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REVIEW

Employing of machine learning and wearable devices in healthcare system: tasks and challenges

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Abstract

Disease outbreaks are nowadays a critical issue despite the development and rapid growth of technology. One of the major challenges facing healthcare professionals and healthcare industries is disease prevention and control by technology. Due to busy work schedules, maintaining a healthy lifestyle has become impossible, so the solution to these previous challenges is the intelligent health monitoring system. Over the past few years, a lot of research has been done on the use of Machine learning (ML) techniques in healthcare applications. With wearable devices, ML greatly helps in tracking human activities and vital signs as well as helping to monitor and diagnose patients' health so it plays a huge role in elderly care. Research and development of more applications for wearable devices has been underway in the past five years, due to significant technological advances in medical sensors. Despite the widespread use of wearable devices, there is little research on machine learning applications of these devices. This paper presents a review of the different areas of recent ML research for healthcare wearable devices. It also discusses the different challenges facing ML applications on wearable devices.

Keywords Wearable devices · Healthcare machine learning · Medical sensors · Bio-signals

1 Introduction

The successful diagnosis and treatment of the disease are not complete, as contemporary medicine suffers from its shortcomings. Providing unnecessary or harmful treatment or delaying appropriate treatment due to delays in diagnosis or inaccuracies can cause harm to patients, resulting in psychological burdens and financial costs [1, 2]. Globally, if the diagnoses were correct, 1.5 million lives could be saved each year because 1 in 7 diagnoses are misdiagnosed, and 30% of total healthcare budgets could be saved [3].

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As a result, continuous and immediate monitoring is necessary to track the conditions of patients, especially those with chronic diseases [4, 5]. Therefore, wearable devices have become very important because they help to monitor and diagnose diseases using different strategies [6–8]. Wearable devices are devices that can be worn by humans such as rings, glasses, smart watches, prosthetic sockets, and chest straps, as shown in Fig. 1 [9]. Wearable devices can continuously monitor different human signals because they include different types of sensors. These sensors like temperature sensors, optical sensors, accelerometers, and biometric sensors.

Readings from stationary devices in hospitals can be more accurate than these devices but are sometimes considered acceptable depending on the application [10, 11]. In the context of cardiovascular arrhythmias, the electrocardiogram (ECG) serves as the primary diagnostic and therapeutic tool. However, conventional ECG monitors can be inconvenient for patients because they require the use of gel-based electrode cables and external electronic instruments to obtain the signals. Furthermore, these monitors are usually limited to controlled settings such as hospitals and laboratories, making them impractical for continuous

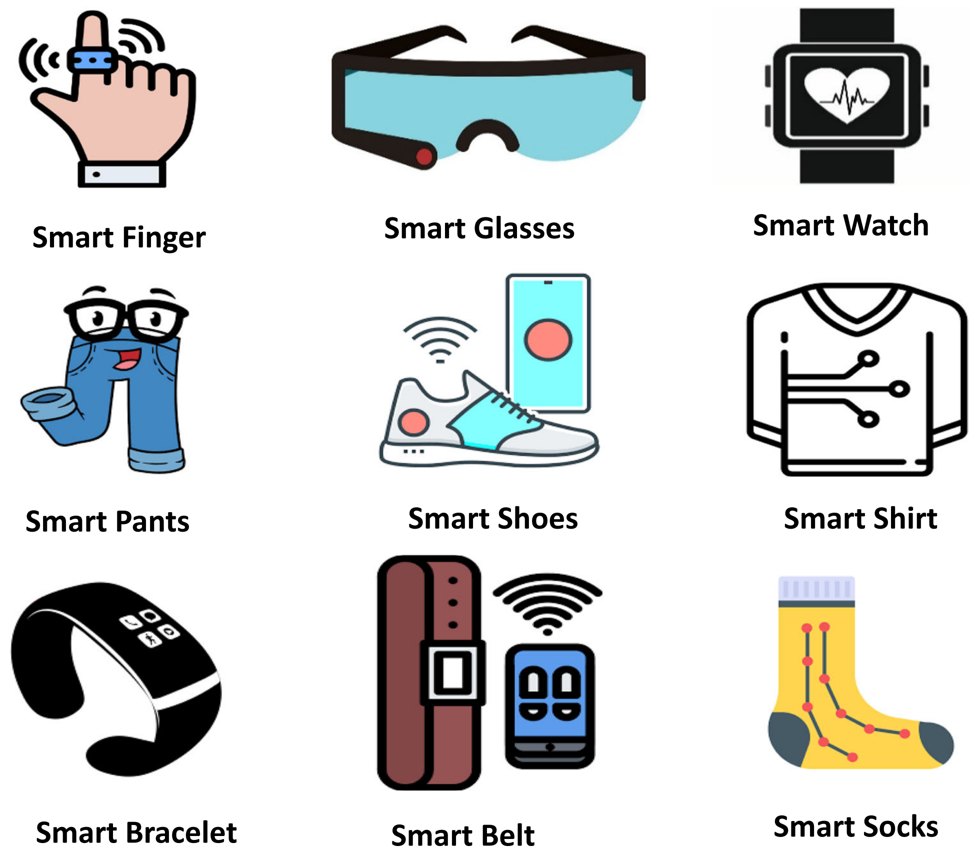

Fig. 1 Examples of wearable devices

monitoring. This presents a challenge for patients with heart disease who need continuous systems analysis but who cannot afford the economic burden and schedule of daily hospital visits. Therefore, wearable ECG devices provide a more flexible and convenient solution for continuous monitoring [12, 13]. Wearable devices are categorized under the Internet of Medical Things (IoMT) category, which includes fixed, implantable, and peripheral devices used in hospitals. These devices usually communicate remotely with mobile devices and are also able to connect to the network, as shown in Fig. 2 [14].

This study represents recent applied research related to wearable devices using healthcare Machine Learning (ML) tasks, the techniques used in these tasks, body signals, datasets used in the research from 2018 to November 2023, and the challenges that facing ML applications on these devices, such as data availability and reliability, model selection, security and privacy, connectivity, power consumption, and storage.

1.1 The contributions

The main contributions of this paper can be summarized as follows:

- It discusses the importance of wearable devices and the data collected from these devices for diagnosing various diseases.
- Explaining the importance of machine learning in healthcare research for use in the classification process to determine whether a disease is present or not.
- The latest research work in the field of machine learning for wearable healthcare devices for all tasks and explains the type of devices used and the different machine learning methods used in each research.
- The challenges facing ML applications on wearable devices and how researchers are trying to solve these problems.

The presented paper is structured as follows: Sect. 1 illustrates the introduction. Section 2 defines the different human body signals used in wearable devices research, the relation between ML and wearable devices. Section 3 presents the literature reviews that show the different areas of the recent research on the use of ML with wearable devices. In addition, recent studies related to each field have been published. Section 4 provides a comprehensive review of the various obstacles currently encountered in machine learning research for wearable devices. Finally, in Sect. 5, the study conclusion is provided.

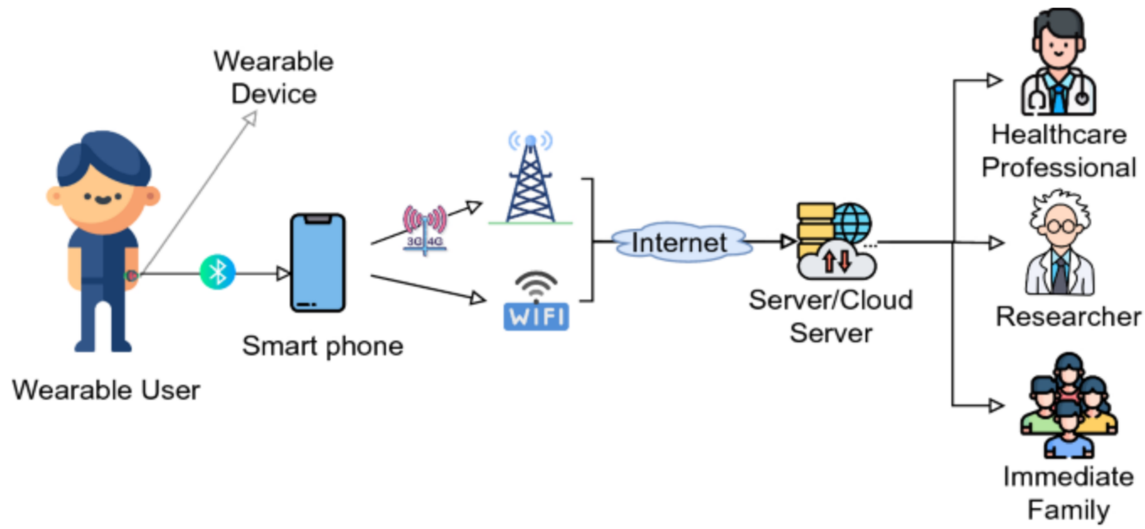

Fig. 2 Wearable device application model [14]

2 Wearable devices and machine learning

Artificial intelligence (AI) has captured the interest of researchers and biomedical industries due to its immense potential in processing vast amounts of data, generating precise outcomes, and controlling processes in a manner that is optimized. While the use of machines for decision-making and predicting the effects of diseases is not new, it is noteworthy that in today's world, machines and algorithms assist us with most day-to-day tasks [15–17]. Reliable machine algorithm coordinated outcomes are achieved by considering several factors such as fairness, reliability, accountability, explainability, and acceptance. The computer or robot's ability to replicate human intelligence using software and algorithms is the essence of AI. AI is capable of performing intellectual processes like advanced imaging, drug discovery, logical reasoning, guided surgery, and knowledge-based learning [18, 19].

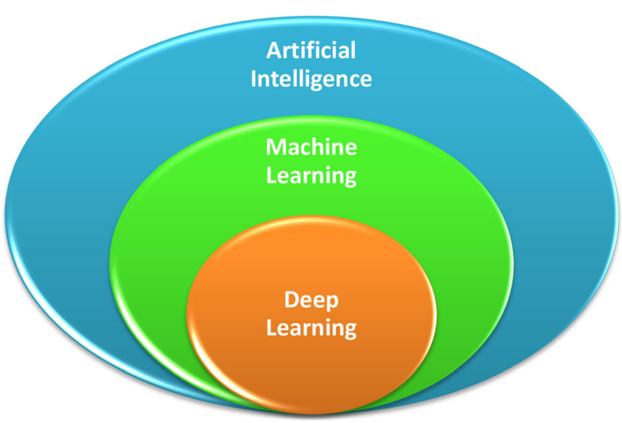

Fig. 3 Relation between AI, ML, DL

Machine learning is a commonly used AI technique for pattern prediction as depicted in Fig. 3. ML can be categorized into various types based on the algorithm structure and learning method. Learning methods can be further classified into three types: supervised, unsupervised, and reinforcement learning. In supervised learning, the algorithm is trained with input data. It is useful in predicting future events when historical data is available. As these algorithms rely on historical data for training, they are more straightforward and accurate. Unsupervised learning methods, on the other hand, can identify patterns in datasets even if the data are not correctly classified or labeled [20–23]. Reinforcement learning (RL) refers to a process whereby an agent interacts with the environment, acquiring knowledge of an optimal policy through a series of trial-and-error methods, to solve sequential decision-making problems [24, 25].

In healthcare, there is little research on machine learning applications for wearable devices, but this poses a problem because dealing with huge amounts of data—such as patient information—is challenging due to the difficulty of individually analyzing and maintaining these comprehensive records [26–29]. In order to address this issue, machine learning systems have emerged as a solution, as they are capable of automatically uncovering patterns and making predictions based on the data at hand. This advancement empowers healthcare professionals to administer precision medicine through personalized care. By leveraging machine learning systems, the efficient management of large volumes of medical data becomes achievable. These systems offer a variety of algorithms designed for data classification and prediction, serving as a key component in medical data analytics aimed at enhancing decision-making processes with a heightened level of accuracy [30–32].

ML also enables wearable devices to make autonomous decisions without the need for explicit programming designed for a particular scenario, by drawing on knowledge gained from past experiences. Many healthcare and elderly care applications use ML algorithms such as disease diagnoses, seizure detection, arrhythmia detection, fall detection, stress detection, activity recognition, emotion recognition, and rehabilitation tasks, as shown in Fig. 4 [30–35]. The use of ML applications for wearable devices is sparse in the market, despite the huge research effort in the use of these devices, and the remarkable growth of it.

Sensors in these devices are considered a big source of data and ML algorithms can be used to extract features from these data to detect and learn useful patterns. Examples of these sensors include electrocardiogram (ECG) sensor to capture electrical changes in the skin corresponding to heartbeats. As well as, electroencephalogram, commonly referred to as an EEG, which is used to obtain characteristics of brain and nerve electrical activity, electroophthalmograph (EOG) is used as a way to record eye movement and can be measured using electrodes placed around the eye area, and electrogastrogram (EGG) to capture the electrical activity of the stomach, etc. [36–40]. Despite the grand growth of wearable devices, ongoing research is still needed in this area for enhancing the accuracy of those devices and effectively deal with the complexity of the human body because it contains different signals [41].

3 Literature review

Table 1 shows the different areas of the recent research on the use of ML with wearable devices. The table also shows the machine learning technique(s), dataset(s), sensor(s), and results in each study.

3.1 Disease diagnoses

AI techniques, ranging from machine learning to deep learning, play a vital role in various domains related to the well-being of individuals [104]. These domains include enhancing clinical systems, managing patient information and records, and treating different types of illnesses. The efficiency of these AI methods in identifying various diseases is noteworthy. The use of artificial intelligence (AI)

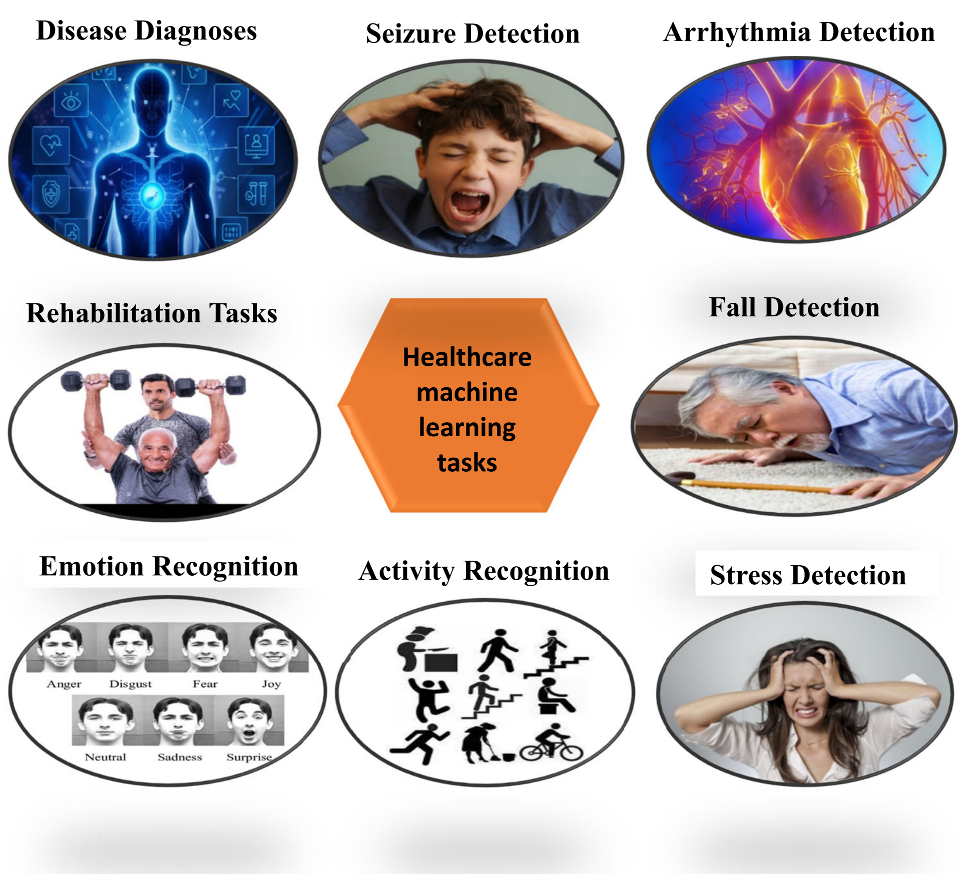

Fig. 4 Healthcare machine learning tasks

Table 1 Machine learning research work for healthcare wearables for all tasks

Task	Research work	ML technique (s)	Dataset (s)	Sensors/signals used	Results
Disease diagnoses	[42]	Convolution Neural Network (CNN) for COVID-19	Information is collected and updated on a web page	Accelerometer, Temperature, GPS, ECG, Oxygen rate and photoplethysmography (PPG)	Accuracy (97.5%)
	[43]	Support vector machine (SVM) and feedforward neural network (FNN) for Brain Hemorrhage Diagnosis	Collected from UCI machine learning dataset repository. The dataset name is “intracranial brain hemorrhage dataset”	Complementary metal oxide semiconductor (CMOS) sensor	Accuracy: SVM: (80.67%) FNN: (86.7%)
	[44]	The continuous wavelet transform (using Morse) and (CNN) (GoogLeNet) for Hypertension Risk Stratification	Collected from Multiparameter Intelligent Monitoring in Intensive Care Database (MIMIC)	Arterial blood pressure (ABP) and (PPG) signals	–
	[45]	Multivariate regression for case deterioration	34 patients with PCR confirmed COVID-19	Oxygen saturation, skin temperature, Heart rate, heart rate variability, actigraphy, blood pulse wave, and respiration rate	–
	[46]	Machine learning techniques for early detection of COVID-19	Under quarantine in Hong Kong, 200–1,000 people are asymptomatic and in close contact with COVID-19	Daily activities, blood pressure, blood oxygen saturation, skin temperature, respiratory rate, and pulse rate	–
	[47]	ResNet with LSTM for hypertension detection	A database of patients with cardiac arrhythmias collected from Fuwai Hospital, Chinese Academy of Medical Sciences and (MIMIC III) waveform database for ICU patients	invasive Blood Pressure (BP), ECG, and PPG in Intensive Care Units (ICUs)	–
Seizure detection	[48]	K-nearest neighbor (KNN)	170 patients	In-Ear, PPG and ECG sensors	Sensitivity: 65.1%
	[49]	SVM, Random Forest (RF), Naïve Bayes (NB), Neural Network (NN), and KNN	Available at the UCI machine learning repository	EEG	Accuracy: SVM (97.31%) NN (93.53%) KNN (90.01%) RF (97.08%) NB (95.98%)
	[50]	Deep learning methods	Dataset comes from the $REPO_2MSE$ cohort [51]	EEG	Detecting 90% of the seizures and classification F1-score of 0.873
	[52]	LSTM and 1DConv	69 patients with epilepsy	Blood volume, electrodermal activity (EDA), temperature, and accelerometer	–
	[53]	SVM	135 patients with generalized tonicclonic seizures	EDA and accelerometer from Empatica Embrace	Sensitivity > 92% and bearable FAR (0.2–1))

Table 1 (continued)

Task	Research work	ML technique (s)	Dataset (s)	Sensors/signals used	Results
Arrhythmia detection	[54]	Mobilenet-50 Hz vs., Resnet-50 Hz, Mobilenet-100 Hz vs. Resnet-100 Hz	28,308 unique patients from Korea University Anam Hospital in Seoul, Korea	ECG	Accuracy: Mobilenet-50 Hz (97.2%) Resnet-50 Hz (97.3%) Mobilenet-100 Hz (97.9%) Resnet-100 Hz (98.2%)
	[55]	A 1-D CNN based deep learning model	MIT-BIH arrhythmia database (contains ECG signals recorded for 24-h from 47 subjects) [56]	ECG	Accuracy: (94.03%)
	[57]	Deep neural network	Dataset from the DeepQ Arrhythmia Database using the wearable ECG and dataset from the MIT BIH Arrhythmia Database using Non-wearable ECG	ECG	Reaching nearly 100% accuracy
	[58]	Deep learning	13,038 30-s PPG samples (7188 for AF and 5850 for SR)	PPG sensor in a ring-type device	Accuracy: (94.7%)
	[59]	DNN	Dataset of 53,549 patients with 91,232 single-lead ECGs	ECG patch (from iRhythm)	0.837 F1 score
	[60]	50-Layer convolutional network	NSR dataset from 53 healthy free moving subjects contains 341 PPG recordings and 402 PPG recordings for 29 free-moving subjects	PPG sensor	95% AUC
Fall detection	[61]	Recurrent Neural Network (RNN) model with underlying LSTM blocks	The publicly available SisFall dataset	3D-axis accelerometer and gyroscopes sensors	–
	[62]	K-NN, SVM, LR, Decision Tree (DT), and Linear	792 signals are available	accelerometer, gyroscope and magnetometer	Accuracy: KNN (99.0%) SVM (97.4%) LR (97.4%) LDA (96.4%) DT (95.8%)
	[63]	DT, ensemble, LR and Deepnets	The SisFall dataset contains records from 38 participants [64]	6LowPAN wearable device with 3D-axis accelerometer	Ensemble: Accuracy: 98.72% Sensitivity: 96.22% Specifity:94.60% DT, LR, and Deepnets: –
	[65]	SVM	Public fall detection dataset [66]	Gyroscope and accelerometer	99.7% recall and 97% F1 score
	[67]	ANN, SVM, NB, and KNN	UMAFall dataset [68]	Magnetometer, gyroscope, and accelerometer	Accuracy: ANN (72%) SVM (68.25%) NB (61.5%) KNN (84.1%)
	[69]	Temporal signal angle measurements	7 subjects with 12 features performing 5 fall types	Inertial measurement unit (IMU)	Accuracy: 93.3%@200 Hz to 91.8% @10 Hz

Table 1 (continued)

Task	Research work	ML technique (s)	Dataset (s)	Sensors/signals used	Results
Stress detection	[70]	k-NN, LDA, RF, AdaBoost (AB), and SVM	Publicly available multimodal dataset, WESAD	ECG, body temperature (TEMP), respiration (RESP), electromyogram (EMG), and EDA	Accuracy: KNN (77.26%) LDA (78.47%) RF (84.17%) AB (82.24%) SVM (76.01%)
	[71]	C4.5 DT, Bayesian Networks and kNN	Raw sensor data [72]	Accelerometer and gyroscope sensor	Accuracy: C4.5 DT (74.26%) Bayesian Networks (67.86%) kNN (87.56%)
	[73]	NN model	30 participants with 312 biosignal records	BP, glucose level, body temperature, SpO2, GSR, and ECG	Accuracy: − 92% for metabolic syndrome patients − 89% for the rest
	[74]	SVM and LR	HR and RR data for 44 children (18 without ASD and 26 with ASD)	ECG sensor in a chest strap	Accuracy: SVM (93%) LR (87%)
	[75]	J48, KNN, SVM, BN, RF and AB	324 instances from 2 participants at exercise and rest sessions	- Shimmer3 GSR for EDA - Zephyr BioHarness for ECG	–
Activity recognition	[76]	(CNN-LSTM)	1 A relatively small dataset in the lab 2 Dataset from the University of California Irvine human activity recognition (UCI HAR)[77]	WithRobotTM sensor strapped to the left-hand wrist of a subject contains accelerometer and gyroscope signals	92% accuracy on the UCI HAR public dataset and 99% accuracy on the internal dataset (iSPL dataset)
	[78]	CNN	Standard dataset from UCI Machine Learning Repository [77] and a new dataset created collecting data with the proposed sensor	A designed wearable sensor embeds an Inertial Measurement Unit (IMU) and a Wi-Fi section	Accuracy: 97%
	[79]	CNN, LSTM, BLSTM, MLP and SVM	UCI and Pamap2 datasets	3D-axis accelerometer and gyroscopes	Avg. Accuracy: CNN (91.855%) LSTM: (87.435%) BLSTM: (89.46%) MLP: (84.45%) SVM: (87.285%)
	[80]	SVM	3 motion states of virtual vehicle from 6 males and 6 females: left turn, stop, and right turn	Accelerometer and sEMG signals of the upper limb by Delsys	Accuracy: 90%
	[81]	CNN	UCI-HAR dataset and study set 21 participants and 6 ADLs	Gyroscope and accelerometer	(Study set: 93.77%, UCI-HAR dataset: 95.99%)
	[82]	ATRCNN	6550 pieces of data for 4 activities: climbing stairs, running, sitting down, and walking	Triaxis gyroscope and Tri-axis accelerometer	Accuracy: 97%

Table 1 (continued)

Task	Research work	ML technique (s)	Dataset (s)	Sensors/signals used	Results
Emotion recognition	[83]	SVM	DEAP dataset [84]	Photoplethysmography and galvanic skin response	acc. up to 100%
	[85]	Adoption of deep-learning and hybrid approach using (CNN-LSTM)	The EnvBodySens dataset [86]	EEG, GSR, body temperature, motion data (accelerometer and gyro)	–
	[87]	RF, SVM, and LR	DEAP dataset [84]	fingertip temperature sensor, PPG, and Respiratory belt (RB)	Accuracy improved from 69.53 to 72.18% for valence, and from 69.86 to 73.08% for arousal
	[88]	KNN	54 subjects watching 24 pictures	Shimmer GSR + device (SC and HR) and MUSE headband (EEG)	Accuracy ranges from 53.6 to 69.9%
	[89]	Liquid state machine (LSM)	DEAP dataset [84]	EEG sensor	Above 94% accuracy for liking recognition, arousal, and valence
Rehabilitation tasks	[90]	CNN	17 and 6 participants were enrolled for statistical analysis in the HBR group and control group	Accelerometer, gyroscope or accelerometer combined with gyroscope data	CNN (accuracy ranging from 86.5 to 100%)
	[91]	Artificial neural network (ANN), SVM, and K-means clustering	81,654 samples for 10 people data	Plantar pressure measuring foot insoles and IMU sensor module	Avg. accuracy: ANN: (91.16%) SVM: (89.81%) K-means clustering: (91.17%)
	[92]	SVM	Muscle signals sEMG for 3 users doing 9 hand gestures 12 times	sEMG acquisition module	Average accuracy up to 96.20%
	[93]	RF, inference tree, and multiple regression	30 Participants, each doing 120 steps with Kinematic and pressure features	Two-sensor (fore and aft) insole (LoadsolTM)	Accuracy: RF: (94.1%) Inference tree: (93.9%) Multiple regression: (90.4%)
	[94]	Support vector regression (SVR)	14 healthy subjects with Inertial features and anthropometric characteristics	IMU in SportSole	–
Sleep monitoring	[95]	Deep learning methods and SVM	MrOS sleep study (Visit 1) database [96–99]	oximetry sensor on the patient's finger, and chin EMG, EEG, EOG on the patient's head	Deep learning methods (Avg. of acc. 79.45%) and SVM (Avg. of acc. 55.94%)
	[100]	CNN	Publicly available'Sleep EDF' database [101]	EEG and EOG	–
	[102]	RF	Accelerometer data during one night for 134 participants	Accelerometer in wristband	F1 score: 73.93%
	[103]	Auto-correlated wave detection with an adaptive threshold (ACAT)	Study set of 21 participants and 6 ADLs and UCI-HAR dataset	Gyroscope and accelerometer	Accuracy for study set: 93.77%, UCI-HAR dataset: 95.99%

to enhance healthcare services offers exciting possibilities that can lead to positive outcomes for patients and the clinical team, reduce costs, and achieve other related benefits. [105–108].

The authors in [42] proposed a device based on IOT and wearable devices to measure various vital signs related to COVID-19. In addition, the system could instantly notify the appropriate medical authorities if any probable COVID-19 patients breach quarantine regulations by tracking their GPS data in real-time with accuracy (97.5%). The wearable sensor, affixed to the body, was linked to the edge node within the IoT cloud architecture, where the information was processed and assessed to ascertain the patient's current health status. The sensors used in that work are Accelerometer, Temperature, GPS, ECG, Oxygen rate, and PPG. In [43], an application based on IOT was proposed for the human brain hemorrhage diagnosis. Machine learning algorithms, feedforward neural network, and SVM were used for the process of classification with an accuracy (86.7%) for feedforward neural network and (80.67%) for SVM. Intracranial CT scan images were used as datasets for that application using a CMOS sensor. A deep learning method was used in [44] for the classification and evaluation of hypertension using PPG signals and arterial blood pressure (ABP) based on the pre-trained CNN (using GoogLeNet) and continuous wavelet transform (using Morse).

Due to the limited availability of hospital care for patients in some countries as a result of the COVID-19 pandemic, researchers [45] have utilized machine learning-based analytical systems to identify early indicators of clinical decline in order to optimize resource allocation. Additionally, they have employed the Everion biosensor to track various physiological parameters, including skin temperature, blood pulse, heart rate, heart rate variability, oxygen saturation, respiration rate, and actigraphy, to monitor mild COVID-19 cases and make predictions regarding clinical deterioration. The authors in [46], also proposed a protocol to analyze the biosignals (blood oxygen saturation, respiratory rate, skin temperature, pulse rate, blood pressure, and daily activities) that were recorded by Everion wearable using a mobile health platform. Additionally, cough recording was included in that protocol for early detection of individuals with COVID-19. The diagnosis of hypertension had been the subject of examination in a recent study [47], which employed deep learning techniques to enable the ongoing monitoring of blood pressure. This was achieved through the analysis of a single-channel electrocardiogram and photoplethysmography signal, both of which could be collected via a wearable device.

As shown in Table 1, selecting a singular model for problem-solving is dependent on various factors such as

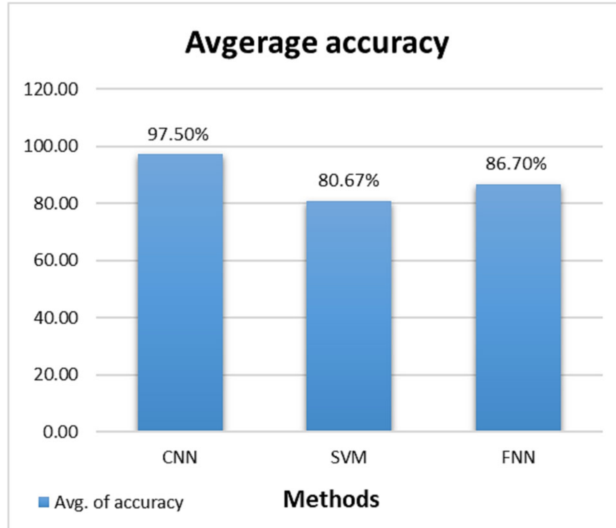

Fig. 5 Average accuracy for most of types used for diseases diagnoses

dataset size, feature extraction, and the problem at hand. Comparing and contrasting different techniques and results documented in research studies poses a major challenge due to the diversity of datasets, features, and multiple experiments used to solve different problems. Figure 5 shows the types used for the classification process used in the literature investigated in the diagnoses of diseases and the average accuracy for them.

While no model can achieve perfect classification, some models remain practical and amenable to improvement by using larger data sets, extracting more useful features, and modeling for personalization. Personalization is especially important since the signals produced by the human body vary according to factors such as lifestyle, weight, height, and activity level.

3.2 Seizure detection

Epilepsy is a common cause of morbidity and mortality, especially among children. Monitoring and tracking seizures accurately are crucial in assessing the seizure burden, recurrence risk, and response to treatment. Seizure tracking outside of the hospital is mainly reliant upon self-reporting by patients and their families, which is often unreliable due to underreporting, missed seizures, and patients' difficulties recalling seizures. The use of EEG within the epilepsy monitoring unit (EMU) is vital for accurate diagnosis and evaluation of epilepsy. However, this approach is associated with significant costs, time consumption, and potential stigmatizing implications, which may lead to additional challenges for both patients and caregivers, particularly when compared to the use of wearable devices for seizure monitoring. [109–111].

The ML framework proposed by the authors in [48] utilizes K-NN and demonstrates a sensitivity of 65.1% in detecting epileptic seizures. This framework is developed with the assistance of In-Ear, PPG, and ECG sensors and aims to set up a networking infrastructure for exchanging medical data among relevant actors. The data used were collected from 170 patients over an average period of four days. In [49], five machine learning algorithms i.e., NB, RF, SVM, NN, and K-NN were used in terms of accuracy to detect epilepsy with an EEG sensor. The five algorithms achieved an accuracy of 95.98, 97.08, 97.31, 93.53, and 90.01%, respectively. The dataset is available at the UCI machine learning repository. A DL model from EEG signals was developed in [50] for online detection of epileptic seizures with the results of detecting 90% of the seizures and classification F1-score of 0.873. The dataset used in that study comes from the REPO2MSE cohort [51]. The authors in [52] proposed a model to forecast seizures using DL on a multimodal wristband sensor. The dataset collected from the sensor was from 69 patients with epilepsy. The study in [53] used the Embrace Empatica Watch with the sensors, EDA, and accelerometer, to detect seizures. The number of participants in the study is 135.

Figure 6 shows the most used types for the classification process used in the literature investigated seizure detection and the average accuracy for them.

3.3 Arrhythmia detection

Heart disease is an important contributor to the global burden of disease. An accurate diagnosis of heart disease is essential to prevent chronic heart disease. The diagnostic process includes further evaluations, such as obtaining blood samples and checking for ECG signals. Due to the high incidence of heart disease, there is an urgent need for a system or device that can identify heart problems in their early stages and provide appropriate recommendations to expert physicians [112–114].

In [54], Mobilenet and Resnets were used with ECG signals to classify arrhythmia in an embedded wearable device. The dataset contained 28,308 unique patients from Korea University Anam Hospital, Korea. Resnet and Mobilenet were similar in terms of accuracy, i.e., Resnet-100 Hz (98.2) vs. Mobilenet-100 Hz (97.9), Resnet-50 Hz (97.3) vs. Mo-bilenet-50 Hz (97.2). 50 Hz/100 Hz denoted the down-sampling rate. A wireless, low-power and low-cost ECG monitoring system was developed in [55] using a 1-D convolutional neural network (CNN)-based deep learning model to detect arrhythmias. The system features a flexible, fabric-based design that is comfortable for patients and allows for continuous monitoring. CNN has a high accuracy of 94.03% in identifying abnormal heart rhythms in the MIT-BIH arrhythmia database [56].

The MIT-BIH arrhythmia database was also used in [57] for the non-wearable ECG dataset and the DeepQ wearable arrhythmia database for the ECG dataset to detect arrhythmias. The ML algorithm used was a deep neural network with an accuracy of nearly 100%. PPG signal was implemented in [58] as an alternative method for diagnosing atrial fibrillation. The patient's PPG readings were obtained using both a conventional oximeter and a heart tracker loop, yielding comparable results. The convolutional neural network outperformed various SVM variants, achieving over 10 s recording periods, a worst-case accuracy of 94.7%. The researchers concluded that the heart-tracking ring, using PPG-based wearables, was a reliable diagnostic tool for detecting atrial fibrillation and could be an alternative to ECG-based monitoring, although there are limitations associated with PPG signals, such as noise introduced by motion artifacts. 91,232 single-lead ECGs

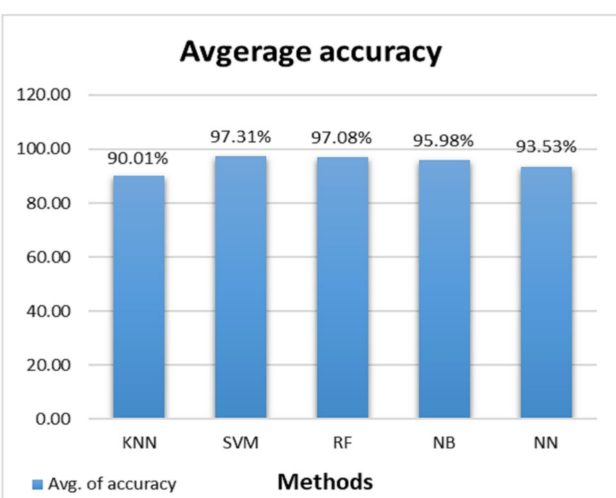

Fig. 6 Average accuracy for most of types used for seizure detection

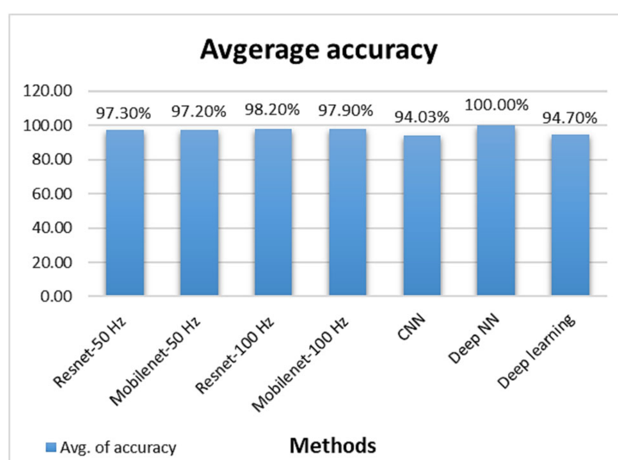

Fig. 7 Average accuracy for most of types used for arrhythmia detection

from 53,549 patients were used in [59] with a DNN to classify 12 rhythm classes. The patients used a single-lead ambulatory ECG monitoring device. In [60], the 50-layer convolutional neural network was used to detect Atrial Fibrillation (AF) episodes. 4000 h of PPG were recorded from a wrist-worn device.

Figure 7 shows the types used for the classification process that were used in the literature investigated in the arrhythmia detection and the average accuracy for them.

3.4 Fall detection

Falls are unusual actions that cause a significant health risk among older people. Thus, automated detection of falls among the elderly is a crucial aspect of healthcare applications, as it allows rapid medical responses. Extensive research has been conducted regarding the issue of fall detection over the past 10 years. However, developing accurate and applicable algorithms that can be embedded in wearable devices while accommodating limited hardware resources remains a challenge for researchers [115–117].

The technical aspects of fall detection systems (FDSs), using wearable devices and AI techniques such as deep learning (DL) have been studied by the authors in [61]. Their goal was to develop an efficient online fall detection algorithm, using a 3-axis accelerometer and gyroscope sensors. To achieve this, they proposed a classifier based on a recurrent neural network (RNN) model, with long short-term memory (LSTM) blocks. The publicly available SisFall dataset was used to test the proposed method, with an extended explanation, and compared with the results obtained by the SisFall authors. In [62], accelerometer, gyroscope, and magnetometer sensors were used to develop and evaluate a wrist-worn fall detection solution. 792 signals were available for this system as a dataset. Five ML algorithms, such as K-NN, SVM, Logistic regression, LDA, and decision tree, were used for the classification process.

In [63], a 3D-axis accelerometer was embedded into a 6LowPAN wearable device for detecting falls of elderly people in indoor environments. Four machine learning algorithms (classifiers): deepnets, logistic regression, ensemble, and decision trees are evaluated in terms of AUC ROC, training time, and testing time. The SisFall dataset contains records from 38 participants [64]. A Fall Detection System is developed in [65] using gyroscope and accelerometer sensors with SVM to classify the features as falls or regular daily activities. The method proposed in the literature was evaluated against the SisFall dataset [66], which had been made available to the public with an expanded annotation. Results were compared with those obtained in previous studies of the same dataset. The proposed method was found to significantly outperform the original analysis technique originally developed for the SisFall dataset, exhibiting an F1 score exceeding 97% and a recall rate exceeding 99.7%. Magnetometer, gyroscope, and accelerometer sensors are also used in [67] for Fall Detection Systems. The ML algorithms used in the literature for the classification process are ANN, SVM, naive Bayes, and KNN, with accuracy of 72, 68.25, 61.5, and 84.1% respectively.

The classification of various types of falls using temporal signal angle measurement (TSAM) was developed in [69] at different sampling frequencies, with the results being compared to those of three distinct ML algorithms (SVM, KNN, RF). The performance of the TSAM was comparable to that of the ML algorithms overall, although the former outperformed the latter when frequencies were within the range of 10 to 20 Hz. The accuracy of the TSAM was found to range from 93.3 to 91.8% as the sampling frequency decreased from 200 to 10 Hz. The sensitivity and specificity values for the same frequency range ranged from 93.3 to 91.8% and 98.3 to 97.9%, respectively.

Figure 8 shows the most used types of classification processes that used in the literature investigated the fall detection and the average accuracy for them.

3.5 Stress detection

The present society is grappling with the growing problem of mental stress, which is being experienced by more and more individuals day by day. Stress is a physiological response that prepares our bodies to face challenging circumstances. Hence, it is essential to manage mental stress as it can lead to several harmful outcomes. Timely recognition of stress can help avoid health complications caused by stress [118–120].

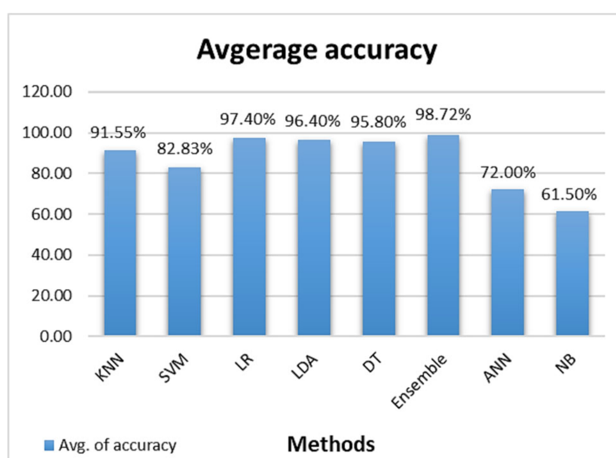

Fig. 8 Average accuracy for most of types used for fall detection

The authors in [70] used five ML algorithms such as k-NN, Random Forest, SVM, AdaBoost, and Linear Discriminant Analysis, to detect stress using a publicly available multimodal dataset, WESAD. The sensors used are respiration (RESP), electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG), and body temperature (TEMP). In [71], accelerometer and gyroscope sensor data were used to detect stress and the data were classified by k-NN, Bayesian Networks, and C4.5 Decision Trees. The result of the classification process for each algorithm was 87.56, 67.86, and 74.26%, respectively. The authors in [73] used a neural network model with an accuracy of 92% for patients with metabolic syndrome and 89% for the rest. The sensors used were glucose level, blood pressure, GSR, body temperature, SpO2, and ECG. The dataset is 312 biosignals recorded from 30 participants. ECG sensor in a chest strap was used in [74] to detect stress and anxiety in children with autism spectrum disorder (ASD). SVM and LR were used for the process of classification with accuracy of 93 and 87%, respectively. J48, KNN, SVM, BN, RF, and AB learning methods were used in [75] to detect stress. The dataset used is from 2 participants with 324 instances at rest and exercise sessions.

Figure 9 shows the types used for the classification process used in the literature investigated in stress detection and the average accuracy for them.

3.6 Activity recognition

The improvement in people's living standards has led to a surge in the need for health monitoring and exercise detection. As a result, there is a pressing need to investigate human activity recognition (HAR) techniques [121, 122].

In [76], the authors used signals from an accelerometer and gyroscope, which were obtained from a WithRobotTM sensor fastened onto the left-hand wrist of a participant, and applied an ML algorithm known as convolutional neural network-long short-term memory network (CNN-LSTM). The proposed model was both spatially and temporally deep. It demonstrated a high degree of accuracy, achieving 99% on the iSPL dataset, an internal dataset, and a 92% accuracy on the UCI HAR public dataset. In [78], wearable sensors were designed, incorporating an Inertial Measurement Unit (IMU) and Wi-Fi section, to investigate human activity recognition. The ML algorithm, CNN, was used in the classification process with an accuracy of 97%. The dataset used was the standard dataset from the UCI Machine Learning Repository [77] and a new dataset created from collecting data with the proposed sensor.

In [79], smartphone inertial accelerometer-based architecture was developed for HAR. The ML algorithms, SVM, LSTM, BLSTM, MLP, and CNN, are utilized on the UCI and Pamap2 datasets. The proposal presented in Reference [80] involves creating powerful techniques for virtual driving control and gait recognition. These methods rely on triaxial acceleration and plantar pressure signals of the lower limb, in addition to using multimodal information including surface electromyography (sEMG) signals of the upper limb. The identification of gait was conducted through the optimized SVM, resulting in an average accuracy of 90.48%. The experimental results have demonstrated that the motion posture information can be dynamically detected through the implementation of various combinations of wearable sensors on the upper and lower limbs. The information was utilized in the design of virtual rehabilitation and walking auxiliary systems. The authors in [81] have conducted research on the recognition of human activity through the utilization of convolutional neural networks. The results of their study demonstrated an accuracy rate of roughly 96% for the UCI-HAR dataset and 94% for their study dataset.

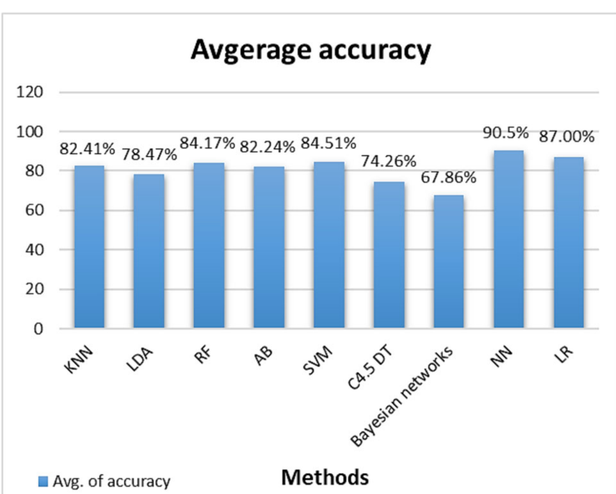

Fig. 9 Average accuracy for most of types used for stress detection

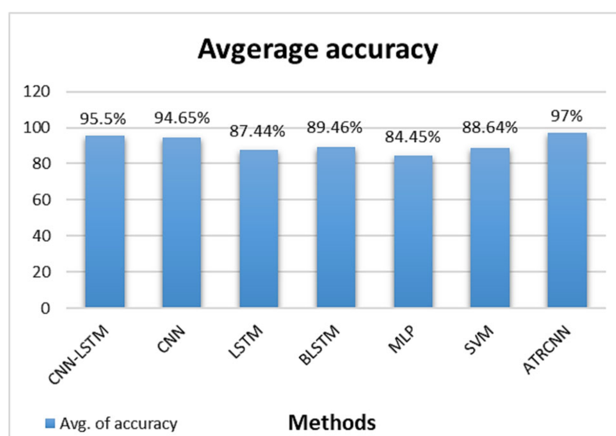

Fig. 10 Average accuracy for most of types used for activity recognition

A wearable device utilizing ZigBee technology with low weight and low cost was used [82] to monitor human activity. An end-to-end neural network model named ATCRNN was used. It was capable of predicting the actions that a user will undertake in the future based on their past behaviors. By utilizing both CNN and RNN techniques were used to extract features. The results demonstrated that ATCRNN has achieved an impressive 97% accuracy rate for behavior inference.

Figure 10 shows the most used types for the classification process that used in the literature investigated in activity recognition and the average accuracy for them.

3.7 Emotion recognition

Analyzing the emotional conditions of individuals who have difficulty expressing their feelings, such as those on the autism spectrum, can greatly benefit their relatives, acquaintances, and mental health professionals by providing them with a richer understanding of their daily experiences. Although the investigation of emotion identification techniques using physiological signals has been a focal point of research for several years, there is a relatively limited amount of literature regarding the use of wearable devices to extract such data [123–125].

In [83], the signals from photoplethysmography galvanic skin response are used to propose a model for the recognition of three emotions: neutral, amusement, and sadness. The ML algorithm, SVM, was used for the classification process with an accuracy of up to 100%. The dataset used was the DEAP dataset [84]. The authors in [85] used the hybrid approach CNN-LSTM and the adoption of deep learning methods for emotion classification. The dataset used was the EnvBodySens [86] and the sensors used were EEG and GSR. DEAP dataset was also used in [87] for the emotion recognition model. The sensors used were a fingertip temperature sensor and Respiratory belt (RB), PPG and the ML algorithms used for the classification process are SVM, Random forest, and logistic regression with an accuracy of 72.18% for valence and 73.08% for arousal. In a study documented in [88], the emotional state of individuals during stimuli exposure was evaluated through the employment of the MUSE headband together with the Shimmer GSR + device. KNN was used for the process of classification and the accuracy ranges from 53.6 to 69.9%. Liquid State Machines (LSM) were used in [89] with EEG data to recognize the emotional state of an individual.

Figure 11 shows the types used for the classification process that were used in the literature investigated in emotion recognition and the average accuracy for them.

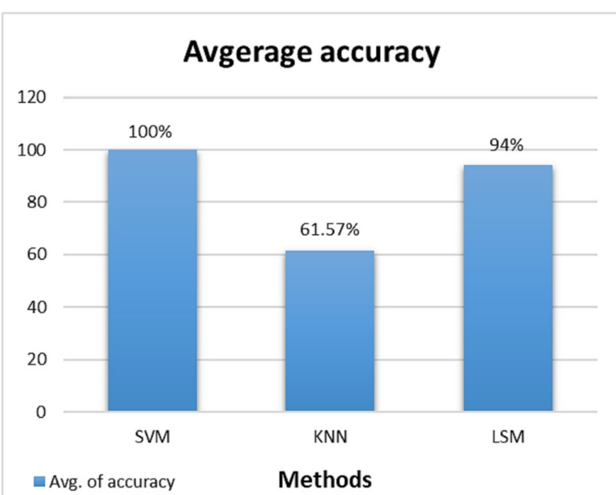

Fig. 11 Average accuracy for most of types used for emotion recognition

3.8 Rehabilitation tasks

Rehabilitation tasks include tasks aimed at strengthening the basic capabilities of routine existence and include physical and cognitive abilities that may have been compromised or lost due to trauma, underlying diseases, genetic anomalies, or congenital anomalies [126, 127].

The scholars described in their publication numbered [90] advanced a home-based rehabilitation (HBR) system that can recognize and record the type and frequency of rehabilitation practices executed by the user deploying the ML algorithm, CNN, for the classification process. The signals used were sourced from the accelerometer, gyroscope, or accelerometer combined with gyroscope data. In [91], the authors proposed a model for both walking and running exercises using the ML algorithms artificial neural network (ANN), SVM, and K-means clustering. Plantar pressure measuring foot insoles and IMU sensor module

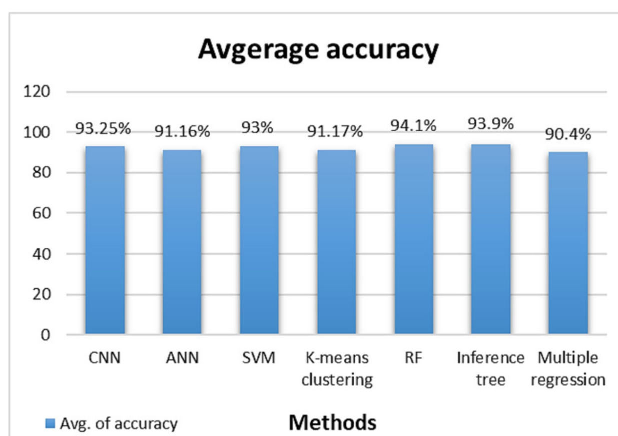

Fig. 12 Average accuracy for most of types used for rehabilitation tasks

are used for the dataset. The authors in [92] used SVM to propose an IoT-enabled stroke rehabilitation system that was based on a smart wearable armband (SWA) using a surface electromyography (SEMG) acquisition module.

The authors in [93] discussed foot strike angle prediction, which can help in the consumer-based shoe prescription and coaching of running movements. Various machine learning methods were assessed, and it was determined that random forest yielded the highest accuracy at 94.1%. Support vector regression (SVR) models were used in [94]. The gait parameters of foot clearance, stride velocity, and stride length underwent analysis for both walking and running exercises. The utilization of support vector regression (SVR) proved to be successful in generating excellent intraclass correlation coefficients (ICC).

Figure 12 shows the types used for the classification process used in the literature investigated in the rehabilitation tasks and the average accuracy for them.

3.9 Sleep monitoring

Adequate sleep is critical to maintaining good health and has been suggested as a valuable tool for the diagnosis and treatment of various diseases [128–130]. In a typical sleep laboratory, conventional analysis of sleep measurements focuses on distinguishing between different stages of sleep based on guidelines established by the American Academy of Sleep Medicine (AASM) [131]. This involves assigning one of five labels (WAKE, REM, non-REM 1, non-REM 2, and non-REM 3) to every 30 s, a task traditionally performed manually by qualified electrophysiologists. However, due to the growing awareness of the importance of sleep to public health and the growing availability of personal sleep tracking devices, such as portable EEG devices, there is a renewed interest in developing automated processes to handle the high volume of sleep data that is generated [132–134].

The authors in [95] proposed a new methodology for Obstructive Sleep Apnea (OSA). Deep learning methods and SVM were used to classify features with an average of accuracy 79.45 and 55.94%, respectively. The publicly available'Sleep EDF' database [101] was used in [100] with the CNN method for personalizing a general sleep scoring model. The classification of sleep episodes has been the subject of scrutiny in [102]. Different sleep–wake states were detected in the literature by implementing the random forest model, which produced an F1 score of 73.93%. Training the model involved using data obtained from wrist-worn accelerometers for a total of 134 individuals. In recent studies, sleep monitoring applications have been explored, specifically in detecting episodes of sleep apnea [103]. Sleep apnea is a condition associated with an increased risk of cardiovascular complications and a lower overall quality of life. The authors compared the autocorrelated wave with the adaptive threshold (ACAT) of both PPG sensor data and electrocardiogram (ECG) to quantify the cyclic variation of heart rate (CVHR). The analysis revealed that the classifier was able to distinguish between episodes of OSA and non-OSA episodes with a sensitivity of 82%, specificity of 89%, and accuracy of 85% based on PPG signals.

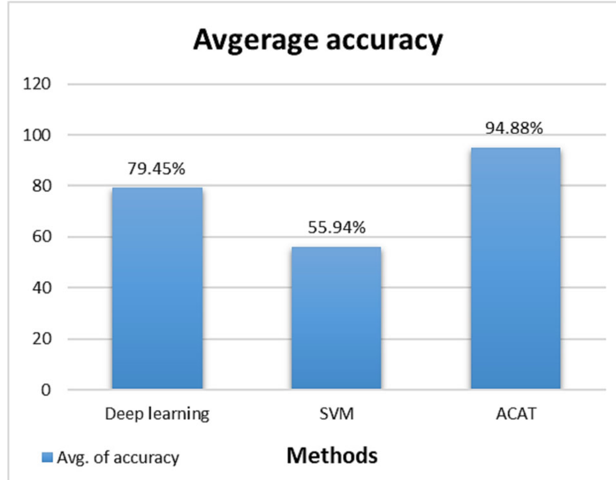

Fig. 13 Average accuracy for most of types used for sleep monitoring

Figure 13 shows the types used for the classification process used in the literature investigated in sleep monitoring and the average accuracy for them.

4 Challenges for ML applications on wearable devices

While the integration of wearable devices with ML is becoming commonplace in healthcare, some hurdles need to be addressed by developers of ML applications designed for such wearable devices. Figure 14 shows these challenges.

4.1 Data availability and reliability

Machine learning methods, particularly in healthcare applications, require sufficient training data to be available to produce accurate results for new datasets. Also, the data received from the wearable devices must be reliable. In healthcare, data reliability is of paramount importance to patients and clinicians for making informed medical decisions, which may have life-threatening consequences in some situations. To guarantee the reliability of data, it is crucial to carry out a diverse array of clinical trials and provide clear reporting of findings. This is essential in appraising various technologies and determining prospects

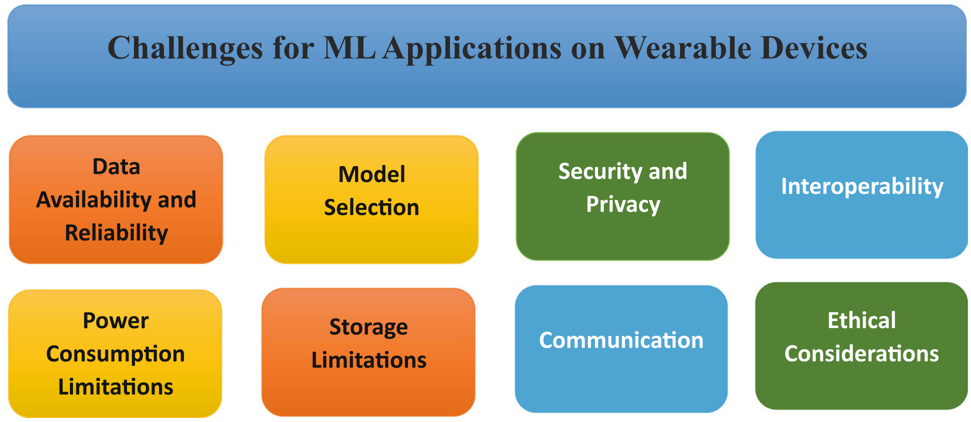

Fig. 14 Challenges for ML applications on wearable devices

for future research endeavors. Moreover, the medical and legal aspects must be clearly defined and regulated [135–137].

4.2 Model selection

When selecting a model for wearable devices, there are several factors to consider. One of the primary criteria is to minimize the error measure used for regression problems or to maximize the evaluation scale used to report classification accuracy. It is commonly observed that training a combination of different models produces the best possible performance. Moreover, a key factor to consider is the interpretability or explainability of the model, which holds great importance, especially in healthcare applications. In such situations, the classification/regression or clustering result must be understandable and meaningful to the user, making it a crucial criterion [138]. In this context, tree-based models are often considered to be more interpretable than neural network-based models. Another important factor is the model size which must be taken into consideration when fitting a model to a wearable device with limited memory. In addition, it is imperative to take into account the computational intricacies of both inference and online training on the device for personalization. This is particularly crucial given the current restricted computational capability of wearable devices [139, 140].

4.3 Security and privacy

The act of obtaining data from users through wearable devices and the consequent transfer of such data to machine learning services on cloud platforms, as illustrated in Fig. 1, is a process that is vulnerable to several security and privacy threats [141]. The confidentiality of users' sensitive data may be compromised as the information collected may be targeted by cyber attackers [142]. Most contemporary smartphones come equipped with Bluetooth and Wi-Fi modules, which are necessary to connect fitness trackers to their applications, but remain vulnerable to various security breaches, increasing the possibility of unauthorized leakage of users' private information [143].

The emergence of cloud-based IoT architectures has given rise to a set of fundamental security and privacy requirements to protect data integrity, particularly with respect to identity and location privacy. It is necessary to protect users' sensitive data to avoid revealing personal habits. To create a secure cloud-based Internet of Things (IoT) framework, measures must be implemented to ensure the privacy of inputs, outputs, and functionality. Efforts should be made to prevent attackers from accessing private data and to effectively mitigate packet forwarding attacks. Furthermore, maintaining forward and backward security is critical to enable new users to only decrypt encrypted messages when joining the network, while revoked users should not be able to decrypt encrypted communications after leaving [144]. Therefore, it is essential to define IoT security strategies and protocols as well as provide users with the autonomy to select the preferred option every time [145].

The primary function of the advanced encryption standard (AES) is to guarantee confidentiality, whereas the RSA asymmetric algorithm is utilized for asymmetric encryption, digital signatures, and key management. Secure hash functions (SHA) standards are used along with Diffie–Hellman (DH) and elliptic curve cryptography (ECC) to establish privacy through asymmetric cryptography [145]. Researchers are particularly interested in the security mechanisms of combined mode, as it facilitates both encryption and authentication, which are essential for devices that are compact, embedded, or portable. Presently, there is a significant focus on optimizing ciphers, and encryption algorithms are being scrutinized, taking into account the resources available on various IoT devices [146].

4.4 Interoperability

Interoperability refers to the ability to integrate data and use it alongside various other forms of data [147]. Many philosophical, historical, and sociological examinations of the importance of data in scientific endeavors have emphasized that the value of broad data sets for research lies in the possibility of integrating and linking diverse data sets [148]. A high degree of interoperability is critical to exploit the benefits of new and large data sets, such as those captured through wearable technology. Conversely, a low level of interoperability hinders the integration of wearable data with other health-related data, hindering the comparison and evaluation of results collected from different devices, sensors and methodologies. Thus, ensuring interoperability of wearable data can facilitate comparison of results obtained by alternative methods and assess the potential problem of overestimation. Furthermore, data interoperability is intertwined with interoperability at the software and hardware levels of wearable technology. For example, integrating wearable devices into healthcare services presents challenges due to the need for additional staff to assist patients with the technology, necessitating distinct training programs as software and hardware configurations vary across devices [149]. In addition, interoperability standards play a vital role in data management, enabling the integration of wearable devices into healthcare services, such as personal and electronic health records, despite the current high costs [150], and addressing cybersecurity risks by emphasizing transparency. And accountability within healthcare systems [151, 152]. Therefore, ensuring wearable device interoperability is an essential approach to address overvaluation and enhance the potential for personalized and precise healthcare in digital health.

4.5 Power consumption limitations

The primary limitation of wearable devices is their power consumption, which is mostly due to their limited battery life [153]. For cloud calculations, in the case of ML applications, physiological data collected by device sensors is transmitted to the cloud which greatly affects power consumption [154]. For wearable devices, many factors negatively affect power consumption including the board, the operating system and other software running on the board, its components of different biosensors and their sampling rate, the amount of data transmitted over the communication channel, the rate of logging data on the device, and the wearable display. It is believed that sending and receiving data consumes more power than sensing and logging data. Reducing the amount of data stored and sent to the cloud is a potential strategy to reduce energy consumption [155]. The current processing power and battery life of wearables might constrain the use of advanced machine learning algorithms [5]. Therefore, Sopic et al. created a unique, two-level classification system for myocardial infarction (MI) [156]. This system included an initial screening level, which considered only a few features to detect if any ischaemic abnormalities needed further evaluation, followed by a second-level classifier, which was more computationally demanding but more accurate compared with the screening level. The algorithm was tested on SmartCardia INYU devices (SmartCardia, Switzerland) and achieved a clinically relevant accuracy of 90% for classifying MI. These multi-layered algorithms require extensive validation before being considered for clinical implementation.

4.6 Storage limitations

The feasibility of implementing a machine learning application on a wearable or edge device is influenced by various factors such as the intricacy of the model, which includes the number of parameters and layers, the dimensions of the device, the magnitude of data, and the use of batch or real-time processing. The small device size and weight requirements of today's wearable devices make these devices memory-limited. Due to the number of parameters and layers in the model, a high-accuracy model requires more memory than a low-accuracy model. Nonvolatile memory (e.g., F-RAM, MRAM, EEPROM, and flash) is used in wearable and IoT devices to ensure short boot time and to ensure resilient system recovery on sudden shutdown [157]. Depending on the particular application of machine learning, certain models may exceed 100MB or even gigabytes in size, particularly those that include image inputs. These models are not compatible with wearable devices due to memory limitations needed to perform the computations [158, 159].

4.7 Communication

In the case of the edge computing model, one of the standards such as UWB, NFC, RFID, Zigbee, and Bluetooth can be used to communicate between the wearable device and the edge. Lightweight Bluetooth technology is usually preferred due to its lower power consumption. However, the Bluetooth 5 specification allows up to seven simultaneous connections to the device, but performance may deteriorate, and pairing problems may arise when multiple connections are established with a smartphone. The choice of communication technology depends on various factors such as the data rate required for the wearable device, the maximum distance between the wearable device and the device, and latency requirements [160, 161].

4.8 Ethical considerations

Ethical considerations play a crucial role in integrating machine learning (ML) into the healthcare, covering a range of aspects that require careful consideration [162, 163]. One ethical concern that arises is the potential for algorithmic bias, where machine learning models may inadvertently perpetuate inequalities in healthcare outcomes due to biased training data or algorithmic decision-making processes. Furthermore, it is important to ensure Patient confidentiality and data security are essential to support trust and privacy in healthcare systems that rely on machine learning. The transparency and interpretability of machine learning algorithms is also a key ethical consideration, as healthcare providers and patients need to understand the underlying mechanisms and rationale behind algorithmic predictions. Furthermore, the ethical implications of automation and decision-making autonomy in healthcare settings require careful consideration and consideration of patient autonomy and benevolence. To address these ethical dilemmas, collaboration between disciplines such as healthcare professionals, ethicists, policy makers, and technologists is essential to establish ethical standards and regulatory frameworks that promote the responsible and equitable use of machine learning in healthcare [164]. Proactively addressing these ethical considerations enables healthcare organizations to uphold ethical principles and ensure ethical implementation of machine learning techniques for the betterment of patients and society.

5 Conclusion

Wearable medical devices play an important role in extracting high-accuracy biosignals, which are indispensable for the realization of digital medicine. The area of medicine that deals with the merging of technology and the human body to facilitate ongoing data collection and advancements in artificial intelligence (AI) for successful treatment, diagnosis, and prevention of disease is known as this field. To achieve this goal, the use of wearable devices that can be worn continuously to provide uninterrupted streams of clinical-grade vital signs is crucial. Furthermore, AI must be implemented to recognize trends and markers that may indicate changes in underlying physiology or the onset of disease. However, the development of artificial intelligence has surpassed wearable technology in achieving these goals. This article presents a systematic review of the importance of using wearable devices in healthcare and the importance of using artificial intelligence techniques with these devices. Furthermore, we have also provided a comprehensive and state-of-the-art literature on ML tasks in the field of healthcare wearable devices, different ML technologies used, biosensors, and datasets. An in-depth analysis of the strengths and weaknesses of the use of machine learning in healthcare is also provided, providing readers with valuable insights into the field and enabling them to begin their research by choosing a topic from a range of available technologies. The discussion also touched upon various research problems and obstacles, encouraging researchers to delve deeper into them.

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Data availability We confirm that no datasets were users, generated, or analyzed during the current study.

Declarations

Conflict of interest The authors declare that they have no competing interests nor conflict of interests for the current study.

References

1. Carlos Sánchez J, Santos P, Lozano J (2019) Use of electronic noses for diagnosis of digestive and respiratory diseases through the breath. Biosensors 9(1):35. https://doi.org/10.3390/bios9010035
2. Cui F, Susan Zhou H (2019) Diagnostic methods and potential portable biosensors for coronavirus disease. Biosens Bioelectron 165(2020):112349
3. Durmaz S et al (2019) WhatsApp embedded in routine service delivery for smoking cessation: effects on abstinence rates in a randomized controlled study. BMC Public Health 19(1):1–12
4. Iqbal S et al (2021) Advances in healthcare wearable devices. NPJ Flex Electron 5(1):1–14
5. Bayoumy K et al (2021) Smart wearable devices in cardiovascular care: where we are and how to move forward. Nat Rev Cardiol 18(8):581–599

6. Sujith AVLN et al (2022) Systematic review of smart health monitoring using deep learning and Artificial intelligence. Neurosci Inf 2(3):100028
7. Wang Y-C et al (2022) Current advancement in diagnosing atrial fibrillation by utilizing wearable devices and artificial intelligence: a review study. Diagnostics 12(3):689
8. Lee S et al (2022) Artificial intelligence for detection of cardiovascular-related diseases from wearable devices: a systematic review and meta-analysis. Yonsei Med J 63(Suppl):S93
9. Xie J et al (2020) Wearable graphene devices for sensing. J Electrochem Soc 167(3):037541
10. Chow H-W, Yang C-C (2020) Accuracy of optical heart rate sensing technology in wearable fitness trackers for young and older adults: validation and comparison study. JMIR Mhealth Uhealth 8(4):e14707
11. Somathilake E et al (2022) Assessment of fetal and maternal well-being during pregnancy using passive wearable inertial sensor. IEEE Trans Instrum Measure 71:1–11
12. Iqbal SMA et al (2021) Advances in healthcare wearable devices. NPJ Flex Electron 5(1):9
13. Nahavandi D et al (2022) Application of artificial intelligence in wearable devices: opportunities and challenges. Comput Methods Programs Biomed 213:106541
14. Saifuzzaman M et al (2022) A systematic literature review on wearable health data publishing under differential privacy. Int J Inf Secur 21(4):847–872
15. Athanasopoulou K et al (2022) Artificial intelligence: the milestone in modern biomedical research. BioMedInformatics 2(4):727–744. https://doi.org/10.3390/biomedinformatics2040049
16. Agarwal P, Swami S, Malhotra SK (2024) Artificial intelligence adoption in the post COVID-19 new-normal and role of smart technologies in transforming business: a review. J Sci Technol Policy Manag 15(3):506–529
17. Welch V et al (2022) Use of mobile and wearable artificial intelligence in child and adolescent psychiatry: scoping review. J Med Internet Res 24(3):e33560
18. Loh HW et al (2022) Application of explainable artificial intelligence for healthcare: a systematic review of the last decade (2011–2022). Comput Methods Programs Biomed 226:107161
19. Ravali RS et al (2022) A systematic review of artificial intelligence for pediatric physiotherapy practice: past, present, and future. Neurosci Inf 2(4):100045
20. Das PK et al (2022) A systematic review on recent advancements in deep and machine learning based detection and classification of acute lymphoblastic leukemia. IEEE Access 10:81741–81763
21. Jiang T, Gradus JL, Rosellini AJ (2020) Supervised machine learning: a brief primer. Behav Ther 51(5):675–687
22. Bi Q et al (2019) What is machine learning? A primer for the epidemiologist. Am J Epidemiol 188(12):2222–2239
23. Berahmand K et al (2024) Autoencoders and their applications in machine learning: a survey. Artific Intell Rev 57(2):28
24. Li Y (2017) Deep reinforcement learning: an overview. arXiv preprint arXiv:1701.07274
25. Weltz J, Volfovsky A, Laber EB (2022) Reinforcement learning methods in public health. Clin Ther 44(1):139–154
26. Escobar-Linero E et al (2023) Wearable health devices for diagnosis support: evolution and future tendencies. Sensors 23(3):1678
27. Shandhi MMH et al (2022) A method for intelligent allocation of diagnostic testing by leveraging data from commercial wearable devices: a case study on COVID-19. NPJ Digit Med 5(1):130
28. Balli S, and Ensar Arif Sağbas (2017) The usage of statistical learning methods on wearable devices and a case study: activity recognition on smartwatches. Advances in statistical methodologies and their application to real problems: 259–277
29. Pardamean B et al (2019) Comparing the accuracy of multiple commercial wearable devices: a method. Procedia Comput Sci 157:567–572
30. Mansour RF et al (2021) Artificial intelligence and internet of things enabled disease diagnosis model for smart healthcare systems. IEEE Access 9:45137–45146
31. Nayyar, A, Gadhavi L, and Noor Zaman. (2021) Machine learning in healthcare: review, opportunities and challenges. Machine Learning and the Internet of Medical Things in Healthcare: 23–45
32. Forouzandeh S et al (2024) Health-aware food recommendation system with dual attention in heterogeneous graphs. Comput Biol Med 169:107882
33. Torres-Soto J, Ashley EA (2020) Multi-task deep learning for cardiac rhythm detection in wearable devices. NPJ Digital Med. https://doi.org/10.1038/s41746-020-00320-4
34. Bruno E et al (2021) Wearable devices for seizure detection: practical experiences and recommendations from the wearables for epilepsy and research (WEAR) international study group. Epilepsia 62(10):2307–2321
35. Chen J, Abbod M, Shieh J-S (2021) Pain and stress detection using wearable sensors and devices—a review. Sensors 21(4):1030
36. Midani W, Ouarda W, Ayed MB (2023) DeepArr: an investigative tool for arrhythmia detection using a contextual deep neural network from electrocardiograms (ECG) signals. Biomed Signal Process Control 85:104954
37. Raab D, Theissler A, Spiliopoulou M (2023) XAI4EEG: spectral and spatio-temporal explanation of deep learning-based seizure detection in EEG time series. Neural Comput Appl 35(14):10051–10068
38. Hossieny RR et al (2023) Development of electrooculogram based human computer interface system using deep learning. Bull Electr Eng Inf 12(4):2410–2420
39. Gharibans AA et al (2019) Spatial patterns from high-resolution electrogastrography correlate with severity of symptoms in patients with functional dyspepsia and gastroparesis. Clin Gastroenterol Hepatol 17(13):2668–2677
40. Cheng Y et al (2021) Recent developments in sensors for wearable device applications. Anal Bioanaly Chem 413(24):6037–6057
41. Sabry F et al. (2022) Machine learning for healthcare wearable devices: the big picture. J Healthcare Eng 2022
42. Al Bassam N et al (2021) IoT based wearable device to monitor the signs of quarantined remote patients of COVID-19. Informatics in medicine unlocked 24:100588
43. Chen H et al (2020) A smart machine learning model for the detection of brain hemorrhage diagnosis based internet of things in smart cities. Complexity 2020:1–10
44. Liang Y et al (2018) Photoplethysmography and deep learning: enhancing hypertension risk stratification. Biosensors 8(4):101
45. Un K-C et al (2021) Observational study on wearable biosensors and machine learning-based remote monitoring of COVID-19 patients. Sci Rep 11(1):4388
46. Wong CK et al (2020) Artificial intelligence mobile health platform for early detection of COVID-19 in quarantine subjects using a wearable biosensor: protocol for a randomised controlled trial. BMJ Open 10(7):e038555
47. Miao F et al (2020) Continuous blood pressure measurement from one-channel electrocardiogram signal using deep-learning techniques. Artific Intell Med 108:101919

48. Houta S, Bisgin P, and Dulich P (2019) Machine learning methods for detection of Epileptic seizures with long-term wearable devices. Eleventh international conference on eHealth, telemedicine, and social medicine
49. Resque P et al. (2019) An investigation of different machine learning approaches for epileptic seizure detection. 2019 15th international wireless communications & mobile computing conference (IWCMC). IEEE
50. Gabeff V et al (2021) Interpreting deep learning models for epileptic seizure detection on EEG signals. Artific Intell Med 117:102084
51. Rheims S et al (2019) Hypoxemia following generalized convulsive seizures: risk factors and effect of oxygen therapy. Neurology 92(3):e183–e193
52. Meisel C et al (2020) Machine learning from wristband sensor data for wearable, noninvasive seizure forecasting. Epilepsia 61(12):2653–2666
53. Regalia G et al (2019) Multimodal wrist-worn devices for seizure detection and advancing research: focus on the Empatica wristbands. Epilepsy Res 153:79–82
54. Lee K-S et al (2022) Compressed deep learning to classify arrhythmia in an embedded wearable device. Sensors 22(5):1776
55. Huda, N et al. (2020) A low-cost, low-energy wearable ECG system with cloud-based arrhythmia detection. 2020 IEEE Region 10 Symposium (TENSYMP). IEEE
56. Moody GB, Mark RG (2001) The impact of the MIT-BIH arrhythmia database. IEEE Eng Med Biol Mag 20(3):45–50
57. Wu M-H, Chang EJ, and Chu T-H (2018) Personalizing a generic ECG heartbeat classification for arrhythmia detection: a deep learning approach. 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR). IEEE
58. Kwon S et al (2020) "Detection of atrial fibrillation using a ring-type wearable device (CardioTracker) and deep learning analysis of photoplethysmography signals: prospective observational proof-of-concept study. J Med Internet Res 22(5):e16443
59. Hannun AY et al (2019) Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nat Med 25.1:65–69
60. Shen Y et al. (2019) Ambulatory atrial fibrillation monitoring using wearable photoplethysmography with deep learning. Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining
61. Musci M et al. (2018) Online fall detection using recurrent neural networks. arXiv preprint arXiv:1804.04976
62. de Quadros T, Lazzaretti AE, Schneider FK (2018) A movement decomposition and machine learning-based fall detection system using wrist wearable device. IEEE Sens J 18(12):5082–5089. https://doi.org/10.1109/JSEN.2018.2829815
63. Yacchirema D et al (2019) Fall detection system for elderly people using IoT and ensemble machine learning algorithm. Personal Ubiquitous Comput 23:801–817
64. SISTEMIC: Research group on Embedded Systems and Computational Intelligence of the Electronics and Telecommunications Department at the Faculty of Engineering, University of Antioquia, "SisFall Dataset." Online. Available: http://sistemic.udea.edu.co/investigacion/proyectos/english-falls/?lang=en. Accessed 2 Feb 2018
65. Giuffrida D et al. (2019) Fall detection with supervised machine learning using wearable sensors. 2019 IEEE 17th international conference on industrial informatics (INDIN). Vol. 1. IEEE
66. Casilari E, Santoyo-Ramón J-A, Cano-García J-M (2017) Analysis of public datasets for wearable fall detection systems. Sensors 17(7):1513
67. Ramachandran A et al. (2018) Machine learning-based techniques for fall detection in geriatric healthcare systems. 2018 9th International conference on information technology in medicine and education (ITME). IEEE
68. https://figshare.com/articles/dataset/UMA_ADL_FALL_Dataset_zip/4214283
69. Kwon SB et al (2019) An energy-efficient algorithm for classification of fall types using a wearable sensor. IEEE Access 7:31321–31329
70. Garg P et al. (2021) Stress detection by machine learning and wearable sensors. 26th international conference on intelligent user interfaces-companion
71. Sağbaş EA, Korukoglu S, Balli S (2020) Stress detection via keyboard typing behaviors by using smartphone sensors and machine learning techniques. J Med Syst 44:1–12
72. https://tinyurl.com/2019-stress-detection-dataset
73. Akbulut FP, Ikitimur B, Akan A (2020) Wearable sensor-based evaluation of psychosocial stress in patients with metabolic syndrome. Artific Intell Med 104:101824
74. Masino AJ et al. (2019) M-Health and autism: recognizing stress and anxiety with machine learning and wearables data. 2019 IEEE 32nd international symposium on computer-based medical systems (CBMS). IEEE
75. Delmastro F, Di Martino F, Dolciotti C (2020) Cognitive training and stress detection in mci frail older people through wearable sensors and machine learning. Ieee Access 8:65573–65590
76. Mutegeki R and Dong SH (2020) A CNN-LSTM approach to human activity recognition. 2020 international conference on artificial intelligence in information and communication (ICAIIC). IEEE
77. Bianchi V et al (2019) IoT wearable sensor and deep learning: an integrated approach for personalized human activity recognition in a smart home environment. IEEE Internet Things J 6(5):8553–8562
78. Anguita D et al. (2013) A public domain dataset for human activity recognition using smartphones. Esann. Vol. 3
79. Wan S et al (2020) Deep learning models for real-time human activity recognition with smartphones. Mob Netw Appl 25:743–755
80. Li X et al (2021) Human posture detection method based on wearable devices. J Healthc Eng 2021(1):8879061
81. Yen C-T, Liao J-X, Huang Y-K (2020) Human daily activity recognition performed using wearable inertial sensors combined with deep learning algorithms. Ieee Access 8:174105–174114
82. Zhang D, Zhang H, Zhao C (2022) Prediction of behavior and activity of patients through wearable devices based on deep learning. J Sens 2022:1–12
83. Domínguez-Jiménez JA, Campo-Landines KC, Martínez-Santos JC, Delahoz EJ, Contreras-Ortiz SH (2020) A machine learning model for emotion recognition from physiological signals. Biomed Signal Process Control 55:101646
84. https://www.eecs.qmul.ac.uk/mmv/datasets/deap/
85. Kanjo E, Younis EM, Ang CS (2019) Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection. Inf Fusion 49:46–56
86. Kanjo E, Younis EM, Sherkat N (2018) Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach. Inf Fusion 40:18–31
87. Laureanti R et al. (2020) Emotion assessment using Machine Learning and low-cost wearable devices. 2020 42nd annual international conference of the IEEE engineering in medicine & biology society (EMBC). IEEE
88. Al Zoubi O, Awad M, Kasabov NK (2018) Anytime multipurpose emotion recognition from EEG data using a liquid state machine based framework. Artific Intell Med 86:1–8

89. Ayata D, Yaslan Y, Kamasak ME (2020) Emotion recognition from multimodal physiological signals for emotion aware healthcare systems. J Med Biol Eng 40:149–157
90. Chae SH et al (2020) Development and clinical evaluation of a web-based upper limb home rehabilitation system using a smartwatch and machine learning model for chronic stroke survivors: prospective comparative study. JMIR Mhealth Uhealth 8(7):e17216
91. Potluri, Sasanka, et al. (2019) Machine learning based human gait segmentation with wearable sensor platform. 2019 41st annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE
92. Yang G et al (2018) An IoT-enabled stroke rehabilitation system based on smart wearable armband and machine learning. IEEE J Trans Eng Health Med 6:1–10
93. Moore SR et al (2020) Foot strike angle prediction and pattern classification using LoadsolTM wearable sensors: a comparison of machine learning techniques. Sensors 20(23):6737
94. Zhang H, Guo Yi, Zanotto D (2019) Accurate ambulatory gait analysis in walking and running using machine learning models. IEEE Trans Neural Syst Rehabil Eng 28(1):191–202
95. Banluesombatkul N, Rakthanmanon T, and Wilaiprasitporn T (2018) Single channel ECG for obstructive sleep apnea severity detection using a deep learning approach. TENCON 2018–2018 IEEE region 10 conference. IEEE
96. Blackwell T et al (2011) Associations between sleep architecture and sleep-disordered breathing and cognition in older community-dwelling men: the osteoporotic fractures in men sleep study. J Am Geriatr Soc 59(12):2217–2225
97. Blank JB et al (2005) Overview of recruitment for the osteoporotic fractures in men study (MrOS). Contemp Clin Trials 26(5):557–568
98. Dean DA et al (2016) Scaling up scientific discovery in sleep medicine: the national sleep research resource. Sleep 39(5):1151–1164
99. Orwoll E et al (2005) Design and baseline characteristics of the osteoporotic fractures in men (MrOS) study—a large observational study of the determinants of fracture in older men. Contemp Clin trials 26(5):569–585
100. Mikkelsen K, and Maarten De Vos (2018) Personalizing deep learning models for automatic sleep staging. arXiv preprint arXiv:1801.02645
101. Kemp B et al (2000) Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG. IEEE Trans Biomed Eng 47(9):1185–1194
102. Sundararajan K et al (2021) Sleep classification from wrist-worn accelerometer data using random forests. Sci Rep 11(1):24
103. Hayano J et al (2020) Quantitative detection of sleep apnea with wearable watch device. PLoS ONE 15(11):e0237279
104. Rostami M et al (2024) A novel healthy food recommendation to user groups based on a deep social community detection approach. Neurocomputing 576:127326
105. Kumar Y et al (2023) Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. J Ambient Intell Human Comput 14(7):8459–8486
106. Uysal G, Ozturk M (2020) Hippocampal atrophy based Alzheimer's disease diagnosis via machine learning methods. J Neurosci Methods 337:108669
107. Woldaregay AZ et al (2019) Data-driven modeling and prediction of blood glucose dynamics: Machine learning applications in type 1 diabetes. Artific Intell Med 98:109–134
108. Awotunde JB et al. (2021) Disease diagnosis system for IoT-based wearable body sensors with machine learning algorithm. Hybrid Artificial Intelligence and IoT in Healthcare: 201–222
109. Tang J et al (2021) Seizure detection using wearable sensors and machine learning: setting a benchmark. Epilepsia 62(8):1807–1819
110. Sayeed MA, Mohanty SP, Kougianos E, Zaveri HP (2019) Neuro-detect: a machine learning-based fast and accurate seizure detection system in the IoMT. IEEE Trans Consum Electron 65(3):359–368
111. Esmaeili B et al (2022) The potential of wearable devices and mobile health applications in the evaluation and treatment of epilepsy. Neurol Clin 40(4):729–739
112. Farooq A, Seyedmahmoudian M, Stojcevski A (2021) A wearable wireless sensor system using machine learning classification to detect arrhythmia. IEEE Sens J 21(9):11109–11116
113. Torres-Soto J, Ashley EA (2020) Multi-task deep learning for cardiac rhythm detection in wearable devices. NPJ Digital Med 3(1):116
114. Mishra B, Arora N, and Vora Y (2018) A wearable device for real-time ECG monitoring and cardiovascular arrhythmia detection for resource constrained regions. 2018 8th International Symposium on Embedded Computing and System Design (ISED). IEEE
115. Saleh M, Le Bouquin R, Jeannès (2019) Elderly fall detection using wearable sensors: a low cost highly accurate algorithm. IEEE Sens J 19(8):3156–3164
116. Usmani S et al (2021) Latest research trends in fall detection and prevention using machine learning: a systematic review. Sensors 21(15):5134
117. Araújo I et al (2022) Machine learning and cloud enabled fall detection system using data from wearable devices: Deployment and evaluation. Anais do XXII Simpósio Brasileiro de Computação Aplicada à Saúde, SBC
118. Iqbal T et al (2022) Exploring unsupervised machine learning classification methods for physiological stress detection. Front Med Technol 4:782756
119. Zubair M et al. (2015) Smart wearable band for stress detection. 2015 5th International conference on IT convergence and security (ICITCS). IEEE
120. Zamkah A et al (2020) Identification of suitable biomarkers for stress and emotion detection for future personal affective wearable sensors. Biosensors 11.4:40
121. Xu Y, Qiu TT (2021) Human activity recognition and embedded application based on convolutional neural network. J Artific Intell Technol 1(1):51–60
122. De Leonardis G et al. (2018) Human activity recognition by wearable sensors: comparison of different classifiers for real-time applications. 2018 IEEE international symposium on medical measurements and applications (memea). IEEE
123. Pollreisz D, and TaheriNejad N (2017) A simple algorithm for emotion recognition, using physiological signals of a smart watch. 2017 39th annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE
124. Lian Z et al (2021) An ear wearable device system for facial emotion recognition disorders. Front Bioeng Biotechnol 9:703048
125. Vijayakumar S, Flynn R, and Murray N (2020) A comparative study of machine learning techniques for emotion recognition from peripheral physiological signals. 2020 31st Irish signals and systems conference (ISSC). IEEE
126. Kos A, Umek A (2018) Wearable sensor devices for prevention and rehabilitation in healthcare: swimming exercise with real-time therapist feedback. IEEE Internet Things J 6(2):1331–1341
127. De Cannière H et al (2020) Wearable monitoring and interpretable machine learning can objectively track progression in patients during cardiac rehabilitation. Sensors 20(12):3601

128. Carr O et al (2018) Variability in phase and amplitude of diurnal rhythms is related to variation of mood in bipolar and borderline personality disorder. Sci Rep 8(1):1649
129. Yousfi N et al (2020) The COVID-19 pandemic: how to maintain a healthy immune system during the lockdown—a multidisciplinary approach with special focus on athletes. Biol Sport 37(3):211–216
130. Cho JW, Duffy F (2019) Sleep, sleep disorders, and sexual dysfunction. World J Men's Health 37(3):261. https://doi.org/10.5534/wjmh.180045
131. Berry R, Brooks R, Gamaldo C, Harding S, Lloyd R, Quan S, Troester M, Vaughn B (2017) AASM scoring manual updates for 2017 (version 2.4). J Clin Sleep Med 13(05):665–666. https://doi.org/10.5664/jcsm.6576
132. Debener S et al (2015) Unobtrusive ambulatory EEG using a smartphone and flexible printed electrodes around the ear. Sci Rep 5(1):16743
133. Looney D et al (2016) Wearable in-ear encephalography sensor for monitoring sleep. Preliminary observations from nap studies. Ann Am Thoracic Soc 13(12):2229–2233
134. Mikkelsen KB et al (2017) Automatic sleep staging using ear-EEG. Biomed Eng Online 16(1):1–15
135. Mateen BA et al (2020) Improving the quality of machine learning in health applications and clinical research. Nat Mach Intell 2(10):554–556
136. Keerthy AS, and Manju Priya S (2021) Artificial intelligence in healthcare databases. Deep Learning and Edge Computing Solutions for High Performance Computing: 19–34
137. Fuller D et al (2020) Reliability and validity of commercially available wearable devices for measuring steps, energy expenditure, and heart rate: systematic review. JMIR mHealth uHealth 8(9):e18694
138. Arrieta AB et al (2020) Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fusion 58:82–115
139. Tonacci A et al (2021) Wearable sensors for assessing the role of olfactory training on the autonomic response to olfactory stimulation. Sensors 21(3):770
140. Qolomany B et al (2020) Trust-based cloud machine learning model selection for industrial IoT and smart city services. IEEE Internet Things J 8(4):2943–2958
141. Al-Garadi MA et al (2020) A survey of machine and deep learning methods for internet of things (IoT) security. IEEE Commun Surv Tutor 22(3):1646–1685
142. Mnjama J, Foster G, and Irwin B (2017) A privacy and security threat assessment framework for consumer health wearables. 2017 Information Security for South Africa (ISSA). IEEE
143. Goyal R, Dragoni N, and Spognardi A (2016) Mind the tracker you wear: a security analysis of wearable health trackers. Proceedings of the 31st annual ACM symposium on applied computing
144. Saraiva DAF et al (2019) Prisec: comparison of symmetric key algorithms for IoT devices. Sensors 19(19):4312
145. Ioannidou I, Sklavos N (2021) On general data protection regulation vulnerabilities and privacy issues, for wearable devices and fitness tracking applications. Cryptography 5(4):29
146. Cilliers L (2020) Wearable devices in healthcare: Privacy and information security issues. Health Inf Manag J 49:150–156
147. Blasimme A et al (2018) Data sharing for precision medicine: policy lessons and future directions. Health Aff 37(5):702–709
148. Leonelli S, Tempini N (2020) Data journeys in the sciences. Springer Nature, Berlin
149. Adler-Milstein J, Nong P (2019) Early experiences with patient generated health data: health system and patient perspectives. J Am Med Inform Assoc 26(10):952–959
150. Canali S, Schiaffonati V, Aliverti A (2022) Challenges and recommendations for wearable devices in digital health: data quality, interoperability, health equity, fairness. PLOS Digital Health 1(10):e0000104
151. Radanliev P et al (2021) The ethics of shared Covid-19 risks: an epistemological framework for ethical health technology assessment of risk in vaccine supply chain infrastructures. Health Technol 11(5):1083–1091
152. Radanliev P, De Roure D (2021) Epistemological and bibliometric analysis of ethics and shared responsibility—health policy and IoT systems. Sustainability 13(15):8355. https://doi.org/10.3390/su13158355
153. Jin X et al (2022) A survey on edge computing for wearable technology. Digital Signal Process 125:103146
154. Fafoutis X et al. (2018) Extending the battery lifetime of wearable sensors with embedded machine learning. 2018 IEEE 4th World Forum on Internet of Things (WF-IoT). IEEE
155. Qaim WB et al (2020) Towards energy efficiency in the internet of wearable things: a systematic review. IEEE Access 8:175412–175435
156. Sopic D et al (2018) Real-time event-driven classification technique for early detection and prevention of myocardial infarction on wearable systems. IEEE Trans Biomed Circuits Syst 12(5):982–992
157. Klus L et al. (2020) Lossy compression methods for performance-restricted wearable devices. CEUR workshop proceedings
158. Baek SH, Park K-W (2020) A durable hybrid RAM disk with a rapid resilience for sustainable IoT devices. Sensors 208:2159
159. Indrakumari R et al (2020) The growing role of Internet of Things in healthcare wearables. Emergence of Pharmaceutical Industry Growth with Industrial IoT Approach. Academic Press, Cambridge
160. Balakrishna C et al. (2019) Challenges of wearable health monitors: a case study of foetal ECG monitor. 2019 Global IoT Summit (GIoTS). IEEE
161. Hale ML et al (2019) Developing a platform to evaluate and assess the security of wearable devices. Digital Commun Netw 5(3):147–159
162. Martínez-García M, Hernández-Lemus E (2022) Data integration challenges for machine learning in precision medicine. Front Med 8:784455
163. Chotrani A (2021) Ethical considerations in deploying machine learning models in healthcare. Eduzone Int Peer Rev Refereed Multidiscip J 101:63–67
164. Javed H et al (2024) Ethical frameworks for machine learning in sensitive healthcare applications. IEEE Access 12:16233–16254. https://doi.org/10.1109/ACCESS.2023.3340884