Application of artificial intelligence in wearable devices: Opportunities and Challenges

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Application of artificial intelligence in wearable devices: Opportunities and Challenges

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Abstract

Background and objectives: Wearable technologies have added completely new and fast emerging tools to the popular field of personal gadgets. Aside from being fashionable and equipped with advanced hardware technologies such as communication modules and networking, wearable devices have the potential to fuel artificial intelligence (AI) methods with a wide range of valuable data.

Methods: Various AI techniques such as supervised, unsupervised, semi-supervised and reinforcement learning (RL) have already been used to carry out various tasks. This paper reviews the recent applications of wearables that have leveraged AI to achieve their objectives.

Results: Particular example applications of supervised and unsupervised learning for medical diagnosis are reviewed. Moreover, examples combining the internet of things, wearables, and RL are reviewed. Application examples of wearables will be also presented for specific domains such as medical, industrial, and sport. Medical applications include fitness, movement disorder, mental health, etc. Industrial applications include employee performance improvement with the aid of wearables. Sport applications are all about providing better user experience during workout sessions or professional gameplays.

Conclusion: The most important challenges regarding design and development of wearable devices and the computation burden of using AI methods are presented. Finally, future challenges and opportunities for wearable devices are presented.

Keywords: Wearable devices, Healthcare, Machine learning, Deep learning, Internet of things

1 Introduction

Wearables are small electronic and mobile devices, or computers with wireless communication capabilities incorporated into gadgets, accessories, or clothes, which can be worn on the human body. There are also invasive versions of the wearables such as micro-chips or smart tattoos [1]. Nowadays, different types of wearable devices have been invented. Some of the most common wearable devices are smart glasses and smart watches. The consumer market of the wearable devices is increasing steadily. The wearables are used to collect, transmit and even analyse the data commonly collected from the body of a human or animal. They are purely mechanical devices or intelligent mechatronic systems which are commonly built using sensors, actuators, and computation parts. They can be used for early diagnosis and management of medical conditions as well as measuring the vital signs such as body and skin temperature, blood pressure [2], heart rate, electrocardiogram (ECG) [3], and electroencephalogram (EEG) [4]. All these wearable devices are implemented with various technologies, capabilities and costs. People who use these technologies may need some skills to work with them.

Wearable devices are classified based on their requirement and usage. Some of them are used according to the instructions of physicians to avoid serious problems. However, some wearables are not used in medical fields [5-7]. In [8], a comprehensive review of wearable devices was done in which, smart wearable devices such as watches, eyewear, headsets, jewellery, rings, chains, garments, and bracelets were described. The list of these devices can be seen in Figure 1 [9].

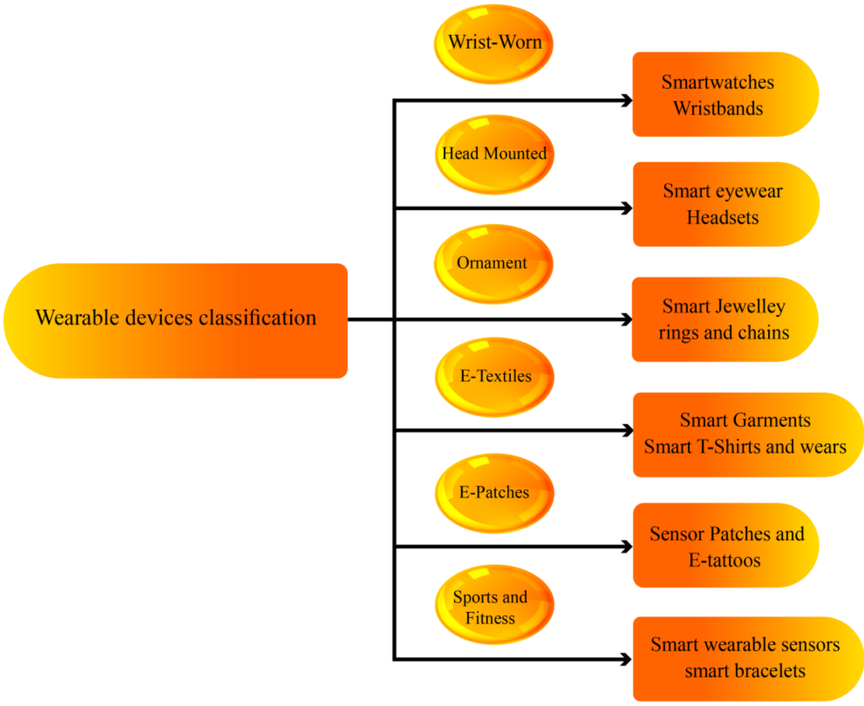


Figure 1. Different categories of wearables used.

Wearable devices are made in different forms to meet their usage requirements. They are commonly in small size while they are expected to sense continuously. They should be able to collect data and process them to improve the quality of life. Therefore, wearables need to communicate in a secure way while keeping their power consumption as low as possible. The security of wearable devices is a big challenge. They may be able to collect the data locally or send them to an external device. In both cases, the data should be encrypted to enforce their privacy. Given that wearable devices usually have low computational power, a lightweight authentication test is needed. In addition, wearable devices must be able to communicate in real-time; such requirement impacts on the challenge of power consumption management.

The motivation behind this review is the fact that the emerging field of wearable devices has the potential to open new application opportunities in various domains. The focus of this review is on medical, industrial, and sport applications. We focused on the medical domain since it is directly related to the lives of people. With enough development, wearables have the potential to revolutionize the medical domain leading to cost-effective healthcare services and longer lifetimes. In the industrial domain, wearable devices can make workstations more ergonomic. To this end, the workers can be equipped with appropriate wearable devices in order to accelerate the industrial processes leading to shortened working hours and better psychological health. The sport domain is also important since it can be used for medical diagnosis and treatment. Additionally, sport is directly related to the general well-being of society. Therefore, sport domain is also an important domain that is worth reviewing.

A comprehensive review of existing wearables, their capabilities and shortcomings can shape future research directions. In this review, wearable devices as well as the role of AI methods to achieve various tasks with wearables are investigated. The employed paper collection strategy is outlined in section 2. Various wearables are reviewed briefly in section 3. Denoising methods used in wearables are explained in section 4. Feature extraction, engineering and artificial intelligence methods used are described in Section 5. The applications of machine learning in wearable devices are presented in Section 6. Applications of wearables are explained in section 7. The challenges of developing wearables are reported in section 7.4. Discussion and future insights will be presented in Section 9 and the conclusion is given in Section 10.

2 Paper collection strategy

For reviewing previous papers in the field of wearables, all datasets supported by Google scholar such as IEEE, Science Direct, Springer, ACM Digital Library, and Hindawi were searched. The search query used in this work was:

(wearable technology healthcare OR wearable devices OR wearables OR smart wears OR wearable technology OR industrial wearable OR sports wearable) AND (artificial intelligence OR data mining OR deep learning OR machine learning).

Three authors inspected the papers collected based on the search phrases mentioned above. Papers that two out of three authors agreed on their relevance to this review were selected for further analysis. Based on the above phrases and the opinion of the three authors, 132 papers published in high-ranked journals and conferences were selected. The paper selection mechanism is presented in Figure 2 in which the number of selected papers from each publisher is reported separately.

We did not limit our search to medical applications since wearable devices used in different domains share common hardware/software technologies. Hence, it was necessary to take a broader view during data collection for this review. In addition to medical domain, this review considered industrial and sport applications of wearables as well. The motivation was that industrial and sport applications are closely related to medical applications. In industrial domain, well designed wearables can be used to make the working environment more ergonomic reducing workers' injuries. In sport domain, wearable devices can help individuals with their fitness programs leading to healthier society.

The selected papers were carefully studied by the three authors. The study of papers related to each of three major fields (medical, industrial, and sport) was assigned to one of the authors. Each author extracted and organized the necessary information for this review. The investigation of the selected papers was primarily focused on the main approach used during software/hardware implementation of the wearable devices.

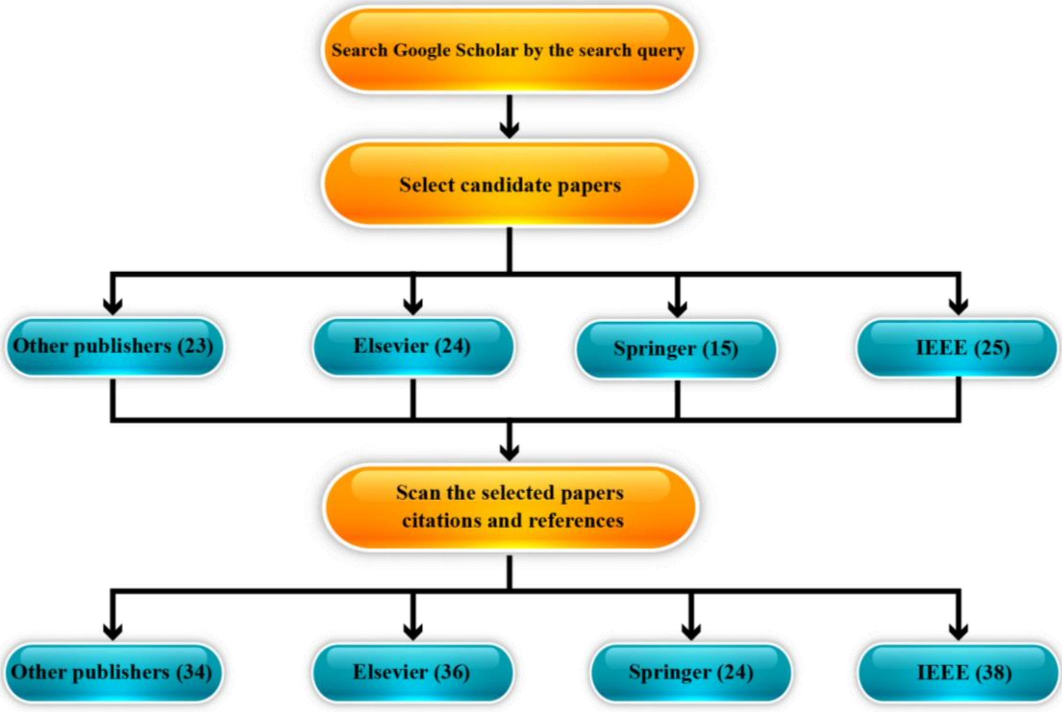


Figure 2. Paper selection mechanism

Certainty about the outcome of the reviewed papers is verifiable since most of these papers have been published in top-ranked journals and conferences. Additionally, many of the reviewed papers or wearable devices have already been used in practice proving their capabilities.

3 Brief review of wearables

Wearables can be used for data collection in daily activities, sport performance, and health monitoring. There are different types of wearables such as smartwatches, hearing aids, electronic tattoos, wristbands, subcutaneous sensors, head-mounted displays, electronic textiles, and footwear as shown in Figure 3(a) [10]. These devices are placed on different body parts to measure electrophysiological and biochemical signals or deliver drugs.

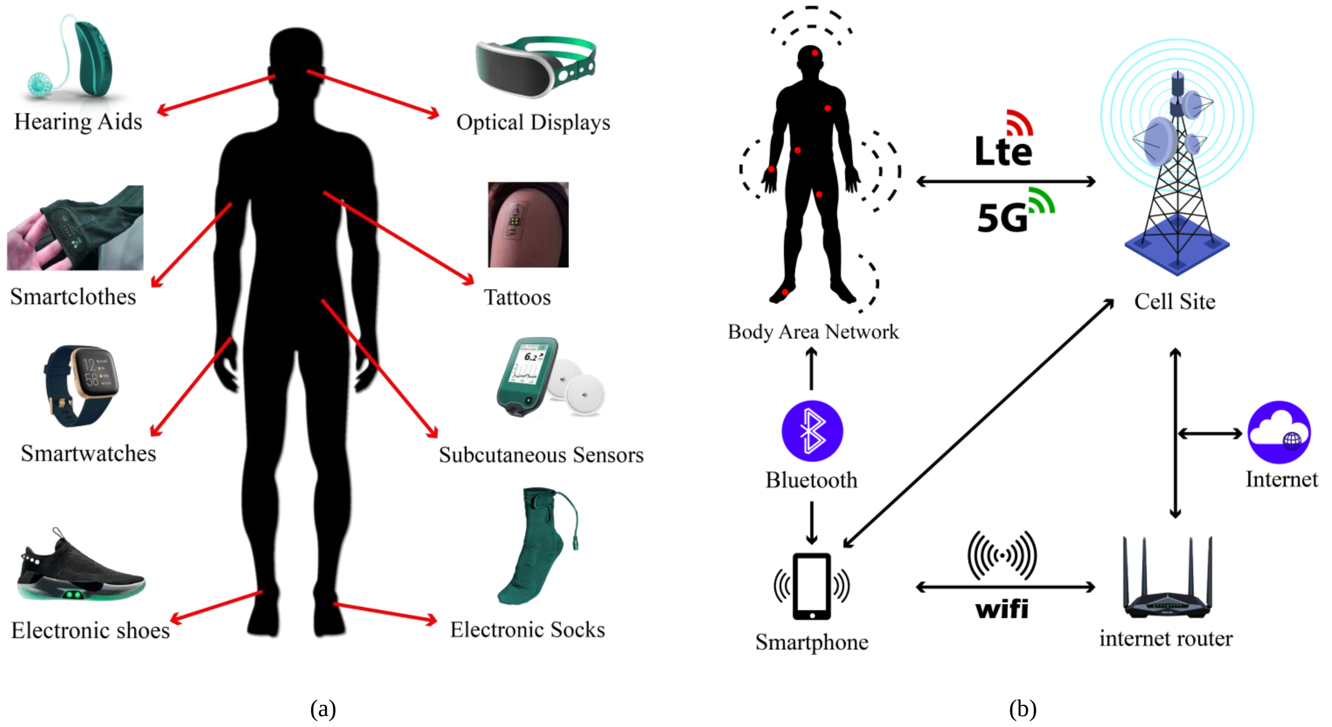


Figure 3. Wearables devices used to monitor physiological parameters: (a) different wearable devices which have been designed for different parts of human body, (b) various technologies used to transfer data collected from wearables to other devices.

Wearable devices are used for augmented, virtual, and mixed reality, artificial intelligence, and pattern recognition [11, 12]. These technologies commonly contain microprocessors and sensors. Additionally, these devices are usually capable of recording data and exchanging them over wireless connections [13]. Sensors used in wearable devices include barometers and inertial measurement unit (IMU) which is combination of gyroscopes, accelerometers, and sometimes magnetometers. Optical sensors needed in spectrophotometers, cameras, chemical probes, electrodes, microphones, shock detectors, and pressure sensors are other types of sensors used in wearables [14]. Utilizing the sensors in multiple wearables provides a rich collection of data which can be analysed by researchers or used by experts to provide medical treatment remotely. These data can be transmitted by different types of networks [15]. As shown in Figure 3.b, these networks can even transmit the data over the internet. The capability of wearables to operate in a network of connected devices paves the road towards implementing Internet of things (IoT) [16].

The existing wearable devices can be categorized based on their applications and the body parts on which they are mounted. Since 2016, the distribution of number of wearables in different application domains is shown in Figure 4.a [17]. As can be seen, the "lifestyle" application has the highest number of wearables (about 200) while the "pet animals" application has the least number of existing wearables. Since 2016, the distribution of existing wearables based on their target body part is shown in Figure 4.b [17]. It is clear that most of the existing wearables are mounted on the head (about 65 devices), followed by torso and neck and then body parts have the third highest number of wearables. Figure 5 illustrates two samples of wearables with medical applications. Figure 5.a shows a typical head-mounted wearable used for EEG analysis and Figure 5.b shows a torso-mounted wearable used for ECG analysis.

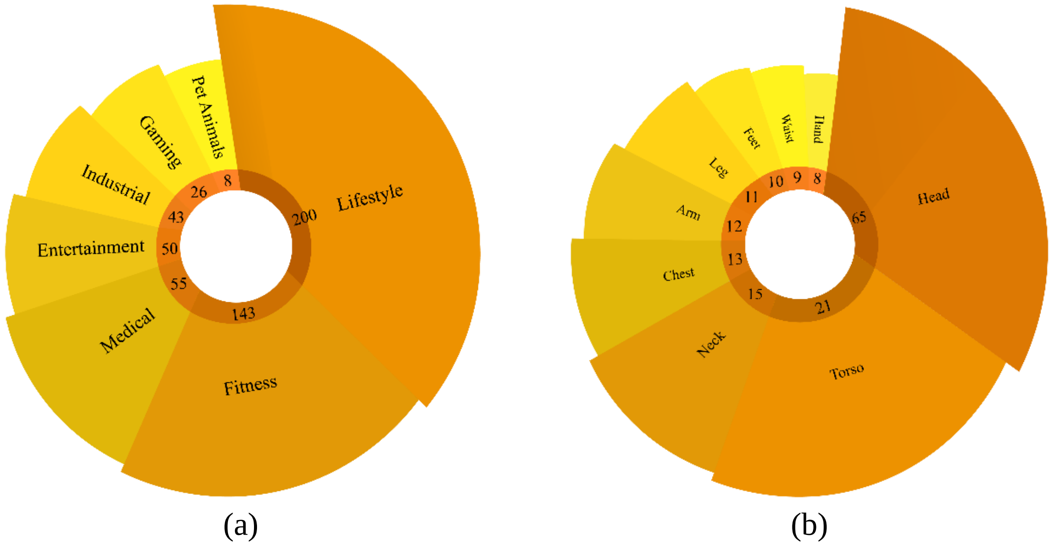


Figure 4. Distribution of number of existing wearables (as of 2016) based on: (a) application domains, (b) target body parts.

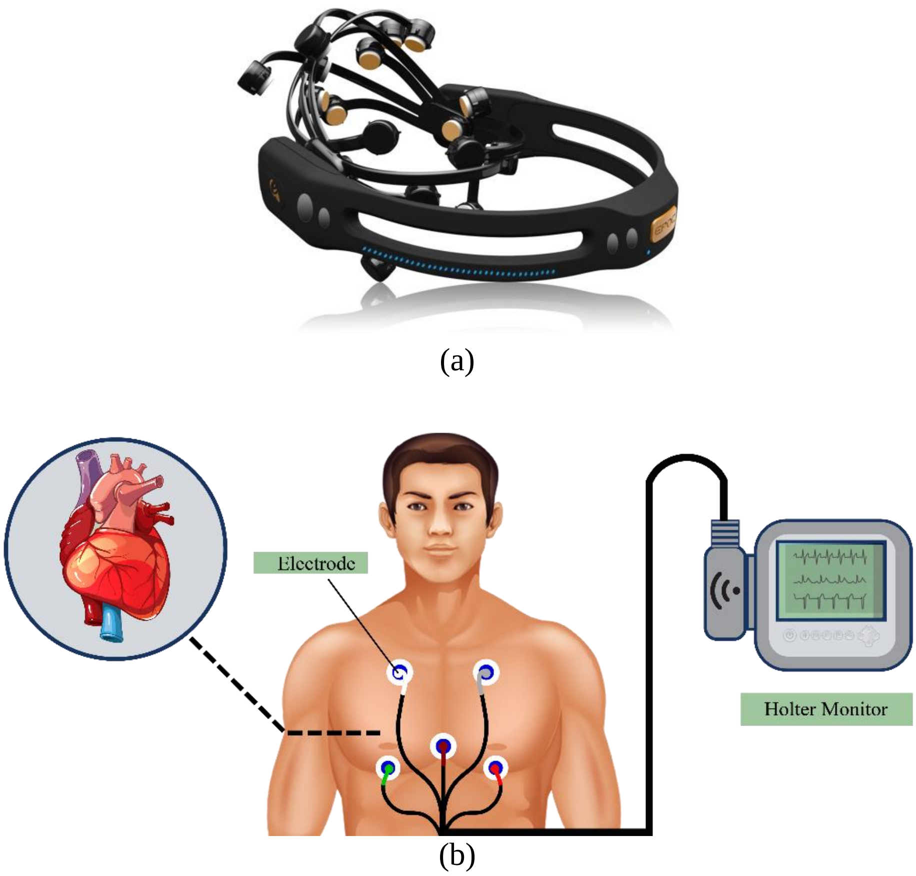


Figure 5. Illustration of two typical wearables with medical applications: (a) head-mounted wearable device for EEG measurement, and (b) torso mounted wearable device for ECG measurement.

4 Denoising methods used in wearables

Signals, which have been gathered from wearable sensors, are commonly affected by noise. The noise sources are generated when the measuring element and the data collection system try to collect the signals. This section aims to introduce the AI-based hardware designed for denoising. As real information generated by biological systems, randomness of these systems are relatively low while the real information collected in time are often correlated.

For denoising, researchers have used different methods. In [18], a sixth-order bandpass IIR filter was used to eliminate the noise. In another research [19], a deep convolutional neural network was used. In [20], the noise and baseline removal of all ECG signals were performed with Daubechies wavelet filters. In [21], as one of the pre-processing steps, an 8-point moving average filter was used to remove noise. To this end, finite windows of moving average filter were convolved with the signal. It took an average of the output signal for discrete-time noise reduction and enhanced the peak value identification.

Chen et al. [22] developed a statistical model to simulate structured noise processing derived from a wearable sensor. Synthetic data generated using a structured noise model was studied and a factor analysis-based method was proposed for denoising. Lee et al. [23] proposed a denoising method that references photoplethysmography to alleviate intrinsic and extrinsic noise in electrodermal activity. Their method attenuates the extrinsic noises by applying several filters such as high-pass and wavelet filters. Then, intrinsic respiration noises were detected and attenuated by a subject independent machine learning model that could detect noise.

A new electrocardiogram (ECG) denoising technique was proposed in [24]. In their work, denoising was done by variable frequency complex demodulation algorithm. To remove the noise, this algorithm is used to perform the sub-band decomposition of the noise-contaminated ECG. More improvement in ECG quality is done by not only removing baseline drift but also smoothing via adaptive mean filtering. Two datasets were used to validate the proposed method. The performance of the proposed denoising algorithm was compared with other denoising algorithms and its superiority with respect to other methods is shown.

5 Artificial Intelligence Methods

In this section, at first, feature extraction and engineering is reviewed and then different categories of AI methods i.e. supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning are introduced. These learning methods and their main subfields are shown in Figure 6.

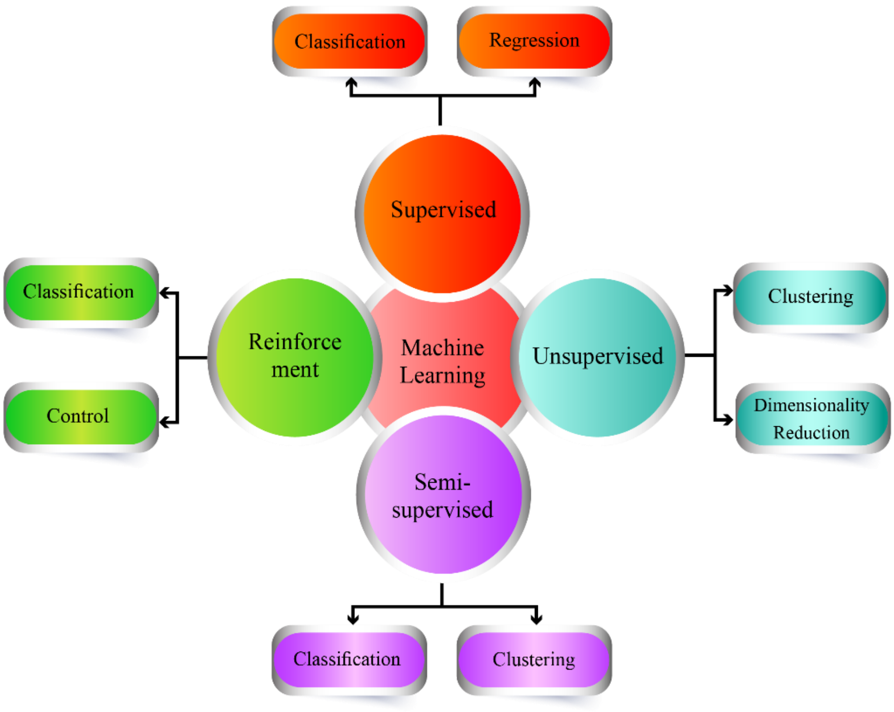


Figure 6. Different AI methods and their main subfields.

5.1 Feature Extraction and Engineering

Feature extraction is one of the fundamental steps in machine learning. Having too many features could easily confuse the machine learning algorithms [25]. Therefore, feature selection algorithms are used to select the clinically significant features. The mean and mode [26] or algorithms such as principal components analysis (PCA) [27], linear discriminant analysis (LDA) [28], independent component analysis (ICA) [29], locally linear embedding (LLE) [30], and autoencoders [31] can also be used to select the statistically significant features. Such features can be exploited by learning methods.

The process of extracting useful features from raw data based on domain knowledge is called feature engineering [32]. The first step in feature engineering is developing useful features by (i) automatic, (ii) manual, or (iii) fusion of both manual and automated feature extraction. The next step is feature selection in which a subset of extracted features is selected according to some feature scoring measure. The performance of selected features is then evaluated based on the target dataset. This process is repeated until satisfactory results are obtained.

5.2 Supervised Learning

The learning algorithms are divided into two main types: supervised and unsupervised. In supervised learning, the desired output for the training samples is known and the model is trained using the given samples of data and their desired outputs [33]. Generally, supervised learning is used for classification in which the goal is to map an input sample to the output label [34]. It is also used for regression whose goal is learning a mapping from inputs to continuous output. In both classification and regression, we want to find the correct relationships between the input and output. Indeed, we are looking for a model that can produce correct output data effectively. If the training data are noisy or have incorrect labels, the effectiveness of the trained model will be clearly degraded. Some of the common supervised learning algorithms are support vector machine (SVM) [35], artificial neural network (ANN) [36], Naïve Bayes [37, 38], and random forest [39].

5.3 Deep Learning

Deep learning (DL) is part of a broader family of machine learning methods based on artificial neural networks (NNs). In the realm of deep learning, we often come across convolutional neural network (CNN) which is a special type of NN capable of handling 2D image data [40]. The primary component of a CNN is the convolutional layer which performs convolution on a given image. To this end, one needs to specify a 2D array of weight values called a kernel which is smaller than the image. The convolution operation is simply the dot product of the kernel with a kernel sized patch of the given image [41]. The convolutional layer output is passed through an activation function such as ReLU[1]. Automatic feature extraction is one of the most important characteristics of CNNs. However, training CNNs usually demands high computational resources. In recent years, such a burden has been alleviated due to the advent of powerful graphics processing units (GPUs) [42].

5.4 Unsupervised learning

In unsupervised learning, the objective is to learn the inherent structure of unlabelled data. The most usual tasks within unsupervised learning are clustering, density estimation, and representation learning. For this purpose, some of the algorithms such as principal component analysis (PCA) and auto-encoders have been proposed [43]. Exploratory analysis and dimensionality reduction are two common use cases used in unsupervised learning. In scenarios where the dataset analysis is impossible for humans; unsupervised methods can be used to gain initial insights into the data. The insights can be used for testing different hypotheses. For dimension reduction, the data are represented by fewer features. This process can also be done using unsupervised learning. To this end, the relationship between features must be discovered. It can help us to eliminate the redundant features. Consequently, processing the data can be done by a much less intensive solution [44].

5.5 Semi-supervised learning

In scenarios where the number of labelled samples is small while number of unlabelled samples is large, supervised and unsupervised learning cannot be used effectively. In this situation, semi-supervised learning algorithms can help. They can be trained by a small number of labelled and a large number of unlabelled data to predict a new example. When there are some labelled data, they can help the algorithms to use the unlabelled data more efficiently and produce considerable improvement in learning accuracy. Acquisition of labelled data to be used in learning problems commonly requires expert agents. Labelling the samples may

[1] Rectified Linear Unit

be costly and in some cases impossible due to large number of unlabelled samples. Under these circumstances, the importance of semi-supervised learning becomes clear [45].

5.6 Reinforcement learning

The reinforcement learning (RL) is learning to map situations to suitable actions such that a numerical reward signal is maximized [46]. Unlike supervised learning, in RL, the learner is not provided with the desired action and it has to try different actions in different situations (also known as states) to figure out the best actions leading to the maximum reward given the observed states. It is important to learn action selection such that the long term utility is maximized since naively choosing to maximize the immediate reward might lead to suboptimal performance in the long run. RL problems can be modelled as Markov decision processes (MDPs). A MDP is a 4-tuple (S, A, P, R), where:

- S is the set of states (state space)
- A is the set of actions (action space)
- $P(s_{t+1} = s' | s_t = s, a_t = a)$ is called the transition function which outputs the probability of observing state s' at time step t+1 provided that at time step t observed state is s and chosen action is a.
- $r_{t+1} = R(s_t = s, a_t = a, s_{t+1} = s')$ is the expected reward if at time step t, the observed state is s and execution of the chosen action a will lead to state s' in the time step t+1.

6 Application of machine learning algorithms in wearables

Various machine learning methods have been used in the field of wearables. In this section, some of existing works which combine wearable devices with machine learning algorithms are reviewed. The review has been categorized based on type of machine learning methods. The summary of works done using wearables and AI techniques are shown in Table 1.

6.1 Application of supervised learning methods in wearables

Supervised learning methods are widely used in machine learning to develop the automated systems. Saadatnejad et al. [47] suggested a novel electrocardiogram (ECG) classification algorithm. On wearable devices, this method was used for continuous monitoring of cardiac disease. The advantage of this method was its low power consumption. Their method used multiple long short term memory (LSTM) recurrent neural networks and wavelet transform. Their method achieved high ECG classification performance. Similarly in [48], a novel ECG classification algorithm was proposed and used in low-power wearables based on spiking neural networks. A spike-timing dependent plasticity and reward-modulation were employed in which the model weights are trained according to the timings of spike signals. The results showed that it was suitable for real-time operation. Additionally, in the real-time classification of ECG signals, its energy consumption was significantly lower than other similar devices. In another work reported by Acharya and Basu [49], the primary objective was to build classification models to identify anomalies of patients' breathing sounds. These data were used for automated diagnosis of respiratory and pulmonary diseases. A deep learning model was used to classify respiratory sounds. Additionally, a local log quantization strategy was proposed to reduce the memory footprint which can be used in memory constrained wearable devices.

Wearable sensors can be used in disease diagnosis based on physical movement of patients. For instance, Hssayeni et al. [50] used a LSTM recurrent neural network (RNN) to detect early signs of Parkinson's disease (PD) using accelerometers and gyroscopes data. In another study, waist-worn accelerators and SVM were used to detect freezing of gate (FoG) experienced by PD patients [51]. The walking pattern can be used to diagnose Alzheimer disease. Varatharajan et al. [52] monitored walking patterns of patients using a dynamic time warping algorithm and several wearable sensors including accelerometers. Based on the perceived walking pattern, early signs of Alzheimer disease were detected.

6.2 Application of unsupervised learning methods in wearables

In [53], Das et al. proposed an unsupervised learning approach for heart-rate estimation from electrocardiogram (ECG) data collected by wearable devices. Spatio-temporal properties of ECG signals were encoded directly into spike training. In the next step, the spike training was used to excite recurrently connected spiking neurons in a liquid state machine computation model. An unsupervised readout based on fuzzy c-Means clustering of spike responses was designed using particle swarm optimization. Their proposed method was easily implemented on spiking-based systems. The method advantages are its high accuracy and significantly low energy footprint. Consequently, the battery life of wearable devices was extended. Another unsupervised learning algorithm was proposed by Krause et al. [54]. In this work, without external supervision, an online wearable system was designed, implemented and evaluated. It could determine the context of typical user and probabilities of context transition. They used statistical analysis and machine learning in their graph algorithm techniques. The results showed that their proposed method could determine a user context model while it only required data from a device with physiological sensors.

In [55], a new version of unsupervised deep learning was proposed which optimized the data during preprocessing in wearable sensors. It only needed 11.25 ns as its computation time. Its recognition performance has been improved for feature selection and extraction. A new technique for data analysis has been introduced to minimize the computation time.

6.3 Application of semi-supervised learning methods in wearables

Wearable devices have the potential to collect huge amounts of data. However, labeling these data is costly and time-consuming. Therefore, it is desirable to devise methods to exploit unlabeled data while reducing labeling costs as much as possible. Semi-supervised approaches are promising approaches to use a mix of limited labeled data and a large volume of unlabeled data efficiently. Ballinger et al. [56] used off-the-shelf wearable heart rate sensors to collect data from numerous participants across the world using a mobile phone application. The objective was to detect multiple medical conditions such as diabetes, high cholesterol, etc. using a multi-task LSTM. Two semi-supervised approaches were proposed that could outperform hand-engineered biomarkers from the medical literature. In the first approach, a LSTM was pre-trained as a sequence autoencoder. The pre-trained parameters were used to initialize a second supervised phase using pool of limited labeled data. In the second approach, the synthesized dataset was used for pre-training.

In [57], a novel method to automatically detect near-miss falls according to a worker's kinematic data was proposed. These data were captured from wearable inertial measurement units (WIMUs). A semi-supervised learning algorithm was proposed to learn from the data. This algorithm was a support vector machine (SVM) which was designed for near-miss fall detection. For collecting the near-miss falls, two experiments were conducted. These data were used to test the proposed approach. This WIMU-based method can be used to identify ironworker near-miss falls without disrupting jobsite work and can help to prevent fall accidents.

M. Stikic et al. [58] introduced a new method for activity recognition. In a semi-supervised learning process, small amounts of labeled data were combined with unlabeled data. Their proposed method propagated information in a graph that contains both labeled and unlabeled data. Based on feature similarity, two different ways were introduced to combine several graphs. The quality of the label propagation process and the performance of classifiers were evaluated in their research.

For activity recognition, in [59], the feasibility of semi-supervised learning was tested to reduce the level of supervision. Two semi-supervised techniques (self-training and co-training) were used to learn activity models from few labeled data. The results of this work demonstrated that co-training worked better than self-training because it used additional information from sensor modalities during the training process. In addition, in some cases, it even could achieve better recognition accuracy compared to the fully supervised approaches. Their proposed method was conducted based on a pool-based setting. Accordingly, a large number of unlabeled training data were available in addition to a small set of labeled training data. The algorithm was able to select the best informative samples which were then labeled by an expert. Another work on human activity recognition is LabelForest [60]. Data collected from humans via wearables are often accompanied by a significant amount of noise and uncertainty. LabelForest is a non-parametric semi-supervised learning framework for activity recognition which improves the performance of ML algorithms by expanding the training set. LabelForest chooses a subset of unlabeled data for labeling. The sample selection is done based on similarity with the labeled samples. LabelForest framework is made of two algorithms: 1. spanning forest algorithm for sample selection and labeling, and 2. silhouette-based filtering method to select samples with more confident clustering assignment for inclusion in the training set.

Wiechert et al. [61] collected EEG brain signals using a wearable headband called Muse from participants performing different tasks such as reading, listening to music, etc. The objective was to identify participants and the type of activity they were performing when EEG signals were being recorded. To this end, K-medoids with an evolutionary algorithm were combined to perform multi-objective clustering. The genetic algorithm was used to find the most appropriate K medoids. Wiechert et al. reported that their method could outperform K-means.

6.4 Application of reinforcement learning (RL) methods in wearables

RL has also found its way into the field of wearable technologies. ADAS-RL [62] is a modified version of Q-learning algorithm. It not only integrates the behaviors but also the reactions of the driver to adapt and tune the warning interventions of Lane Departure Warning System (LDW) continuously. The proposed method is able to track any changes in driving behavior and adapt the frequency of warnings allowing drivers to stay within a reasonable distance i.e. about 1.75 meters from lane markings. FaiR-IoT (Internet of Things) [63] is another RL-based framework using Q-learning for adaptive and fairness-aware human-in-the-loop IoT applications. The method was evaluated on a human-in-the-Loop smart house IoT application and human-in-the-Loop automotive advanced driver assistance system. In the smart house application, the objective was to control the home thermostats automatically by monitoring human body temperature changes over time. The job of the driver assistance system is to alert the driver when there is a risk of colliding with an object in front of the vehicle. Standard forward collision warning systems measure the time-to-crash based on the distance and the relative velocity of the object in front of the vehicle. If the time-to-crash is below a certain threshold, the system alerts the driver to apply the brakes. However, a better approach is making the threshold adaptive based on the driver characteristics such as his/her response time and whether he/she is distracted or not. FaiR-IoT has taken such factors into account to adjust the time-to-crash threshold dynamically.

In the field of medical applications, some patients are in need of constant monitoring. Wearable sensors can make the monitoring process easier without the need for keeping the patients in the hospital for long periods. Baucum et al. [64] have proposed a data-driven RL framework to optimize PD medication regimens based on wearable sensors data. They conducted their study using a dataset of 26 PD patients who wore wrist-mounted movement trackers for two separate six-day periods. The patients' medication regimens were modified based on physician evaluations of collected data after the first wear period. The method was implemented in two steps:

1. A simulation model was built and evaluated. It provides information about individual patient's movement symptoms response to medication administration.
2. The simulation model was used for training an RL agent using policy gradient [65]. The trained agent was able to recommend optimal medication types, timing, and dosages during the day, while incorporating human-in-the-loop considerations on medication administration.

The existing literature on wearable technologies is not limited to the above paragraphs. The summary of works done using wearables and AI techniques is shown in Table 1.

Table 1. Summary of works done using wearables and AI techniques.

Reference #	Algorithm Name	Application	Learning category: Supervised	Unsupervised	Semi-supervised	Reinforcement
[66]	SVM	Construction Workers' Stress Recognition	✓			
[67]	ANN	Heartbeat Classification	✓			
[68]	Statistical analysis	Activity recognition	✓			
[69]	Decision Trees	Pharmacotherapy Management for Parkinson's Disease Patients	✓			
[70]	Long Short Term Memory (LSTM)	Activity Recognition	✓			
[71]	Random Forest	Physical Fatigue Detection	✓			
[72]	K-means	Telemonitoring of patients with Parkinson's disease		✓		
[73]	K-Means	Human Activity Recognition		✓		
[74]	Spectral Clustering, hierarchical clustering	Human activity recognition		✓		
[75]	K-Means	Human activity recognition		✓		
[76]	Expectation Maximization (EM) algorithm	Activity recognition		✓		
[77]	K-means	Detection of Poor Posture		✓		
[78]	Simple 1-NN classifier and SVM	Location recognition from wearable video			✓	
[56]	LSTM	Cardiovascular risk prediction			✓	
[79]	SVM	Human activity recognition			✓	
[60]	Random forest	Activity recognition			✓	
[61]	Genetic algorithm	Categorization of brain signals			✓	
[80]	Convolutional neural networks	Human activity recognition			✓	
[81]	Deep reinforcement learning	Musculoskeletal modeling and locomotion analysis				✓
[82]	Reinforcement Learning	Activity recognition				✓
[83]	Inverse Reinforcement Learning	Activity forecasting				✓
[84]	Deep Reinforcement Learning	Individualized Treatment Planning for Parkinson's Disease				✓
[85]	ANN	Activity recognition				✓
[86]	Inverse Reinforcement Learning	Activity forecasting				✓

7 Wearable applications

Wearables have already emerged in various application domains such as eyewear, sport trackers, healthcare, industry, etc. The wearable technologies are not exclusive to medical applications and they share common hardware/software across different domains. Therefore, reviewing wearables in different domains provides a broader perspective about wearable technologies. To gain better insight on the potential applications of wearables, applications related to healthcare, manufacturing, and industrial domains are reviewed. Some of existing wearable devices are presented in Table 2. Although performance statistics of wearable devices have not been the primary concern of this review, some performance statistics (Figure 4, Figure 7, and Figure 8) have been restated here from the reviewed papers.

Table 2. Examples of existing wearables in various application domains.

Application	Wearable device name	Device description
Eyewear	Chromatic smart glasses	It is a smartwatch which has built-in activity tracker for fitness purposes, wireless charging capability, and HD camera for taking point of view (POV) photos.
	Vufine+ HD Wearable Display	Vufine+ is a high definition wearable display which can be connected via HDMI to smartphone, laptop, or drone. Vufine+ can be used as a second monitor and it is clear enough for video and text display.
	Omni-Wearable Action Cam Sunglasses	This device is sunglasses which features an integrated HD video camera to record the events happening around the user.
	Focals by North	This device is smart glasses which offer augmented reality (AR). The goal of the device is displaying the notifications from the user's phone directly into his/her field of view.
Training	GAME GOLF Digital Shot Tracking	Accurate GPS shot tracker which is designed to help Golf players improve

assistants	System	their shots and playing experience.
	Basketball Replay Analyser by Blast Motion	This device records the actions of Basketball players and provides them with performance metrics so that the players can improve their performance. The device sensor which is attached to the waist of the body has wireless connection to an IOS device.
	Marlin	Marlin is a waterproof device that helps swimmers with their training, open water navigation, and tracking.
	T-Goal Wearable Soccer Data Tracker	A compact device that can track speed, distance, sprints, and positioning of soccer players as they play.
	Phoenix	A medical exoskeleton which helps people with mobility disorders. The device makes it possible to stand up and walk. The device has two actuators at its hip. The knee joints provide support during stance and ground clearance during swing.
	Alex posture system	This device monitors the posture of the user neck in order to improve his/her neck posture.
Relaxation	Beddr SleepTuner	The sleep tuner helps the user to find out the main causes of poor sleep. The device can measure blood oxygen levels, heart rate, amount of time in bed, etc.
	BrainLink Lite V2.0	A headset which helps the user with focusing and training, meditation and pressure relief.
	Vigo The Stimulating Headset	A Bluetooth headset that monitors the driver's eyelid motion to assess his/her level of drowsiness.
	Lumos Smart Sleep Mask	A device that helps the travellers fight jet lag. To this end, the device transmits short light pulses to adjust the body clock.
Smartwatches	Aipower Wearbuds	Basically, this device is the integration of headphones into smartwatch.
	Garmin Approach S20 Golf Watch	A device for training golf which features a high-sensitivity GPS and provides the player with useful distance data. Using these data, the user can improve his/her shots. The device also provides daily activity tracking and smart notifications (e.g. incoming calls and messages).
	Parkinson Smartwatch	A smartwatch that tracks Parkinson's disease. The patient records his/her condition changes using this device. The recorded data during the day is stored in a cloud service which is accessible anywhere in the world by the patient and his/her doctor. Based on the recorded data, the doctor prescribes optimal dosage of the medicine for the patient.
Smartbands	Misfit Ray	The device automatically tracks the fitness and sleep metrics of the user. For example, number of taken steps, travelled distance, burned calories, and light/heavy sleep are tracked.
	Samsung Galaxy Fit	The device provides fitness statistics such as heart rate. The device also allows the user to reply instantly with pre-set messages for incoming texts.
	Xiaomi Mi Smart Band 4	Xiaomi Mi Smart Band 4 provides health monitoring such as heart rate. It has multiple tracking modes such as Treadmill, outdoor running, cycling, etc. which can be used during sport activities. Incoming calls, messages, and calendar notifications are also supported.
	Huawei Band 3 Pro	Huawei Band 3 Pro supports notifications for incoming calls and messages as well as playing music. It also offers sport-related functionalities such as step count, calories burned, etc.
E-patches	Lief	A wearable device that is designed for stress relief. Using Lief, the users learn how to train their body to stay calm and focused. Lief is an ECG smart patch which improves heart rate variability. Heart rate is a scientifically-proven biomarker of stress.
	Mesana	This is a sensor patch which addresses issues within circulatory diagnostics and cardiovascular-prevention.
	VivaLNK Vital Scout	VivaLNK Vital Scout is wearable patch that measures stress and recovery rates using medical-grade ECG sensors.
	Wearable Ultrasound Patch	This is a patch which can measure internal blood pressure e.g. blood pressure inside deep arteries, heart, or lungs.

7.1 Sports

In the sport applications, the wearable help the players to improve their skills in their favourite sports. Existing wearables in sport applications is shown in Table 2. Injury prevention is critical in any sport and wearable devices may be used to avoid potential injuries while players are enjoying their favourite sports. For example, Chen et al. [87] developed a fuzzy logic inference system which receives data such as temperature, humidity, etc. from wearable devices and determines the wearer's heat stroke possibility. Their approach can detect the possibility of suffering from heat stroke and the wearer can be alerted in time. Skazalski et al. [88] used commercially available wearable devices to monitor functional movements, heart rate, and workloads of volleyball players. The collected data can be used to maximize the players' performance and at the same time minimize possible injuries.

7.2 Healthcare

Considering that wearable devices are worn by their users, these devices have a lot of potential in providing mobile healthcare services. Different types of wearables e.g. smartwatches, on-body cameras [89], masks, E-patches, etc. have been developed for healthcare applications. The most common type of data measured by wearable for healthcare purposes include heart rate, blood pressure, body temperature, blood oxygen saturation, posture, and physical activities.

7.2.1 Fitness

Some of these devices are designed to track fitness-related activities. For example, chromatic smart glasses are an eyewear device which tracks the user activity for fitness purposes. Xiaomi Mi Smart Band 4, Misfit Ray, and Samsung Galaxy Fit are smartbands which provide fitness statistics. A short description of these devices is available in Table 2. Fitness-related wearables can motivate their users to increase their activity and become healthier but their measurements might not be accurate always. For example, Dooley et al. [90] have evaluated the performance of three wearables called Fitbit Charge HR, Apple Watch, and Garmin Forerunner 225. The experiment was conducted using 62 participants with age between 18 to 38 years old. The three devices were used to measure the heart rate and energy expenditures of the participants. They reported that the accuracy of these three devices were within the acceptable range.

7.2.2 Health status monitoring

Some other wearables can be used to monitor the health status of their users. These devices may be capable of forecasting the potential health issues of people wearing them even before they feel sick or discomfort due to those issues. These devices may also take a step further and inform the doctor automatically [91]. It is needless to say that in some cases, early diagnosis of diseases can be lifesaving. Type of healthcare wearables such as Mesana is a sensor patch which addresses issues within circulatory diagnostics and cardiovascular prevention. Another example is a wearable ultrasound patch with the ability to monitor blood pressure in deep arteries. Two ECG-based patches are Lief and VivaLNK Vital Scout can be used. Lief helps to improve the heart rate variability which is useful for stress relief. VivaLNK Vital Scout helps to measure the stress and recovery rates. Two more ECG-based wearables have been developed to monitor the patients with heart disorders by Winokur et al. [92] and Yang et al. [93].

Controlling the condition of patients who suffer from chronic diseases is as important as early diagnosis of diseases. For example, Parkinson patients may need to receive variable dosage of their medicines based on their body condition. The prescription of medicine dosage must be done by medical experts. However, access to experts may not be possible all the time. Hence, wearing Parkinson smartwatch helps to record the patient’s noticeable changes in his/her condition throughout the day. The recorded data can then be sent to a medical expert to receive appropriate dosage of the required medicines. Another Parkinson-related wearable has been developed by Lin et al. [94] helps to assess bradykinesia severity of Parkinson patients based on ten-second whole-hand-grasp action. Delrobaei et al. [95] proposed an objective dyskinesia score based on motion capture data obtained from a mobile full-body wearable system equipped with inertial measurement unit (IMU).

Patients suffering from diabetes require constant monitoring. The wearable devices can play a major role in connecting patients with diabetes to their care teams for effective diabetes management [96]. Various technologies have already been developed to ease diabetes management. For example, Dexcom G6 CGM System is a smartphone-connected system for constant glucose monitoring (CGM) [97]. Receiving the right dosage of insulin based on the glucose level is critical. Hence, MiniMed 770G System [98] has been developed which is an insulin pump delivering appropriate dosage of insulin to the user based on glucose reading. Another wearable used to track the daily insulin intake has been developed by Companion Medical [99]. The wearable is a smart pen which connects to the patient's phone via Bluetooth. The patient uses the pen to inject insulin. The time of injection and the injected dosage is sent to the patient’s smartphone by the smart pen. This way the patient can easily manage the daily intake of insulin. Alfian et al. [100] have used

DL to develop a blood glucose smart sensor. To this end, blood pressure, blood glucose, and heart rate were fed to a LSTM model for real-time diabetes classification using cloud service.

Hemodynamics is the study of blood flow and researchers have developed a wearable cephalic laser blood flowmeter for investigation of hemodynamics upon changing body posture (e.g. rising from a sitting posture). The developed device is worn on the tragus [101]. In another research, site-specific blood flow variations in people during running were detected using a laser doppler flowmeter which is wearable [102].

7.2.3 Helping with movement disorders

Wearables can also help people with movement disorder. For example, Phoenix suit is a wearable exoskeleton which helps in the movement of knees and hips using small motors. The movement of the suit is controlled by pushing buttons integrated into the suit. The movement disabilities may have been acquired later in life. For example, people suffering from stroke may experience acquired disabilities. Patients with stroke need long-term therapy to regain their movement abilities. The therapies may be expensive or even inaccessible due to social and environmental factors. Wearable devices can be used to monitor the patient's activities and provide feedback to the patient and therapist to make home exercise programs possible. An example of such wearable devices was developed by Burridge et al. [103]. Their wearable was equipped with embedded inertial and mechanomyographic sensors. The collected data from these sensors were used to classify functional movements of the patient to provide useful information. Another wearable device to monitor patient's exercises was developed by Burns and Adeli [104]. This device can help patients with brain and spinal cord injuries to manage their exercise programs to recover their movement abilities. The developed wearable records patient's physiological data as he/she performs the required exercises. The recorded data are then sent to clinicians from patient's home. The clinicians carry out the necessary supervision based on the received data from the wearables, remotely.

Even people without disabilities may need help and protection when they get old. Falling during walking is common among elderly people. While falling is not considered a major risk for young people, which may lead to severe injuries for old people. González et al. [105] used two accelerometers that are worn as bracelets and employed genetic algorithm (GA) for fall detection. Pannurat et al. [106] proposed another fall detection attempt using a wireless wearable accelerometer and classification algorithms. Their method is a combination of a rule-based knowledge representation, a time control mechanism, and machine-learning-based activity classification. The method has been used for fall detection at pre-impacts, impacts, and post-impacts, respectively. Another fall detection system for elderly people based on smartwatch data were proposed by Mauldin et al. [107]. They used a GRU RNN as the predictive model to perform fall detection. The predictive model was deployed on cloud to make real-time decision making.

7.2.4 Mental health

Mental health is as important as physical health and researchers have already begun to development of many wearables for mental condition monitoring. These wearables can usually determine human physiology status based on collected data such as heartbeat, blood pressure, body temperature, or ECG. One typical application of wearables is stress assessment. Choi et al. [108] collected heart rate and audio signals from children using wearable devices. These data coupled with support vector machine (SVM) were used to detect the stress patterns in children. Emotion board is another attempt made for stress detection [109] based on electrodermal activity (EDA). In this project, the collected skin conductance signals were processed using linear discriminant analysis (LDA) and classified using SVM.

Wearable technologies can also be helpful in diagnosing and monitoring of psychiatric disorders such as depression. Valenza et al. [110] used PHYCE system to collect data for assessment of the depressive status in bipolar disorder. PHYCE is a wearable system prototype that detects the ECG using textile electrodes and acquires the respiration signal using piezoresistive sensors. In other research, Roh et al. [111] developed a system-on-chip (SoC) to accelerate filtering and feature extraction of heart-rate variability (HRV) from an ECG. They managed to improve the accuracy of depression recognition.

7.2.5 Autism

Children with autism spectrum disorder suffer from emotion recognition deficits. Therefore, they need help to improve their emotion recognition abilities. Daniels et al. [112] developed a prototype therapeutic tool using Google Glass for autistic children. They reported that autistic children had no problem in wearing the device. In their work, set of images illustrating different emotional states were shown to autistic children. Showing the correct emotional classification of images to the children via Google Glass improved their emotion recognition abilities.

Another application using machine learning and wearable technology is the detection of stereotypical motor movements (SMMs) based on real-time measurements from IMU which are sent for processing to a cloud service [113]. SMMs are associated with autism spectrum disorders. The proposed approach consisted of two phases namely feature extraction and decision making. A CNN was used for feature extraction and the extracted features were fed to a LSTM for decision making.

7.2.6 Healthcare wearables shortcomings

Although wearable devices have considerable potential applications in healthcare domain, they have several shortcomings that must be addressed. For example, most of wearable devices are still in the prototype stage and need extensive evaluation before being qualified as final products. Wearable devices may connect to cloud services to process and store the data collected by them. Therefore, enforcing privacy of patients' medical data is crucial. As the number of wearable devices grows, the amount of data generated by them grows as well. Thus big data can be considered both a concern and an opportunity for artificial intelligence research community.

7.3 Industrial and manufacturing

As industrial infrastructures evolve, performing the desired tasks with efficiency, accuracy and speed is highly desirable. With sufficient research and development, wearable devices can have the potential to revolutionize the modern industry. Whether humans can be totally replaced by machines in the future, is always debatable. The machines will take the humans' place in doing repetitive and routine tasks. However, the total removal of human supervision is not likely in cases that human's experience is required [114]. Currently, wearables have gained considerable share of consumer market. However, application of wearables in the industry is still limited.

7.3.1 Examples of real-world industrial wearables

There have been several research attempts to pave the road for application of wearables in the industry. In WearIT@work project, wearable computing group has conducted research in application of wearables in production domain [114]. The research was carried out in Skoda Auto car manufacturing. The objective of the research was to replace the traditional paper-based car quality assurance performed at the end of the assembly line. A wearable device consisting of a belt-computer and a head-mounted display was developed in a way that the workers need not be trained in order to use it. The main achievement of this work was the identification of suitable methods for integrating wearable devices in real-life industrial scenarios. Some of unaddressed challenges of the proposed wearable were battery life for multiple working shifts and lack of reliable wireless communication at the user level.

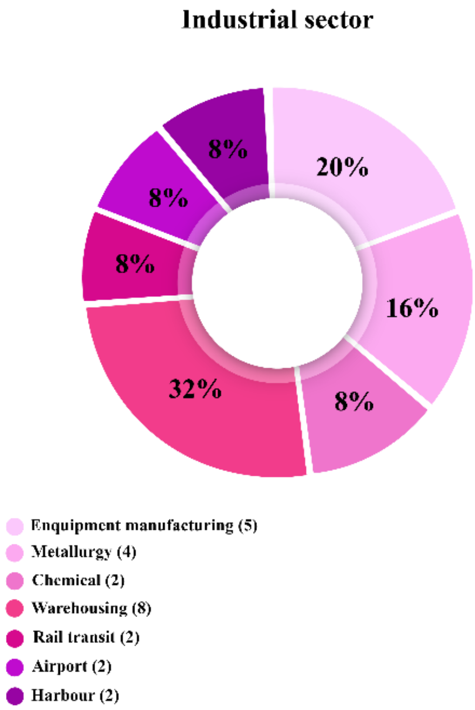
Wearable computer systems group at Carnegie Mellon University (CMU) has conducted another research entitled Navigator 2 about industrial applications of wearables [114]. The aim of this project was improvement of inspection routines of mobile workers. Before using the developed wearable, the workers had to complete a checklist with hundreds of pages. The checklist completion took four to six hours. Performing the same inspection routine but with the help of the developed wearable reduced the inspection time up to 50%. The proposed wearable had support for speech recognition leading to minimum interference of the wearable with the worker during inspection. The tackled challenges during this research were interface design, cognitive model, contextual awareness, and adaptation to tasks being performed. The factors left for further investigation were weight limit of the wearable and its long-term effect on the wearer's body.

Efficient order picking is critical to maximize the gain of any manufacturing line. Contextual computing group at Georgia Institute of Technology (Georgia Tech) has conducted a research to investigate the effect of using wearables for order picking [114]. The research was based on Google Glass which is a head-up display (HUD). The experimental results showed that using HUD to aid the workers with order picking task to reduce the possible human errors and part picking time. The unaddressed challenges of this research were wearability of head-mounted displays and optimization of decision making for mobile workers through wearable computing.

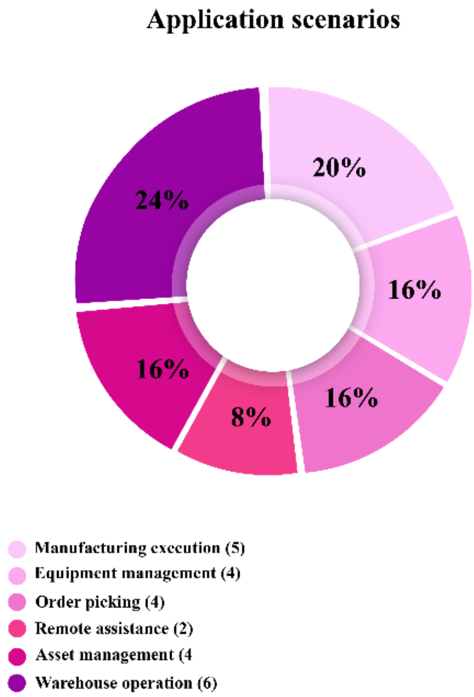
7.3.2 Critical design factors for industrial wearables

An important stepping stone towards making wearables practical in industrial applications is careful inspection of problems of using wearables in the industry. To this end, in [114], 25 enterprises were surveyed based on four aspects: 1. industrial sector, 2. application scenarios, 3. current data processing methods, and 4. data interaction level. The industrial sectors investigated by the survey were equipment manufacturing, metallurgy, chemical, warehousing, rail transit, airport, and harbour. The considered application scenarios were manufacturing execution, equipment management, order picking, remote assistance, asset management and warehouse operation. Manufacturing execution tracks and documents the transformation of raw materials into final products [115]. Equipment management revolves around checking status of large-scale facilities. Order picking is one of the common operations in e-commerce warehousing. Remote assistance is related to the application of augmented reality (AR) glasses. Asset management is related to checking inventory for non-production items. The data processing in the selected 25 enterprises was carried out using paper, personal digital assistant (PDA) or personal computer (PC).

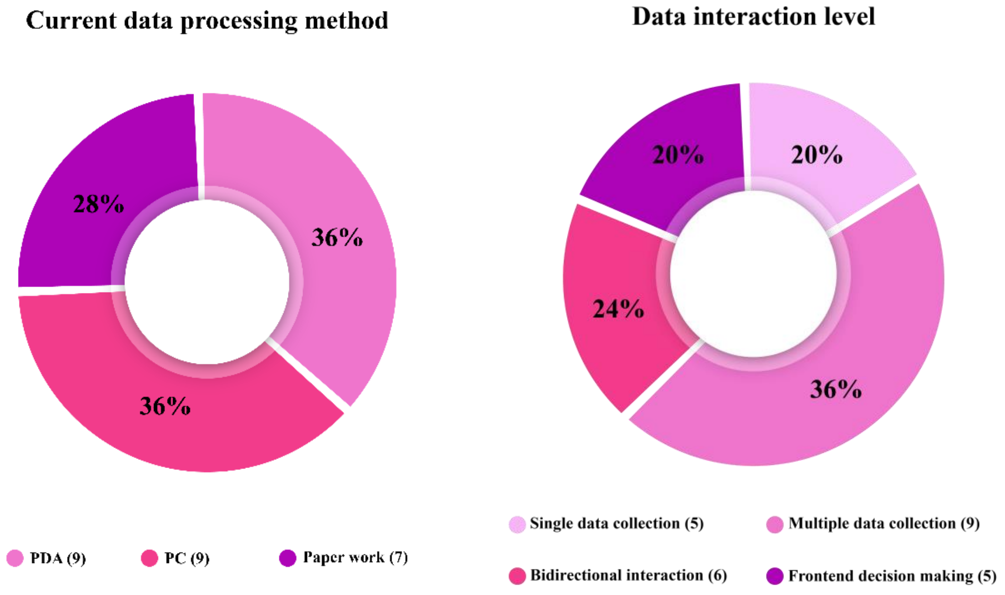
Based on the four aspects (industrial sector, application scenarios, data processing method, and data interaction level), the surveyed enterprises are partitioned and the results are shown in (a)-(d) of Figure 7.



(a)



(b)



(c) (d)

Figure 7. Distribution of 25 enterprises surveyed in [114] for each of the four aspects: (a) industrial sector, (b) application scenarios, (c) data processing methods, and (d) data interaction level.

To identify the key challenges and shortcomings of applying wearables in the industry, in the 25 enterprises, multiple wearable devices have been tested by several users. Based on the received feedback from the users, five critical factors were determined which must be taken into account for designing practical wearables for industrial applications:

1. Ergonomic product design:
    a. The wearables must be lightweight especially if they are head-mounted.
    b. The parts of the wearables that make contact with human skin must be made of comfortable materials.
    c. Wearables must provide hand-free experience for the users since they need to perform various tasks with their hands. Occupying the user’s hands or restricting their movements due to wired connections is not an option.
2. Data interaction on device:
    a. The wearables should provide the key information concisely. Showing too much information on the wearable screen may disturb the user.
    b. Limiting use of touch screen and keyboard for receiving input from users. This factor is due to the fact that wearables usually do not support complicated data typing.
    c. Voice and gesture interaction may be used as supplementary interaction methods.
3. Operational stability:
    a. The industrial wearables should be equipped with batteries that can last for more than eight hours (one work-shift) without charging.
    b. The stability of network connections such as Wifi, Bluetooth, etc. is critical in industrial environments. Moreover, the network connections should be easily deployable and they should be easy-to-use.
    c. Industrial environments are usually harsh with high temperature, humidity, and shock. The industrial wearables must stay operational under such conditions.
4. External software integration:
    a. Considering that industrial wearables cannot work independently, they are required to be integrated into the enterprise systems seamlessly.
    b. The industrial wearables must have the ability to process data in real-time and make-decentralized decisions.
    c. The wearables must allow the involvement of human experience whenever needed.
5. External hardware integration:

a. The wearables must be able to accept/collect data from machines or robots of the manufacturing site.
b. The wearables must be able to control external equipment. Such requirement provides the user to control the equipment and intervene with the operation process if needed.
c. The wearables must support human-machine cooperation. This way the flexibility of the human and the accuracy of the machines can be combined to improve efficiency. Using the wearable, the human can instruct the machines with a series of gestures and signs.

Three wearable projects are reviewed in section 7.3.1 based on the five design factors presented above. The evaluation results are presented in Figure 8. Apparently, all three projects have tried to design their wearable devices in an ergonomic way. Wearable computing group has the best operational stability, whereas contextual computing group has the best data interaction on device.

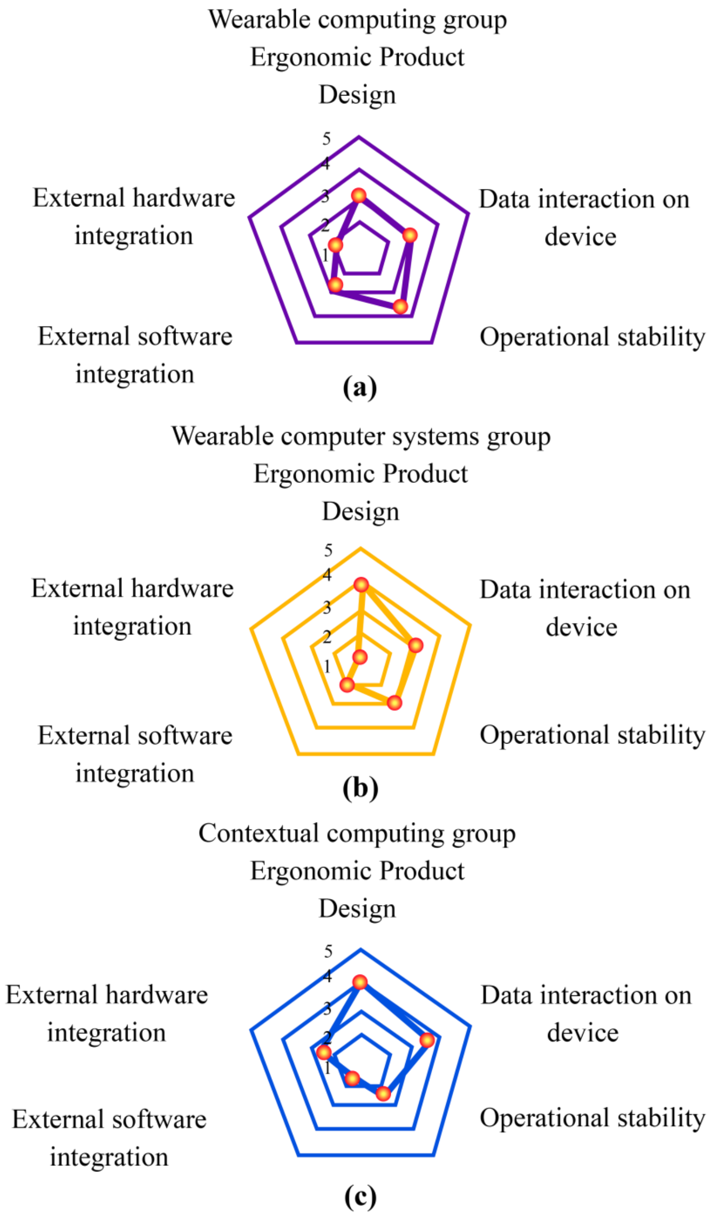


Figure 8. Result of evaluating three world-leading groups: (a) wearable computing, (b) wearable computer systems, and (c) contextual computing based on five factors (ergonomic product design, data interaction on device, operational stability, external software integration, external hardware integration).

7.4 Human-robot interaction

Human-robot interaction (HRI) is about establishing efficient, safe, and comfortable interactions between humans and robots. The interaction usually takes place via a wearable medium. That is where wearable devices come in. One of these wearables is a wrist-worn camera called WristCam [116] which is designed for hand gesture recognition. This wearable relies on speeded up robust features (SURF) [117] which are matched between successive frames of video captured by the camera. The user's hand velocity is determined using feature matching. After hand gesture extraction, it is segmented based on a predefined gesture starting signal. The gesture segments are then classified using the dynamic time warping (DTW) [118] method. In addition to robot control based on hand gesture recognition, it is also possible to command a robot based on the walking pattern. Cifuentes et al. [119] proposed a human tracking approach for a service robot using a wearable IMU and laser ranger finder mounted on the robot. IMU was used to capture the walking pattern of the human and laser range finder was used to detect the human's legs. Based on the sensed data, the human tracking system was able to control the robot such that it followed the human walking pattern. The tracking system was evaluated in an eight-shaped trajectory.

One of the approaches to realizing HRI is skill learning. Fang et al. [120] proposed a skill learning approach for HRI using a wearable device. Their proposed system consists of two subsystems: 1. Robot teleoperation, and 2. Imitation learning. The teleoperation is implemented using the robotic operating system (ROS) [121] and is used to collect training data for imitation learning. Imitation learning relies on dynamic movement primitive (DMP) [122-124] to mimic the trajectory demonstrated by the user during the teleoperation phase. To this end, the user's arm and hand motion are recorded using a wearable device equipped with multiple inertial measurements and magnetic units (IMMUs).

Physical human-robot interaction (pHRI) can be used for rehabilitation, assistive devices, etc. Wearable devices that are used for pHRI must preserve their users' comfort and safety. Ghonasgi et al. [125] proposed a modular sensing panel for pHRI which has the ability to capture the fine nature of force transmission from compliant human tissue onto rigid surfaces in the wearable device. Their sensing panel uses force-sensing resistors (FSRs) and it is low-cost and can be adapted to a variety of human interfaces. Another work regarding pHRI was presented by Lenzi et al. [126]. The authors focus on a distributed approach for monitoring physical interaction between a user and a wearable robot. To this end, a distributed tactile sensor consisting of a matrix of optoelectronic sensors is used. The sensors are embedded in a thin and compliant silicone bulk onto the user-robot contact surface. While the tactile sensor is capable of measuring the pressure distribution on the wearable-human interaction area, it preserves the user's safety and comfort and does not put any specific design constraint on the robot to house it.

8 Wearable technologies challenges

Nowadays, wearable devices are often available in the form of smartwatches which can connect with smartphones. In the future, wearables are expected to be seen in various forms designed for different applications. The world of the future is the world of wearable devices that can help the humankind in doing his duties. They can market in the fastest possible time by sharing the collected data and help to maximize the profit. It can be generalized to other aspects of life like in medical, geographical, or personal fields. The collected data by wearables in the form of text, video, audio or other specified forms can be shared to help with accurate disease diagnosis.

The current generation of wearable devices is still far from perfect. The developed technologies are impressive albeit not mature enough. To unleash the full power of wearable devices, multiple challenges must be addressed. Some of the challenges faced by the wearable devices are briefly discussed in the sections below.

8.1 Data collection

The first challenge is related to data acquisition. The quality, quantity, resolution, and other parameters of the gathered data depend on the wearable device. Spatial resolution, temporal resolution, or data resolution are the factors which may impact data quality and quantity [127]. Collecting data from users in an optimal manner is challenging. The gathered raw data must be pre-processed before its clinical application. To this end, the measured quantities from different devices must be unified and their errors and statistical outliers must be removed. After being pre-processed, the data are ready to be used by data analytics. Data processing solutions for wearable data often rely on machine learning [128, 129]. Obtaining high quality labels for the data is time consuming and requires expert knowledge or intervention of the wearable user [130, 131]. Wearables that require insertion into the user's body like insertable cardiac monitors, continuous glucose monitors, and insertable drug deliverables systems have their own challenges:

- foreign body reaction may impede the functioning of biosensors and their data transmission,
- inserted device might move unexpectedly.

8.2 Data transmission

Coming up with an energy-efficient solution to transmit data (collected by wearables) for further processing is crucial. The emergence of faster connection technologies such as 5G and beyond leads to ever-increasing amount of data generation. Processing and storage of these data is challenging. Relying solely on centralized cloud computing is not an option due to data processing latency and significant load on network performance. Edge computing can reduce latency by moving the necessary computation on the network's edge. However, there are still issues with development of software and hardware of edge devices which must be fixed to meet the cloud computing load [132].

8.3 Security and privacy

Enforcing privacy, security, and trustworthiness while using wearables is still an open challenge [133]. The main feature of the wearables is continuous sensing and data collection. As mentioned in [134], most modern wearables can collect data about position, physical activity level, and mental health of users who wear them. From the user's point of view, these data might be considered sensitive, so enforcing their privacy cannot be overlooked. Currently, there is no unified solution to address all the potential security and privacy threats of wearables so more research and development are required to improve the security and privacy aspects of wearable devices.

8.4 Localization quality

In many applications of wearable technologies, precise localization of the wearable devices is important. Given that wearables are usually resource-constrained, achieving localization with acceptable precision is challenging. Therefore, improving the localization quality of wearable devices under limited computational power is needed.

8.5 User adoption aspects

The success of wearable technologies directly depends on how much the target users would accept to use them. User adoption is specifically challenging in medical and industrial applications. In all other applications, user adoption is a matter of personal choice. However, in medical and industrial domains, using wearables is more of a necessity than a choice. In the medical domain, the patients may feel discomfort and stress about wearing pervasive devices. This is mainly due to the complexity and excessive ''intrusiveness'' of these devices. In the industrial domain, some workers may fail to understand the benefit and purpose of monitoring wearable devices and may resist using them.

8.6 Resource constraints

Providing new services and targeting new users require the development of advanced functionalities for the wearables. However, adding new functionalities increases the power consumption of already resource-constrained wearables. Sometimes, the quality of the final wearable product is not met due to limited resource requirements. Therefore, managing energy consumption and yet achieving the expected performance is one of the most important challenges of the wearables.

8.7 Interoperability

In the internet of wearable things (IoWT), different wearable devices must be able to communicate with each other regardless of their technologies. Such device-to-device (D2D) communication between wearable devices with different computational power (e.g. low-end and high-end devices) is a stepping-stone toward the realization of various smart functions in a decentralized manner. Recall that an individual wearable device does not have much to offer due to its limited resources. However, with efficient management and D2D communication, the processing power of multiple wearables can be combined to achieve the complex tasks. Currently, reliable D2D communication is one of the open problems of wearable technologies. Moreover, to fully benefit from the IoWT, developing end-to-end solutions to achieve seamless integration of wearable things into existing systems is one of the great concerns.

9 Discussion

Wearables provide various monitoring and scanning features such as biofeedback or other sensory physiological functions like biometry-related ones [135]. Moreover, wearables are portable and can be used hands-free. Wearable devices may improve life quality significantly but first, they have to be cost-effective.

According to [136], about half of people who purchase a wearable stop using it. One-third of them do this before six months. As reported in [137], elderly people have shown interest in using wearable devices for physical and mental health purposes. However, due to the lack of awareness about wearable technologies, currently many elderly people do not use wearables. Thus, people need to be trained about the working mechanism of wearable devices and their maintenance.

The design and development of wearable devices must take into account user preferences. This is particularly important when the devices have to be worn for longer durations, for example during chronic diseases monitoring, or data collection about the user's activity level [138]. Being lightweight is one of the important user preferences about wearables which severely limits the battery capacity of wearable devices. Therefore, computational power and wireless communication of wearables will be limited.

The sensors in wearable devices generate lots of data while walking or jogging. These data can be used to discover dominant patterns among the population. Researchers of nursing science have already taken interdisciplinary approaches to study the medical problems based on big data collected from a huge population. To this end, multiple professionals with complementary expertise have worked as a team [139]. Moreover, the growth of IoWT increases the complexity and amount of generated data. These data can be used for implementing IoT sensing-based health monitoring and management [140] and developing mobile health applications [141].

As described in section 8.7, interoperability is one of the challenges of wearable technologies which is an important direction for future works; it is also an important requirement for remote healthcare services. The fifth generation of wireless networking technology (5G) allows the connection of many hospital devices to the network and provides remote access from home. An example of remote healthcare using wearables is the Hospital Without Walls project developed by Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO). This project aims to monitor patients continuously in certain diagnostic categories [142]. In this project, a miniature, wearable, and low-power radio is used to transmit vital signs and activity information to a home computer. The data are then sent by telephone line or through the internet to appropriate medical experts. Another important future trend is the emergence of new wearable devices. For example, in the medical domain, it is expected that drug delivery systems will emerge in the form of wearable devices (e.g. MiniMed 770G in section 7.2.2.). Disease intervention by wearables is also expected via integration with actuators planted insides/on the body. AI methods have already attracted the attention of researchers of wearable devices. Authors in [143] presented a proof-of-concept for a seizure prediction system. This system utilized a deep learning classifier to distinguish between preictal and interictal EEG signals. The deep learning model in combination with neuromorphic hardware formed a wearable seizure warning system which is suitable for patient-specific settings.

10 Conclusion

Wearable technology is an essential building block in future information and communication technology (ICT) systems. However, wearable technology has not reached an acceptable level of maturity yet. Multiple challenges are still unaddressed with regard to data collection, data processing, communications, security, etc. The aim of this review was to give readers a broad overview of applications of wearable devices in sport, medical, and industrial domains. In future, it will be useful to also investigate the application of wearables in other domains. In this review, the role of AI methods in development of wearable devices has been investigated as well. As future research, further applications of AI techniques in wearable devices to improve the quality of life by monitoring physiological parameters or early automated detection of diseases can be investigated.

Competing interests

The authors have no conflicting interests to declare.

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