing and identifying emotions remains challenging. The use frequency of different devices reveals trends and limitations like high cost or limited signal measurement. So, more suitable wearable devices for educational applications need exploration.

These studies largely summarize traditional artificial intelligence algorithms and their applications. This paper seeks to build upon this foundation by discussing and analyzing more advanced methods that can address current challenges and unlock new possibilities for wearable devices.

3. Advanced Applications of AI in smart wearable devices

3.1. Supervised learning

The decision tree algorithm, a commonly used machine learning model, uses a tree structure (root, internal, leaf nodes) for classification and regression. Root holds dataset, internal nodes test features, leaf nodes show category labels (classification) or predicted values (regression). Ba et al.'s 15 studies used it to model data-emotion relations, mainly analyzing correlation between physiological signals and educational emotions [4]. For example, it analyze students' physiological signals in learning to predict emotional states (anxiety, concentration), helping teachers adjust strategies & improve teaching effects .

SVM, a supervised ML algorithm, is mainly for classification & regression. In classification, it seeks an optimal hyperplane to separate data points (line in 2D, plane in 3D, subspace in higher dims).

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Nahavandi et al. and Covi et al. applied SVM in biomedical engineering[5][6]. In disease diagnosis, it processes ECG for heart disease diagnosis, aids in Parkinson's/Alzheimer's activity & near-loss detection via wearable data, detects stress in children & physical fatigue, and identifies construction worker stress. In ECG signal processing, Zhang et al. and Raj et al. used it for heartbeat type classification to detect arrhythmias. In EMG signal processing, Donati et al. combined it with neuromorphic pulse neural networks for gesture recognition, important in human-computer interaction.

Random forest, an ensemble learning algorithm, comprises multiple decision trees. Its basic concept involves constructing independent decision trees and combining their results for classification or regression. In classification, voting (majority decision tree's result) determines the final classification. In regression, the average of all decision trees' prediction results gives the final predicted value. When Beniczky et al. developed a general algorithm using human and canine implantable EEG records for epilepsy detection in Kaggle competition, the random forest classifier achieved an AUC>0.97, highlighting its utility in long-term EEG automatic detection of seizures[7]. In terms of epilepsy prediction, in the Kaggle competition for the three most challenging patients, a weighted combination of random forests was used to achieve an AUC of 0.82, indicating that the algorithm needs to be flexible in responding to patient-specific pre-seizure signals.

The K-nearest neighbor algorithm, a simple yet effective supervised ML algorithm, is mainly for classification and regression. "K" indicates the number of nearest neighbors considered in prediction. Its core principle is to decide the category or value of the sample to be predicted based on the category (for classification) or value (for regression) of the "K" closest samples in the dataset. Sabry et al. use K-NN algorithm for applications such as fall detection, stress detection and emotion recognition [8]. In the fall detection, it is used to analyze the data of accelerometer, gyroscope and magnetometer, and determine whether the human body falls or not by finding the K neighbors nearest to the test data to determine the category, to achieve rapid detection. In the stress detection, the physiological data of wearable device is processed by this method, and the current sample category is determined according to the category of K nearest neighbors to identify the user's stress state. In emotion recognition, K-NN is used to analyze the data of MUSE headband (EEG) and Shimmer GSR + devices (SC and HR) to classify emotions, identify emotional states such as excitement, happiness, fear and anger, and help people understand their emotional changes.

The Naive Bayes classifier, based on Bayes' theorem, assumes feature independence and calculates the probability of different classifications to determine the most likely category. When classifying a sample, it calculates the probability in different categories using prior and conditional probabilities. After complex math, it classifies the sample based on the highest probability. With simplicity and efficiency, it has great application value in text classification (handling various texts) and spam filtering (quickly identifying spam for a cleaner inbox and better info processing). In the study of Sabry et al., naive Bayes classifier was used in stress detection and disease diagnosis [8]. In the aspect of pressure detection, it is used to analyze physiological data collected by wearable devices, and quickly calculate various probabilities based on Bayes' theorem and independent hypothesis of characteristic conditions, to detect the user's pressure state. In the research related to disease diagnosis, it can classify and diagnose the disease according to the patient's symptoms, history and other data, and provide reference for medical decision-making.

Convolutional neural networks (CNNs) are widely used for processing complex data such as images and signals. A CNN consists of convolutional layers, (extracting features like edges and textures), pooling layers (reducing data dimensions while retaining key features), and fully connected layers (integrating features for final classification). In Ravi et al.'s paper, signal spectrum matrix was got via short-time Fourier transform of inertial signal spectrum diagram [9]. In deep learning module, spectrum diagrams were grouped (by axis for columns & sensor for rows), processed with 1-D convolution for weighting & output layer. Convolution results of three axes were added with shared filter weights to cut parameters. Finally, convolution-extracted features combined with shallow ones, and activity was identified by full connection & soft-max layers. Covi et al. employs CNN [5]. In gesture classification benchmark test, a spiking CNN based on pulses is implemented on Loihi for visual input processing, extracting features from event-driven sensor data for gesture recognition. On Loihi, CNN works with other components to process visual signal & convert it for gesture recognition, leveraging low power & high parallelism. On ODIN/MorphIC, MLP is used for gesture recognition & EMG signal processing. Here, CNN application differs from Loihi due to hardware differences. But on both platforms, sensor fusion before classification layer combines outputs from different components (pulse-based CNNs & MLPs on Loihi; two pulse-based MLPs on ODIN/MorphIC) to enhance gesture recognition accuracy by exploiting sensor mode advantages.

Long short-term memory networks (LSTM), a special recurrent neural network for sequential data (time series, natural language), aims to solve RNN's gradient issues. Its unit has input, forget, and output gates. The forget gate decides what to discard from cell state, the input gate what new info to add, and the output gate what to output. For instance, in text processing, the cell state acts like text semantic memory, and via gate control, long sequence data can be efficiently processed with selective memory retention and update. Jin et al. and Saadatnejad et al. proposed an architecture containing wavelet transform and multiple LSTM recurrent neural networks [10][11]. The digital ECG signal samples were first segmented into heartbeat fragments, and RR interval features and small wave signs were extracted. Then these features and ECG signal samples were input into two RNN-based models (model α and model β). LSTM can automatically extract features based on actual dependencies, avoid gradient disappearance or explosion problems, and effectively capture the timing information in the signal. In the model, LSTM controls the transfer and accumulation of information through forgetting gates, input gates and output gates, so that the model can better learn and remember long-term dependencies, to accurately classify heartbeats.

3.2. Unsupervised learning

K-means, a widely used clustering algorithm, groups data into K clusters through an iterative process. It alternates between updating cluster centers and assigning data points to clusters, minimizing the sum of distances between data points and their cluster centers. This method enhances intra-cluster similarity and cohesion, facilitating meaningful analysis. Sabry et al. applied K-means in rehabilitation by classifying gait and movement patterns using IMU and insole pressure data [8]. This clustering helped analyze patient movements and supported training regimens. Additionally, in diet monitoring, K-means was used with wrist-worn accelerometer data to correlate hand movements and activity patterns with eating behaviors. Such applications are valuable for behavior monitoring and managing the health and dietary habits of specific groups, such as individuals with diabetes.

PCA is a vital data dimensionality reduction technique in analysis. It projects high-dim data to low-dim via linear transformation, retaining maximum variance info of original data (as variance shows dispersion, ensuring reduced data reflects original distribution and trend, useful for analysis/modeling or avoiding high-dim issues). Nahavandi et al. used PCA as a feature selection algorithm: converting original features to variance-sorted principal components via data covariance matrix decomposition, choosing top variance principal components as new features [6]. It can handle wearable device's multidimensional physiological data, reducing dimensions, redundancy, and retaining key info for further analysis & model training.

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4. Future work

In the future development of science and technology, device integration and multi-function will become a significant trend in the field of smart wearable devices. With the continuous evolution of technology, people have put forward higher requirements for the convenience and practicality of wearable devices.

Currently, employees usually must carry and use multiple devices at work, increasing physical load and potentially affecting efficiency. Future technological innovation is anticipated to integrate various functions into one wearable device. Khakurel et al. conceived a new wristband. It has advanced activity monitoring to record employees' physical activity data like steps, movement tracks, and exercise intensity for health management [12]. It also has access control, allowing employees to pass workplace access systems with a wrist flick, eliminating the need for extra access cards or other identification tools, enhancing traffic efficiency. Moreover, it has a timestamp function to record key work time nodes such as punch-in/out and task start/end times, facilitating enterprises' detailed work management.

The potential exploitation of specific equipment has become one of the key factors to promote the development of various industries, and wearable exoskeletons are a very representative example.

Wearable exoskeleton equip has workplace app challenges but great potential. Its safety standards are developing, apps are mostly experimental. It has a long way in tech maturity, op specs, and workflow adaption, yet is expected to be crucial in future heavy-labor work. Smart wearables-ML integration has issues in healthcare. Babu.et.al noted ML's clinical challenges like regulatory and performance benchmark problems [13]. ML needs large, consistent data for accurate models, but getting enough high-quality data is tough. For example, in rare epilepsy cases, insufficient seizure data can limit model accuracy in detection or prediction.

Beniczky et al. stated that missing or unreliable data annotation can impair ML model performance [7]. In multi-center data collection, varying standards, equipment accuracy, and recording methods may cause data inconsistency and incompleteness, affecting model training. For example, some centers' records of patient seizure symptoms may be inaccurate or lacking detail, hindering accurate seizure feature identification by trained models. Future data sharing and large database construction are essential for new algorithm development and validation, promoting the advancement of smart wearables in epilepsy care to enhance patient service.

5. Conclusion

Smart wearable devices have attracted significant attention due to their potential to enhance the quality of life, and AI technology plays a crucial role in their development. This article reviews relevant research, elaborating on the development process of smart wearable devices, from their early special-purpose applications to the diverse functions they possess today, with the expectation of explosive growth in the future. In terms of applications, they cover various fields such as healthcare and education. For instance, in epilepsy treatment, although they can assist in detection and prediction, challenges remain in areas like clinical validation and data collection. In education, machine learning and wearable devices are used to measure educational emotions, but face difficulties in data volume and model interpretation. Future trends indicate that device integration and multi-functionality will prevail. For example, new wristband devices will combine multiple functions to reduce the burden on employees in the workplace. Additionally, wearable exoskeletons hold great potential for heavy-labor work despite current limitations. However, issues such as data inconsistency and the need for large databases in machine learning applications need to be addressed. Overall, this review provides a comprehensive understanding of smart wearable devices and their relationship with AI, highlighting both achievements and areas for improvement.

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