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*Review*

# Recent Advances in Artificial Intelligence and Wearable Sensors in Healthcare Delivery

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**Abstract:** Artificial intelligence (AI) and wearable sensors are gradually transforming healthcare service delivery from the traditional hospital-centred model to the personal-portable-device-centred model. Studies have revealed that this transformation can provide an intelligent framework with automated solutions for clinicians to assess patients' general health. Often, electronic systems are used to record numerous clinical records from patients. Vital sign data, which are critical clinical records are important traditional bioindicators for assessing a patient's general physical health status and the degree of derangement happening from the baseline of the patient. The vital signs include blood pressure, body temperature, respiratory rate, and heart pulse rate. Knowing vital signs is the first critical step for any clinical evaluation, they also give clues to possible diseases and show progress towards illness recovery or deterioration. Techniques in machine learning (ML), a subfield of artificial intelligence (AI), have recently demonstrated an ability to improve analytical procedures when applied to clinical records and provide better evidence supporting clinical decisions. This literature review focuses on how researchers are exploring several benefits of embracing AI techniques and wearable sensors in tasks related to modernizing and optimizing healthcare data analyses. Likewise, challenges concerning issues associated with the use of ML and sensors in healthcare data analyses are also discussed. This review consequently highlights open research gaps and opportunities found in the literature for future studies.

**Keywords:** artificial intelligence; machine learning; vital signs; wearable sensors

## 1. Introduction

As in many other research fields, the landscape of healthcare research is being progressively reshaped by the trending use of artificial intelligence (AI) techniques [1]. This can be attributed to the radical progression in the development of new machine learning (ML) algorithms. In recent years, ML algorithms have demonstrated an ability to significantly achieve or exceed human-level performance when it comes to computational tasks [2]. Particularly, the availability of big datasets and computing power improvements are partly responsible for these achievements by ML algorithms [3]. The discovery of beneficial healthcare knowledge brought by the application of AI techniques in analyzing medical datasets has attracted immense attention [4]. Clinicians are widely inclined to adopt the application of ML algorithms to process clinical datasets for their accuracy, robustness, and interpretability [5]. Often, the atmosphere for delivering medical care by health professionals is hasty, with the availability of boundless arrays of technologies and varying individual conclusions and judgments [6]. During a patient's examination, important information is continuously collected by health professionals either automatically or manually using appropriate devices.

Different approaches are being used worldwide to gather patients' vital information [7]. However, the situation in an intensive care unit (ICU) differs as it requires more devices for medical diagnoses and the continuous monitoring of each subject [8]. Accordingly, the electronic health form (EHF) system accepts and stores the volume of measured medical data in real-time [9,10]. Health forms might contain high-dimensional health data ranging from vital signs data such as blood glucose level, blood pressure, heart rate, oxygen saturation level, and body temperature, to other demographic data such as family medical history, laboratory tests, and medication records [11]. Thus, volumes of such high-dimensional health data pose an interpretational challenge to health professionals during the diagnosis and treatment of patients [12].

Amongst the health data parameters are vital signs, also referred to as bioindicators. These are important pieces of clinical information used to objectively measure and assess the general physical health of a person. These vital signs give clues to possible diseases and show progress toward recovery. Likewise, acute, and protracted diseases can also be monitored via vital signs. Thus, they serve as tools for crucial communication concerning the health status of patients [13,14], and they are usually the first intervention commonly observed by health professionals. However, some concerns still exist regarding general health practice issues, such as which health parameters must be measured, the frequency of the optimal measurements and the performance measure of the new health technologies for observing patients [15–17]. Consequently, ML techniques can be used to effectively analyze and efficiently generate actionable insights from vital signs data or through the combination of additional data from the patient's health records. It has been established in medical studies that timely discovery and prompt intervention are very crucial measures to avoid declining a patient's medical condition [18]. Both the cost and optimization of healthcare systems could be achieved through the early prediction of patient health outcomes.

Similarly, the availability of Electronic Health Record (EHR) systems offers abundant and unique prospects for biomedical studies, whereby analytics and predictive modelling are at the core [19]. Disease existence prediction or recognition [20], critical condition assessment [21], evaluating a condition that may require the intervention of life-support [22] and the existence of a specific medical outcome [23,24] are a few examples of tasks that are related to health that could be the objectives of such models. Additionally, it is possible to integrate these with EHR systems to automate real-time health warning systems [25]. There exist several instances where AI techniques are implemented in a variety of medical-care-related fields [26–28]. Many studies are available on the application of AI techniques for a particular disease, environment, health domain and outcome, and in some cases, specific ML algorithms are simply the focus.

For instance, Alanazi et al. [29] reviewed the application of ML techniques in medicine and healthcare. Xiao et al. [30] in their study investigated the usage of deep learning (DL) techniques to process EHR datasets. Several DL techniques for exploring different sources of data and their targeted applications were analyzed. Likewise, Gnaneswar and Jebarani [31] studied the use of data mining techniques for the diagnosis and prediction of heart diseases while Kavakiotis et al. [32] investigated the deployment of data mining techniques for the diagnosis and prediction of diabetes.

Hence, the objective of this review is to investigate and analyze the process of integrating AI techniques with clinical data acquired through wearable sensors. Consequently, a unique taxonomy is developed to highlight the benefits and challenges associated with the application of wearable sensors and AI techniques in the conventional healthcare delivery system.

The remainder of this paper is arranged as follows: the research approach and methods are explained in Section 2. The application of wearable sensors in healthcare is presented in Section 3. Section 4 discusses the deployment of AI in healthcare, while the benefits and challenges of the application of AI in healthcare are addressed in Section 4. The limitations encountered in this study are explained in Section 5, and finally, the conclusions of this review are presented in Section 6.

## 2. Research Methods

This review used the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) methodology to identify research articles for inclusion in the study.

### *2.1. Inclusion and Exclusion Criteria*

This review endeavours to illustrate strategically the need for and the application of AI and wearable sensors in the current healthcare domain, providing a complete evaluation of these technologies as well as the benefits and challenges of their implementation in healthcare. This study focuses on articles and survey papers specifically related to the implementation of AI and wearable sensors in healthcare. This provides insight into hundreds of the papers included in this analysis, as well as the methods used in previous research.

In this research, the paper selection criterion technique is divided into three subsections: keyword selection, inclusion and exclusion, and the final results created by using these methods. In the sections that follow, specifics about these selection criteria are provided.

#### 2.1.1. Selection of Keywords

Multiple well-known research databases and repositories, including IEEE, Science Direct, PubMed, Wiley, Taylor & Francis, JSTOR, ACM Digital Library, EBSCOhost, Springer, Emerald and IET, were searched exhaustively for research publications. The papers in the aforementioned databases were searched using keywords like sensors, wearable sensors, biosensors, AI, ML, healthcare, telemedicine, and e-health.

#### 2.1.2. Inclusion

The study was limited to journals published between 2018 and 2022, with the remainder omitted. These publications were selected for evaluation based on a reexamination of the abstracts and papers that highlighted the applicability of wearable technologies and AI to this research. This study includes an examination of research publications, current review papers, technical notes, and other materials arranged in a logical order and related to the latest developments in wearable sensors, AI, and healthcare.

#### 2.1.3. Exclusion

During the search for research publications, there are many stringent criteria for excluding studies, such as duplication, language (only English), and irrelevance (subject and material). Additionally, papers were eliminated if they were unrelated to wearable technology, AI and healthcare, and had previously published information on the same topic. Also removed were case series and reports, brief communications, and editorial comments resources.

### *2.2. Quality Assessment and Data Extraction*

It is essential to keep in mind that the amount of research papers, notably surveys pertinent to the healthcare field, has been increasing, with more scholars striving to contribute to the body of knowledge. Nevertheless, such research (reviews or surveys) is susceptible to certain problems, besides a rising number of nonrandomized interventional studies.

Researchers are required to recognize high-quality reviews and surveys. Numerous techniques for examining specific parts of feedback have been developed, but there are not many structured tools for comprehensive review [33].

In this regard, the PRISMA approach is used in this study to assess the quality of the selected articles and ensure that only high-quality papers are considered for the research. Moreover, the PRISMA approach is utilized to evaluate objectively the material that is significant to the various selected publications [33]. Articles were chosen using inclusion and exclusion criteria, particularly publication year (as established by the PRISMA checklist). Figure 1 displays the PRISMA methodology used in this study.

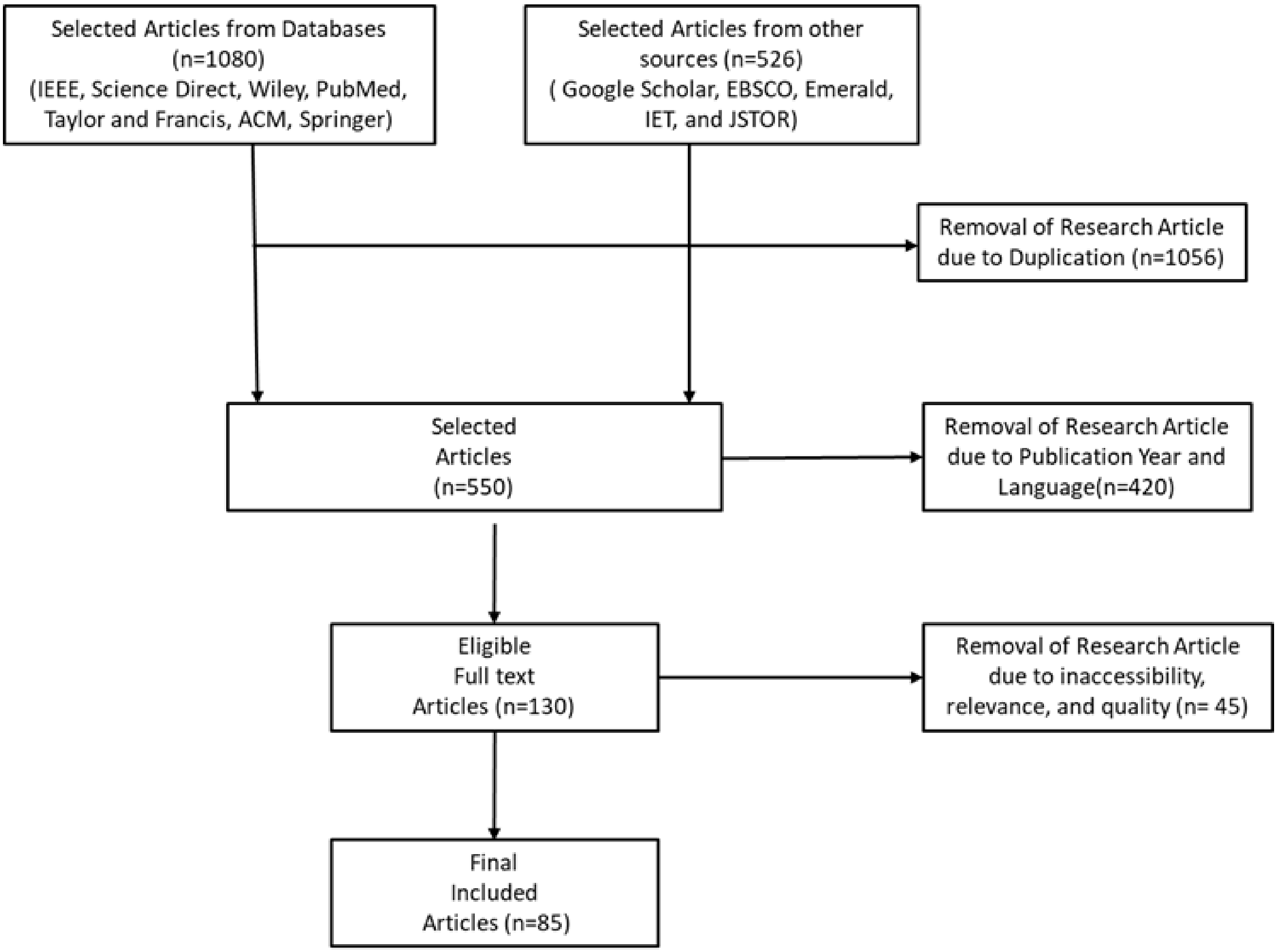


**Figure 1.** PRISMA flowchart of the study methodology.

After an in-depth evaluation of 1606 papers acquired from numerous sources (IEEE, Science Direct, PubMed, Wiley, Taylor & Francis, JSTOR, ACM Digital Library, EBSCOhost, Springer, Emerald and IET) in the first stage, 1056 duplicates were eliminated. Additional 420 papers were omitted due to their publication year and language, and 45 articles were discarded owing to their inaccessibility, lack of relevance, and poor quality. In the end, 85 papers are chosen upon thorough evaluation and analysis.

## 3. Wearable Sensors in Healthcare

The biosensing concept started around the early 20th century. It is a simple concept where potential electrical proportionality is viewed across the membrane [34]. However, the real biosensor device for the detection of oxygen was developed by L.C. Clark, Jr. in 1956. Henceforward, the development of a variety of biosensor platforms and devices was initiated, ranging from glucose [35] and the fibre-optic-based detection of carbon dioxide

($CO_2$) and oxygen, to utilizing surface plasmon resonance (SPR) [36] to detect gas through inventing the first hand-held (i-STAT) blood biosensor in 1992 [37].

At present, biosensor technology is used in wearable devices for different aspects of our daily life activities. For instance, its use ranges from a simple daily steps counter with a fitness band to a highly complicated multiplexed device capable of detecting non-abundant biochemical body fluid markers. Undoubtedly, the evolution of wearable sensors has revolutionized the monitoring of healthcare as wearable sensors technology has made it possible for clinicians and users to obtain dynamic and real-time health-related information on the body's physiological function with a simple click, scan or tap while sitting at home or resting.

Wearable sensor devices can capture different kinds of biosignals such as motion, pulse rate and temperature changes. Furthermore, several biosensors are presently used as quick, point-of-care tools capable of being used on a large scale to screen the populace or to detect viruses such as the latest SARS-CoV-2 [38]. Nonetheless, the competition between giant technology industries has revealed a sneak peek of the wearable sensors' commercial market. Recently, a study from CBINSIGHTS stressed that wearables, telehealth and virtual reality (VR) will champion a clash of industries and technologies that can lead the post-pandemic world [39]. This is based on the premise that sensor devices that are easy to fabricate and most economical with high multimodal throughput and biocompatibility superiority would certainly attain substantial growth in the technology industry, especially when the finished products are readily available and are capable of having a significant impact on the remote monitoring of healthcare. Likewise, comfortability and compatibility with the surfaces and living tissues of human skin are important factors to consider when these devices are used in clinical routines for the constant gathering of biosignals to generate computable results. Furthermore, in dealing with delicate interfaces, wearable sensors require better sensitivity materials to accurately recognize as well as a higher discrimination power to identify specific forms of environmental stimuli in a specified period [40].

There has been a paradigm shift from the period of inflexible electrochemical devices to the current evolution period of flexible, printable and soft functional materials able to adhere to rough skin surfaces regarding the fabrication and utilization of biosensing systems [41]. For example, an ear-worn sensor capable of tracking actions and degrees of energy in patients with chronic obstructive pulmonary disease (COPD) was created by Fennedy, et al. [42]. The researchers were able to use the ear-worn sensor and an efficient ML technique to diagnose different types of physical actions along with the energy used in those actions. Also, Steele, et al. [43,44] conducted a 3D measurement experiment of human (patient) movements. Findings from their experiments showed that patient status measures were correlated with the level of acceleration vectors such as the force expiratory volume in one second (FEV1), distance walk of six minutes, severity of dyspnea and domain of physical function in a health-related quality of life gauge shown in patients with COPD.

Furthermore, Shashikumar, Stanley, Sadiq, Li, Holder, Clifford and Nemati [20] developed a novel ML algorithm for health-related data collection from a single unit to study the minute-by-minute activity levels of patients. A sample of 22 patients was used for 14 days to test the method. The developed algorithm was employed to assess whether the sensing device is active on the patient and to keep track of compliance.

The automation of wearable sensors experienced a fast evolution from what looks like a science fiction concept to a wide range of fine-established devices for medical use [45]. The fast evolution of wearable sensors might be connected but not limited to their affordability, user-friendliness, portability, the existence of mobile smartphones plus other connected devices and the increase in consumer desire for health awareness [46]. Regardless of the initial achievement, there is still a need for advancement in wearable sensors. The current wearable modalities for sensing are non-specific, hence, the wish remains unmet. For instance, the number of factors responsible for increasing one's pulse or causing one to perspire is still unknown. Additionally, most wearable sensor devices are still using techniques that have existed for years. Even the continuous transdermal glucose monitors that appear to be more-complex wearables take advantage of the advancements in enzyme electrodes from over three decades, including the discovery of basic and ultra-low-cost finger-prick glucose test strips. The assessment of transdermal glucose is likely the most widely engaged wearable sensor to regularly monitor the state of a severe condition (diabetes) [47,48]. Figure 2 is an illustration of a conceptual remote surveillance system.

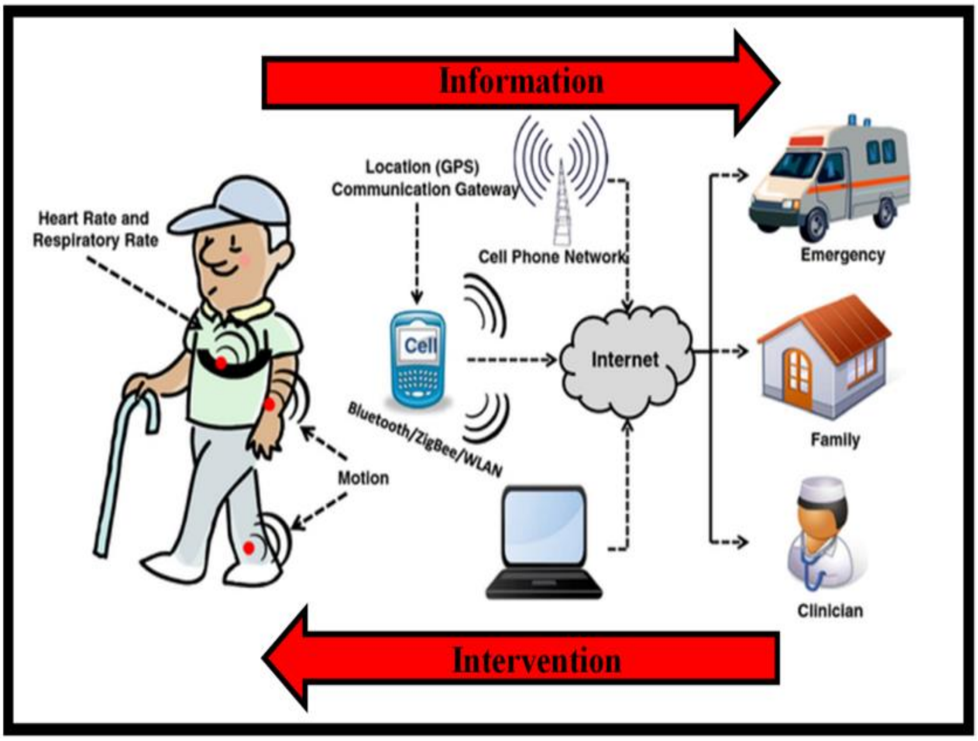


**Figure 2.** A conceptual picture of a remote surveillance system [45].

Wearable sensors are used to collect movement and physiological data, which allows for the monitoring of the patient's health status. There are different ways in which sensors are employed depending on the therapeutic routine of interest. For example, when monitoring congestive heart failure or COPD patients, vital signs monitoring sensors would be deployed.

Likewise, movement-data-recording sensors would be employed to monitor the efficacy of a home-based stroke survivor's recovery program or the usage of mobility assistance gears among elderly people. The data collected from patients or users are transmitted to an access point or mobile phone over wireless transmission before being communicated to a data center or cloud storage via the internet. The ML model embedded in the device detects an emergency and delivers an alert message to the trauma service center to promptly assist the patient. Invariably, in sensor-based healthcare systems, the patient's relatives and caregivers can be contacted in the case of an emergency or whenever the patient needs assistance with taking his/her prescriptions. Clinicians can examine the patient's condition remotely and can be alerted if there is a need to make a medical decision.

### *3.1. Design of Biosensors*

According to Liu, et al. [49], a biosensor is an analytical integrated functional device capable of analyzing particular quantitative or semi-quantitative data using a biological recognition component. The device broadly consists of three main components. First is the biorecognition component often called a bioreceptor. This is the component that uses biomolecules from receptors or organisms modelled after biological systems to interact with an analyte of interest. Subsequently, a transducer will measure the interaction and outputs a quantifiable signal that is proportional to the target analyte present in the sample.

The overall aim of the biosensor design is to enable convenient and quick testing at the point of care or concern where the sample was acquired [50–52]. Second is the transducer, which is an electronic device that converts energy into an electrical current or voltage signal for transmission. The third is the signal amplifier, which simply refers to an electrical circuit that uses electrical power to increase the amplitude of an incoming current or voltage signal and outputs the higher amplitude version at its output terminals.

Figure 3 illustrates the biosensor's basic parts with their working mechanisms. Normally, the analyte is a biomolecule recognizable by a highly specific biorecognition element. Different transduction platforms are used for the reaction, which generates signals that are detectable by transducers and are converted to displayable data.

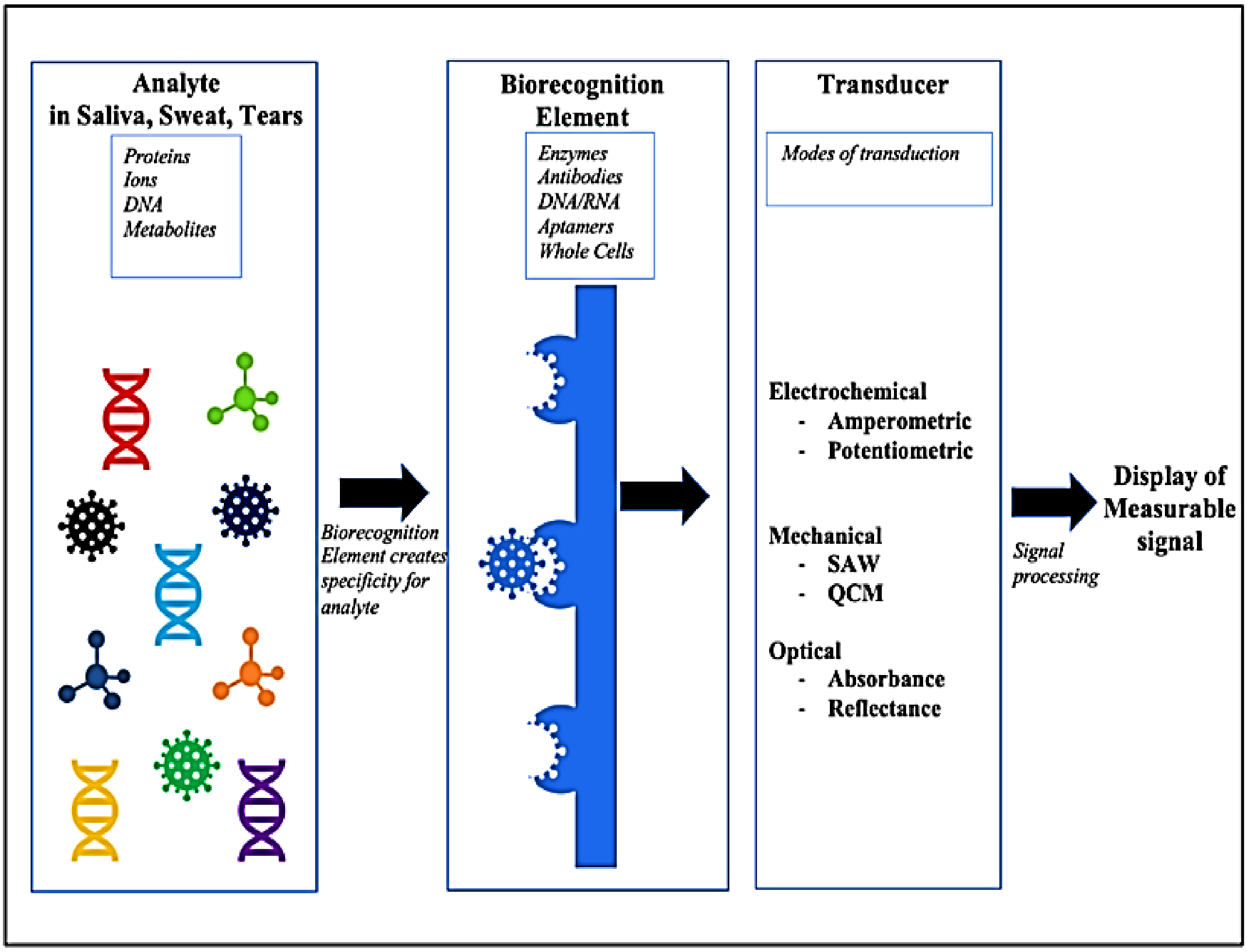


**Figure 3.** Basic parts of biosensors [39].

### 3.2. Categories of Wearable Biosensors

Wearable biosensors in the literature are categorized depending on the bio-analyte/biofluid used, the material of choice, the transduction platform, design, and utility. Several authors are inclined to categorize biosensors based on the bio-analyte/biofluid used, such as saliva, sweat and tears. Likewise, on an invasiveness basis, authors include implantable biosensors, which use other physiological biomarkers to observe health and subcutaneous injections. Based on design and utility, wearable biosensors can further be divided as arm and wrist-based, face and head-based or oral-cavity-based, food-mounted and textile-based (Figure 4).

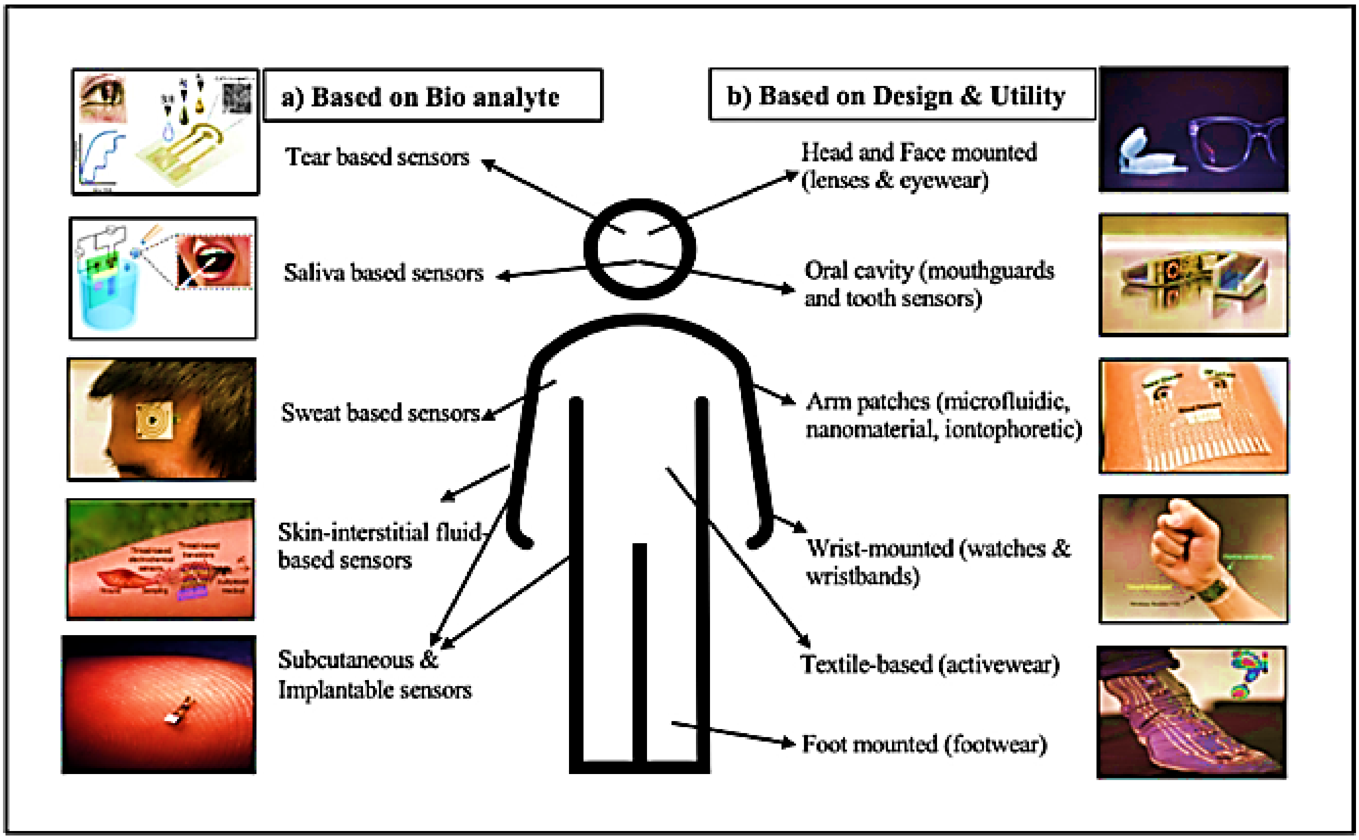


**Figure 4.** Different wearable biosensor devices are categorized based on: (**a**) bio-analytes and (**b**) design and utility [39].

Similarly, wearable biosensors can be categorized as biocompatible, biodegradable, carbon-based, inorganic biomaterials or polymer sensors depending on the source material used for their production. Although the electrochemical, electro-mechanical and optoelectrical/photo-sensing platforms of wearable biosensors all have a similar general mechanism for biorecognition, the transduction mode is what makes them differ. This review mainly focuses on electro-mechanical wearable biosensors.

### *3.3. Electromechanical Biosensors*

The principle of sensing in electromechanical biosensors is fairly like that of electrochemical biosensors, though the generation of electrical responses is the variation between the two. This variation is primarily the result of the strain recorded due to an electrical bias or due to a mechanical force.

Electromechanical transduction does not depend on molecule labelling, which gives it a significant advantage over electrochemical and optical sensors. It also facilitates a wide range of identification and quantification parameters for biomolecules. Accordingly, the most essential feature that dictates the finest operation of electromechanical biosensors is their capability to sense the physical variations that occur on the human skin surface at a macroscale, such as movements in the arm, leg and wrist or slight changes such as stifling or the stretching of the epidermis, which occurs during actions such as breathing [53]. Typically, electromechanical transduction mechanisms are based on any of the following: (a) piezo-capacitive, (b) piezo-electric, (c) piezo-resistive, (d) iontronic or triboelectric nano-generation (TENG) effects [40,54] (Figure 5).

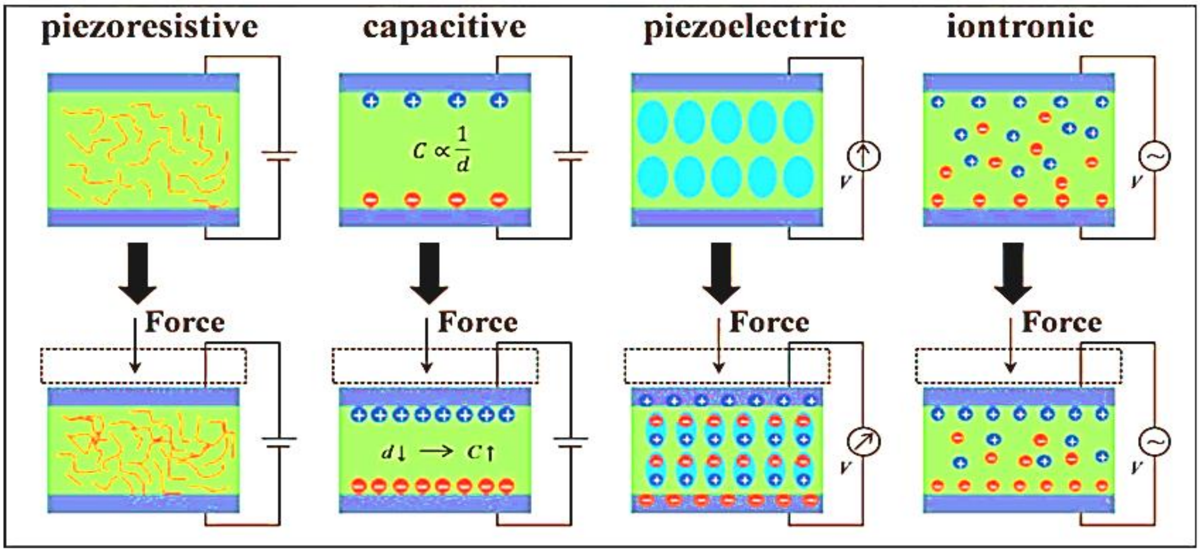


**Figure 5.** Illustration of different categories of electro-mechanical transduction mechanisms [39].

The function of a strain sensor is the quantification of the mechanical deformation concerning the corresponding changes in electrical signals. This can either be piezo-electric (when changes in surface potential due to polarization are captured) or piezo-resistive (when changes in the resistance produced by external forces are captured) [55,56]. The function of wearable strain sensors is the quantification of mechanical deformation for the corresponding changes in electrical signals. This could be in the form of capturing changes in surface potential due to polarization (also known as piezo-electric) or piezo-resistive, which means capturing variations in the resistance produced by exterior forces [53,55].

Capacitive wearable biosensors react to changes in capacitance and have superior sensitivity due to forces that cause geometrical deformations. However, surrounding noise is known to affect the sensors and may consequently impact their performance [57]. Iontronic wearable biosensors use a platform with super-capacitance. This is approximately 1000 times greater than a capacitor with a metal oxide platform. It forms an ion–electric interface between the electrolytes and electrodes, which causes a high capacitance per unit area and ion accumulation on the electrodes [54]. Triboelectric transduction operates on a simple principle known as frictional charges. This is a result of the interaction between two different materials. The principle was used in developing TENG [56]. Surface separation produces potential differences whenever friction is interrupted; hence, without the use of external power, this is used to develop sensors [58].

A flexible functional design that requires a high gauge factor is needed for the detection of minor movements by stretchable strain sensors, which arise on irregular skin surfaces. For example, a strain biosensor was designed by Tang, et al. [59] and was built by aligning a nanowire using a ratio with a high surface-to-volume ratio to monitor intangible human motion. In their study, they succeeded by achieving a high gauge factor of approximately 35.8 that could detect an incitement of deformation with less than 200µm in under 230ms. This achieved result was five times better in comparison with a comparable microwire-based biosensor [59].

Similarly, a stretchable ion-based biosensor was created by Wang, et al. [60]. It was built on surface strain redistributed elastic fiber (SSRE-fiber) where a wrinkle construct was used to improve the surface area together with an island bridge design [60]. Though the principle of the electro-mechanical mode of sense was not used, the strain was minimized on big sizes of the stretch by making the SSRE platform a notable choice in a textile-based wearable biosensor. Likewise, textile-based mechanical biosensors are becoming an attractive tool for detecting human motion and they are paving the way for the personalization of healthcare by working analogously to how the choice of our outfit adapts to our physical attributes.

Nevertheless, there are still challenges; for instance, there is a technology requirement for the fabric to have high conductivity and to be equally strain resistant.

Typically, to improve conductivity in textiles, carbonization is the first line of choice, which can either be performed by adding metal nanoparticles, dip-coating or vacuum filtration [61–65]. An instance of such a wearable biosensor was invented by Yang, et al. [66] using available commercial spandex, in which polyamide was dipped into carbonic pigment inks to fabricate the conductive strain sensor with high fidelity [66]. Figure 6 presents a schematic diagram illustrating the process of fabricating an ink-decorated fabric strain sensor.

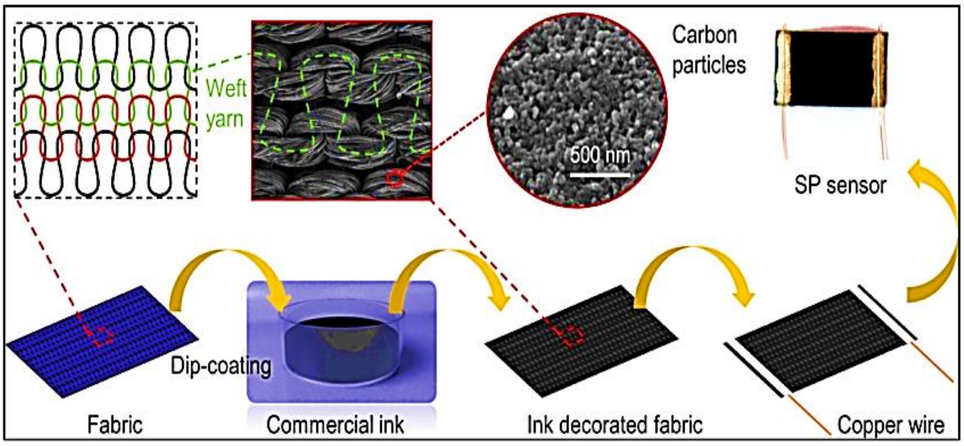


**Figure 6.** Schematic diagram illustrating the process of fabricating ink-decorated fabric strain sensor.

To begin with, deionized water is used to wash the fabric three times; then, after dip coating the fabric into commercial ink, the fabric is then absorbed and dried at 60 °C for about an hour in the oven. Next, silver paste is used to mount two copper wires on the fabric strip's two ends to improve integration, and again the setup is dried and is then ready to use with textiles [39]. Their study effort points to a potential proposed application of the smart textiles by (i) using any of the joints (arm, fingers, wrist) to fix them for pulse rates collection; (ii) sewing or otherwise printing the strain biosensors on the fabrics to capture the functions associated with respiration and breathing; or (iii) applying them in producing protecting devices to monitor joint activities in posture-related illnesses such as Parkinson's disease [66]. Table 1 presents a summary of the application of wearable sensors in healthcare.

Thus, AI will most likely play an important role in healthcare delivery over the next few years due to its capability to handle and process large amounts of information at an effective rate through numerous forms of AI systems. This includes both software-based (such as apps) and hardware-based (such as smartphones) systems. However, as mentioned earlier, technologies of wearable devices already exist, which offer similar functionality with improved accuracy. Therefore, consumers are the ones who will decide what technology to select.

Further, both AI and wearable sensors have an impact on our daily lives and certainly, between them, there is always going to be some overlap. The integration of AI with wearable devices is gaining momentum toward creating smarter devices for consumers (such as smartphones). Wearable devices are also integrating AI systems into their mobile applications to better analyze their abilities for use in predictive analytics applications. Another aspect where wearable devices complement AI is location tracking in smartphones, where wearable devices can be used to determine the location of a person at home or otherwise based on the signal from their smartphone's location when matched with historical records from preceding phone calls made using a similar device.

**Table 1.** A summary of the application of wearable sensors in healthcare.

| Application | Analyte Parameter | Materials | Mode of Transduction | Challenges | Wearable Platform | Reference |
|---|---|---|---|---|---|---|
| Motion detection | Surface deformation | Aligned nanowires | Electrochemical–mechanical | Proof-of-concept sensor needs integration into wearable device | Mountable sensor | [59] |
| Sweat monitoring | Sodium | Ion-based SSRE-fiber | Electrochemical–mechanical | The lack of on-body trials needs optimization for integration to textiles | Textile-based | [60] |
| Breathing, motion detection and pulse rate | Strain and conductivity | Commercial spandex and carbon ink pigment-coated polyamides | Electromechanical | Cleaning, multistep fabrication process and textile/coated ink shelf life | Textile-based | [66] |
| Tactile communication | Vibro-tactile feedback | Velostat-polymer impregnated with carbon black | Electromechanical | Lacks longitudinal study to predict the interface success | Finger–hand based | [67] |
| Motion and pulse detection | Pressure sensations | Ni-coated core-sheath nanofiber yarn with CNT-embedded polyurethane | Electromechanical | Proof-of-concept design needs optimization and authentication for textile integration | Textile-based | [68] |
| Motion detection | Tactile sensations | 3D-printed nanocomposites | Electromechanical | Needs miniaturization to fabricate the skin-compatible, compressible device | Skin-mounted | [69] |
| Patient Monitoring | Sensors used for pulse rate, respiration rate and temperature sensor | - | Sensor operation: measure body temperature, pulse rate and monitor the breath rate of a person | - | - | [70] |
| Stress Detection | - | Sensors used for ECG monitoring sensors and three-axis accelerometer | | Sensor operation: collects ECG signals using three lead and measures the tilt angles between the user and the object | - | [71] |
| Position Alerting | - | Sensors are used as an accelerometer, pulse and ultrasonic sensor | - | Sensor operation: measures the angle between objects measures the heart rate and finds the tilt angle between the object and the user | - | [72] |

**Table 1.** *Cont.*

| Application | Analyte Parameter | Materials | Mode of Transduction | Challenges | Wearable Platform | Reference |
|---|---|---|---|---|---|---|
| Paralyzed | - | Infrared sensor | - | Sensor operation: it encloses an amplifier that acts as a comparator | - | [73] |
| Visually Challenged | - | Ultrasonic sensor | | Sensor operation: uses the SONAR technique for identifying the distance between objects. Not affected by black materials or sunlight | - | [74] |
| Home Monitoring | - | MHZ-19(CO2 sensor) | - | Sensor operation: measure CO2 content levels | - | [75] |
| Elderly | - | Light, nasal airflow and pulse oximeter sensor | | Sensor operation: measure the breathing rate of the user, the amount of oxygen dissolved in the blood, detect haemoglobin content and detect the light | - | [76] |
| Detecting Alcohol Content | – | PID sensor | - | Sensor operation: detects chemical content | - | [77] |
| Diabetes Monitoring | - | Pressure and weight sensor | - | Sensor operation: measures the pressure points in the human body and detects body weight | - | [78] |

## 4. Artificial Intelligence (AI) in Healthcare

AI is fast becoming a catchword globally as it aims to simplify human work and make it more efficient. Thus, AI is playing a critical role in strengthening and transforming industries including the healthcare sector [79]. Moreover, in the healthcare sector, AI technology plays a significant role in minimizing human errors and complementing conventional healthcare processes. The application of AI techniques in healthcare can be done in several ways such as advanced patient diagnostics, disease prevention, medical therapy and informed clinical decision-making [80]. Based on this premise, the application of AI techniques in healthcare delivery has remarkably increased. This section reviews the use of ML, a subfield of AI, in clinical analytics using wearable sensor data. Different types of wearable sensors are available to collect clinical data. Thus, these datasets can often be processed using appropriate ML techniques. Figure 7 presents an ML-based healthcare system modelled with data from wearable sensors.

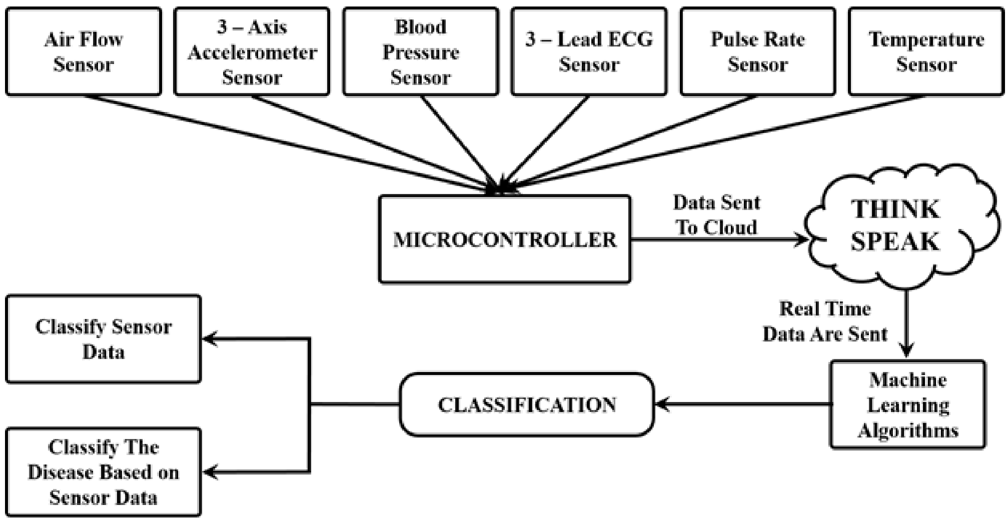


**Figure 7.** Machine Learning-based model via wearable sensors data for healthcare systems.

Wearable sensors enable the monitoring of vital health parameters, which can be used to detect many illnesses such as chronic clinical disorders, diabetes, hypertension, and some others. A patient's vital health signs such as blood glucose level, blood pressure, body temperature, oxygen saturation and pulse rate are measured using a variety of clinical-related sensors. Then, Internet of Things (IoT)-based platforms such as "Think speak" are utilized to send the data values measured from these sensors to the cloud. Think speak is an open IoT platform enabled by Arduino or Arduino-compatible hardware for data visualization. It allows writing or reading data to be put into or taken from the platform. This supports the data storage from the API or sensors in the cloud for either a private or public channel. ML techniques are then used to analyze the stored data in the channel. The diagnosis of the symptoms to identify the disease(s) affecting the patient can be performed using the data collected with the sensor. ML algorithms are hence used to classify and identify the disease. Undoubtedly, the classification capacity of ML algorithms is known to be effective, and the reason for their broad use in the health industry is their ability to classify and predict diseases based on their symptoms (health-related data).

Currently, many technologies are using ML algorithms for data analytics to obtain useful insights [81–84]. Supervised and unsupervised learning algorithms are the two broad classifications of ML algorithms. When the prediction of the values for the training dataset is the goal, supervised learning algorithms are used, while unsupervised learning algorithms are used for the identification of a specific label from the clustered labels [85–87].

Classification and regression are the most commonly used supervised learning algorithms [88]. Some examples of classification algorithms include Naïve Bayes (NB), k-Nearest Neighbor (kNN), Artificial Neural Network (ANN), Decision Tree (DT) and

Support Vector Machines (SVM) [89–92]. Discriminant Analysis (DA), Logistic Regression (Log) and Linear Regression (LR) are prominent regression algorithms. C-Means, K-Means, BIRCH, DBSCAN and X-Means algorithms are examples of clustering techniques which are classified as unsupervised learning algorithms [93–96]. Figure 8 provides a detailed classification of ML techniques.

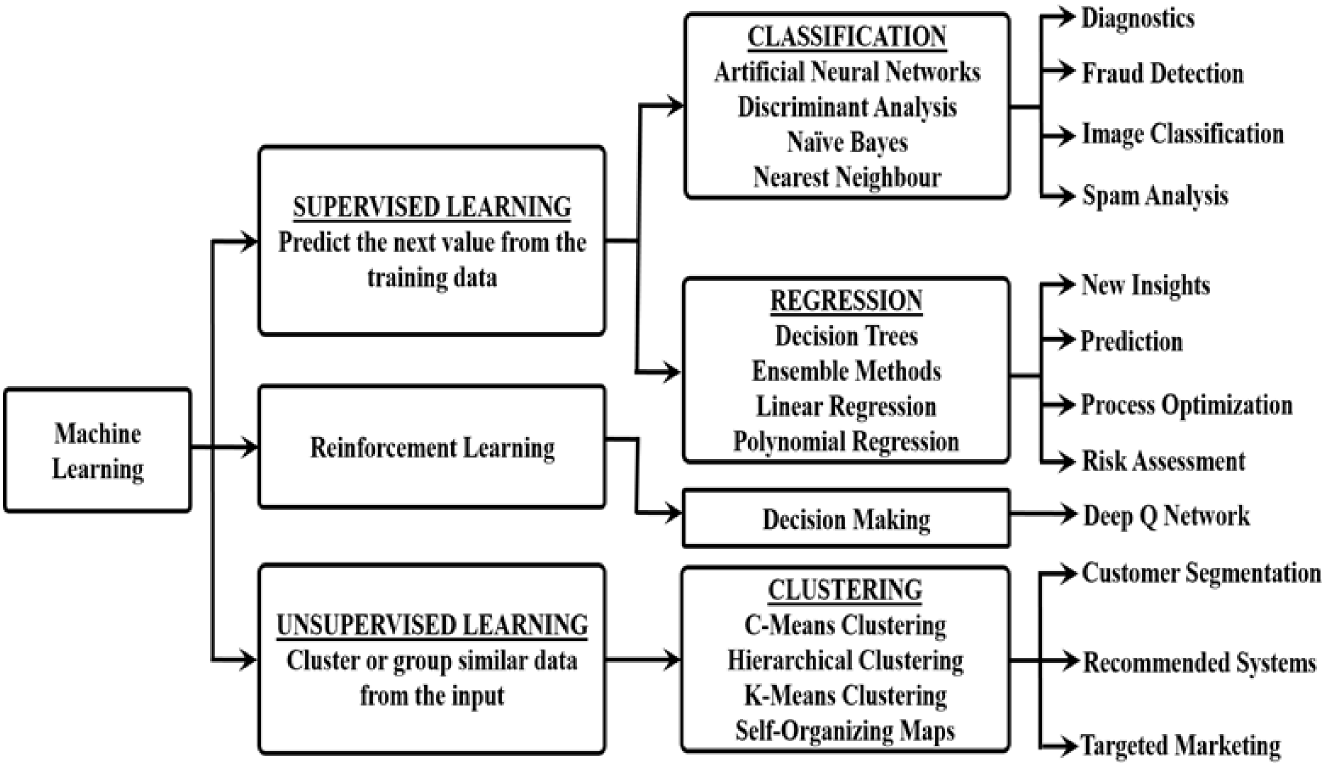


**Figure 8.** Classification of ML techniques into various sub-categories.

In practice, all these ML algorithms can be employed to address problems concerning medical image recognition, prediction and detection of diseases, behavioural adjustments and so on. The recent technological advancement that brought about wearable sensors has prompted several researchers to explore their potential in the concept of integrating AI with wearable sensors in the healthcare domain. Similarly, the affordability and availability of both wearable sensors and smartphones appear to be veritable devices to quickly drive the accumulation of human medical data, whereas an emerging subfield of AI (ML techniques) is also available to map those medical data to provide clinical predictions [97].

The proof-of-concept for an accurate, automatic, patient-specific system that is tunable to a person's needs presented by [98–101] is an example of a seizure-prediction system that can increase an epileptic patient's independence and allow for preventative treatment. A robust classification algorithm in ML (a DL classifier) was used to train a model to distinguish between interictal and preictal signals. DL is an ML technique and is a great computational tool that supports attributes to be automatically learnt from training data [102]. Generally, the use of DL is for training a class of algorithms termed deep neural networks to accomplish specific tasks. The use of neuromorphic hardware in combination with DL models can offer a basis for an always-on, real-time, patient-specific, wearable-sensor seizure early warning system with marginal power consumption with reliable and durable performance.

Furthermore, a different study by [103] aimed at automatic scoring Parkinsonian tremors. The study proposed ML algorithms to predict the Unified Parkinson's Disease Rating Scale (UPDRS). In their study, a wristwatch-type wearable sensor device fitted with an accelerometer and a gyroscope was used to measure the tremor signals of eighty-five Parkinson's disease patients. The number of features initially extracted from each signal was nineteen, but eventually, the dimension of the features was strategically abridged using a pairwise correlation approach. Five commonly used ML algorithms, such as the DT, DA, kNN, RF and SVM, were applied to the selected features to explore the automatic scoring of the severity of Parkinsonian disease tremors. Accuracy, precision, and recall were the metrics used to gauge the performance of the classifiers and compare the findings with similar studies.

These use-cases of successful implementations and applications of AI and wearable sensors has made it critical and necessary to complement conventional healthcare system with these disruptive technologies. The technologies among many things can assist in informed clinical decision-making processes since imprecise results can misinform both clinicians and patients.

Hence, an AI-based sensor healthcare system can assist in diagnosing disease symptoms and obtaining timely aid from clinicians and caregivers. The system will equally be of assistance to elderly or young people for regular in-home-based health monitoring and diagnosis.

## 5. Challenges and Benefits of AI

The field of AI currently appears to be a promising area that can act as an instrument to grow and transform the public health service sector drastically. Although the adoption of AI appears to be momentary, there is a continuous increase in its use largely because of the strong potential at the core of healthcare delivery. AI is anticipated to replace the face-to-face consultation experiences of clinicians and patients. Engaging AI technology to remodel the healthcare sector in many respects has been widely considered possible. EHR, physician-active supervision in clinical decisions and detailed knowledge processing aimed at health management systems constitute concerns at the center of the AI virtual systems [104]. The assistance derived from AI systems by clinical experts to diagnose patients has received research attention recently. Certainly, soon, advancements in technology sophistication with more comprehensive AI data systems will be able to detect many other diseases.

There is a clear benefit to using AI in healthcare, as the choices of patient management and outcomes are improved. Costs reduction, fewer referrals and time saving are other prospective secondary benefits. Additionally, professional isolation, recruitment, promotion and retention in rural areas can be reduced with the application of AI in healthcare [105]. This can in turn contribute toward a more balanced and equitable system of basic medical care in poor-resource locations of low- and high-income countries.

### *5.1. Benefits and Challenges of Artificial Intelligence in Healthcare*

AI is rapidly dominating healthcare systems by replacing the conventional routine work/tasks conducted by personnel in medical services with an automated health system. Nevertheless, the digitization of health services through the application of AI systems in medical care practice comes with benefits and can also pose new associated technical challenges. The following sub-sections discuss the key benefits and challenges of AI in healthcare.

#### 5.1.1. Benefits

The enhancement in patient management choices and outcomes are the primary benefit of technology applications in the healthcare system, while cost efficacy, time-saving, and fewer referrals may as well be the potential secondary benefits. Again, it can assist in health facility retention and promote recruitment in rural areas. Eventually, this can contribute to an equitable global healthcare delivery system [106,107], which addresses the challenges of enabling early acceptability and feasible implementation in the healthcare system and a lack of reflection from the perspective of users. AI adoption in the public healthcare system offers a blueprint for the flow of research that centers on diverse aspects of AI adoption in public healthcare systems [83,108].

#### 5.1.2. Challenges

AI is projected to soon be incorporated into routine clinical care due to its proven efficacy in refining the administrative aspect of health services. However, ethical and privacy implications are reservations that have been expressed about introducing AI into the healthcare system. These reservations include AI application tasks in clinical situations, the fuzziness of some AI algorithms, privacy concerns for the data used in training the AI model, the likelihood of bias and security concerns. Similarly, access, consent, costs, efficacy, information, the right to decide and the right to try are some examples of the ethical concerns faced in clinical applications of AI techniques [107,109]. AI application is the preferable and right approach for progress in the health sector, particularly health services, despite its impact on ethical concerns, regulations, and systems error. The following are some of the open challenges of AI in healthcare.

1. Equity

Clinical datasets for training AI models should be well-structured and in an appropriate format that can make it easy to derive knowledge and actionable insights from it. That is, there should be adequate representations of instances in the datasets via the harmonization of different health-related data of patients [110]. Otherwise, this can cause the AI models to be biased, make imprecise predictions or even large-scale discrimination [111].

2. Transparency

Although the performance of the AI techniques, especially DL models in the prediction of clinical risk and medical image analysis has been significantly promising, nevertheless explaining and interpreting the DL models is difficult. This difficulty is a cause of serious concern in the medical world, where the ability to explain medical decisions and transparency are very vital [111,112].

3. Trust

To apply AI, matters including the cause and effect of a disease, the ML techniques and the models used to support the decision-making process of the medical experts needs to be considered by clinicians. The future of AI applications' autonomous roles and the conceivable exposure to the accidental or mischievous tampering of these applications to yield unjustifiable results may cause a critical obstacle for clinicians to admit AI in their clinical practice [111,113].

4. Accountability

The accountability begins with AI model development and then extends to the level where the model is used in medical care until eventual retirement. Many stakeholders are involved in this scope, which includes software developers, healthcare experts, patient advocacy groups and government officials [114]. The application of AI in healthcare services is not limited to increasing clinical capability but can also be for upgrading administrative capacity. As an example, the distribution of information and services related to health can be conducted using AI in the form of telemedicine by employing communication technology. Certainly, the implementation of telemedicine will impressively affect business models in hospitals [115].

### *5.2. Problems in the Application of AI in Health Services*

1. Bias data: Large-scale data inputs related to clinical health records are a requirement for training or developing a robust AI model. Otherwise, bias can occur when incomplete or insufficient health-related data are used for training the AI models. Likewise, the output from training data that do not truly reflect the target population is usually biased. Under-representative data may occur as a result of accessibility to healthcare services (social discrimination) and/or comparatively lesser samples (such as with data from minority groups) [116].

2. Privacy: Medical service data are one of the most sensitive records that can be kept by an individual about another. Therefore, the principle of respecting the privacy of a patient is of vital importance in the medical care profession. This is also because privacy is bounded by the autonomy of the patient's well-being and a private identity [111]. Accordingly, ethics and moral practices must be deployed to respect the confidentiality of the patient's data as well as to safeguard adequate measures for obtaining the right consent.

### 5.3. Problem of Ethics Related to Biomedical and Health Sciences

As applicable to all new techniques in health sciences, the principles governing biomedical ethics must be followed by AI in medical care applications. This includes security and privacy regarding the available health-related data. They remain manifest as autonomous decision-making, consensus, privacy and safety, deliberate participation, etc., which must be reflected and practised in any implementation [107].

## 6. Conclusions

The recent trend of using AI techniques and wearable sensors in the medical field has progressively reshaped healthcare delivery systems. The adoption of these evolving technologies in healthcare delivery has truly attracted the attention of many researchers. This study proposes a distinctive taxonomy that illuminates the process of integrating AI techniques with the clinical data acquired through wearable sensors. For simplicity, the process is broadly divided into three major sections: wearable biosensors, AI, and the challenges and benefits of AI in healthcare. Wearable biosensors are IoT-enabled devices that facilitate the transmission of health-related data to the cloud for further processing. Of the various AI concepts, ML is utilized to automatically process and visualize the recorded health-related data for clinical decision-making. In this review, various forms of ML techniques were explored. This is to provide a concise and complete review and analysis of the application of AI in healthcare, which is of key importance in this article.

The efforts by the authors will certainly assist researchers and experts in academics and the healthcare domain respectively. For instance, a scholar may obtain an appropriate direction on different kinds of wearable biosensors and ML algorithms that may be engaged for the detection of a particular disease. An additional innovative aspect of this study is highlighting the benefits and challenges yet to be cleared in prospective studies on the application of AI to improve patient medical outcomes. The open research challenges addressed in this study may also offer researchers some clear future research prospects. By investigating further into these technologies and their integration, the future of AI and wearable biosensors is quite promising in healthcare delivery systems, essentially in remote healthcare monitoring.

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