Artificial Intelligence (AI) and Machine Learning (ML) for Latest Trends in Biosensing Applications

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Abstract- **Biosensors are becoming more popular as analytical tools based to their ability to detect and identify biological substances in a variety of applications. Biosensors have proven useful in many important fields such as medicine, food safety, environmental monitoring, security, medicine and verification. One of the leaders in the biosensor market is diagnostic equipment, as diagnostic equipment supports approximately 70% of medical decisions. This article explains on the use of artificial intelligence (AI) and machine learning (ML) in various types of biosensors. Artificial intelligence increases the capabilities of biosensors and is used in automation, electronics, medical devices, etc. It opens up new opportunities in fields. Wearable biosensors are now entering our daily lives and playing an important role in the advancement of technology. Biosensors with micro-nano structure have advantages such as small size, high sensitivity, production, simple arrangement and integration compared to chemical biosensors, and these advantages make them an improved method for pressure sensors. In this article, we review recent advances in machine learning for biosensor applications. We discuss various machine learning techniques applied to biosensors, including models for data processing, feature extraction, classification, and data analysis. Issues related to machine learning and biosensor integration are also touched upon and future trends in this field are presented.**

Keywords**: Artificial intelligence, Machine learning, Biosensor network, Wearable biosensors, Deep learning, Support Vector Machine.**

Introduction

Biosensors are biological and physical devices that detect analytes by generating signals. The first biosensor was discovered by American biochemist "L.L Clark" in 1950. The word "biosensor" was first used by "Cammann" in 1977 [1]. A biosensor is a system that uses partly biological recognition and partly signal transduction to perform selective quantification of analytes or biomarkers [2]. These analytes can be drugs, toxins, dissolved fats, etc. inorganic substances such as cells, proteins, DNA, etc. There may be biological substances such as In biosensors, when a biometric element detects a test of interest, the sensor confirms the presence of the analyte quantitatively or semiquantitatively [3]. Then the signal generated due to the known event is converted into the output signal. There is interest in biosensors in clinical diagnostics. Biosensors have proven to be useful in many important fields such as medicine, food safety, environmental monitoring, safety, medicine, and verification [4]. One of the leaders in the biosensor market is diagnostic equipment. Biosensors for monitoring cells have many advantages, including high performance and fast response, high specificity, and high sensitivity [5]. In addition, other advantages include continuous measurement without the need for experienced personnel, versatility, reaction time, safety, low cost and accuracy. Processing the data generated by biosensors can be considered as an important step affecting the above improvements. In this case, biosensors that can give molecular names of patients may help pave the way for precision medicine. Low-cost, easy-to-use biosensors should find application as self monitoring[6]. Automated and autonomous biosensors are being integrated into public infrastructure (transportation, schools, workplaces, etc.) to increase public safety by informing the public about biological threats [7]. These devices can also be connected via the “Internet of Things” and produce large amounts of population related data. Diagnosis of diseases, bone marrow, image contrast during MRI, cardiac examination, medical mycology, healthcare, etc. These are the important features or general areas of use of biosensors [8,9]. Therefore, future biosensor technology will inevitably need to use AI and ML based algorithms to process more information. In recent years, ML has emerged as a promising method to improve biosensor performance by providing accurate, reliable, and cost-effective data analysis. ML is a part of artificial intelligence, which is a framework that allows algorithms to learn from data. Many ML-based learning methods have been proven to solve complex real-world tasks. Thses are particularly suitable for tasks that require learning many models from data [10]. This is because such models can work very well and with human performance. In recent years, machine learning (ML) has become a powerful tool for disease diagnosis and has helped develop new methods that can analyze large amounts of data and provide accurate predictions. This review aims to provide an overview of various machine learning algorithms and techniques for disease diagnosis, focusing on recent advances, challenges, and future directions in this field.

The Basic Principle of Biosensors and Their components

These two elements are combined together by a number of methods such as covalent binding, matrix entrapment, physical adsorption and membrane entrapment. Biosensors work on the principle of signal transmission. These components include a biorecognition element, a biotransducer, and consisting of a display, a processor, and an amplifier. A bio-recognition element, essentially a bioreceptor, can engaged with a target analyte. The transducer monitors this interaction and outputs a signal. The output signal has a direct relationship to the analyte concentration. This signal is then amplified and processed by an electronic system. Key advantages of biosensors include: fast and continuous measurement, high specificity, very less consumption of reagents needed for calibration, fast response time, etc.[11] Biosensors mainly consist of three main components (Figure 1): a recognition element, a transducer and signal processor, and a display.

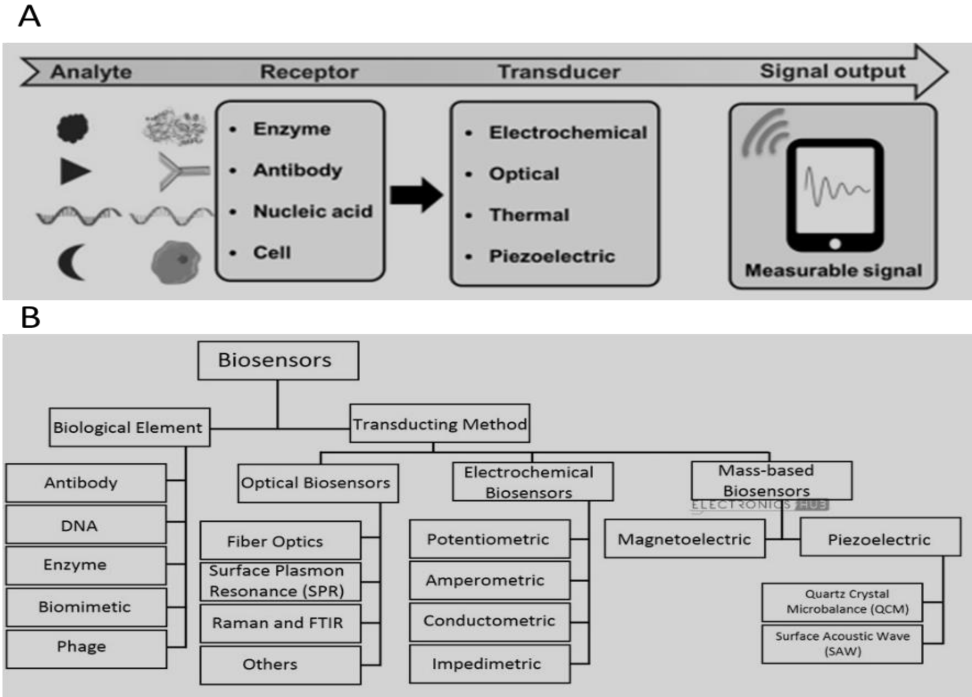


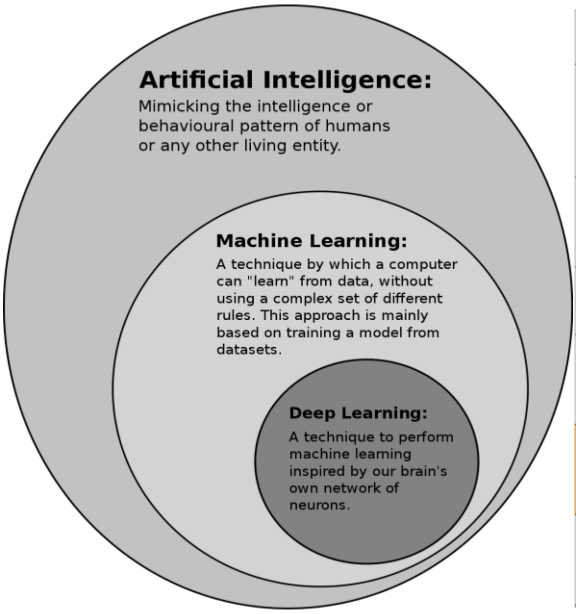
Figure 1. The different working principles of biosensors (A) and (B), various types of biosensors.

The recognition element enables the detection and measurement of specific analytes or target molecules in the sample. It is designed to selectively interact with the target molecule of interest and provide a measurable signal in response to its concentration. The recognition element is often from biological materials [12]. Several common types of recognition elements used in biosensors are enzyme, antibody, nucleic acid, receptor proteins, whole cells, or microorganisms. The transducer element of a biosensor is the key component and acts as a bridge between the biological interaction taking place on the sensing surface and the detection system which provides a quantitative output [13]. A biological recognition element selectively interacts with a target analyte, leading to a specific biochemical reaction. A transducer element then converts this biochemical signal into a measurable physical or electrical signal. Some commonly used transducer elements include: optical transducers, electrochemical transducers, piezoelectric transducers, thermal transducers. The transducer's signal is examined by the signal processor. The desired measurement or diagnostic information is subsequently provided by displaying or further analyzing the processed signal. Biosensors can be categorized according to the different transducers used in the sensor, such as optical, electrochemical, piezoelectric and magnetic sensors [14]. Each type provides distinct benefits and can be tailored to meet specific analytical needs. Biosensors can be classified according to the different transducers used in the sensor, including electrochemical and optical sensors. Depending on other sensing mechanisms, optical biosensors include holographic, fluorescence, and colorimetric biosensors. The output of optical biosensors can be intensity- or wavelength-based optical signals that smartphone applications could read for image capture and processing (Fig. 1). A holographic contact lens sensor was produced for continuous monitoring of glucose in tear fluids [15]. Depending on the targeted biofluid, the sensing components should be integrated with a wearable platform such as a contact lens, mouthguard, and smart watch [16]. As biosensors move into the Internet of Things and Big Data era, the device should communicate wirelessly with smartphones and other sensor nodes. The system should consist of data processing and storage units for processing and storing streaming biosensing data and creating user health profiles.

Advances in biosensing technology have been driven by breakthroughs in nanotechnology, microfabrication techniques, and biotechnology [17]. These developments have resulted in the creation of highly sensitive, portable, and reasonably priced biosensors that can do quick real-time analyses [18]. Biosensing is crucial to healthcare diagnosis, monitoring, and tailored medicine. For instance, glucose biosensors have transformed the management of diabetes by enabling people to quickly and precisely check their blood glucose levels [19]. In order to aid in the early detection of medical disorders, biosensors can also identify disease biomarkers, such as certain proteins or genetic material in cancer, infectious diseases, and other diseases. Continued advances in biosensing technology have enormous potential to improve health care outcomes, improve environmental monitoring, ensure food safety, and support advances in pharmaceutical research [20]. We may lead safer and healthier lives by utilizing biosensor technology, and we can also gain from quick and accurate biological material analysis. Biosensors also have a positive impact on the health and safety of the environment. They can detect contaminants in the air and water, track the health of food and farm produce, and measure the impact of remediation measures [21].

AI-ML for biosensing

A critical point in the use of artificial intelligence-enabled wearable biosensors is to help users understand and interpret the collected data, which includes analyzing data points and drawing correct conclusions. In particular, as continuous and multiplexed sensing becomes a common trend for wearable biosensing technologies, the data dimension is higher and obtaining useful information is more complex. While ML algorithms can efficiently process large amounts of high-dimensional streaming biosensing data, which means their great potential can be used to convert raw sensing data into user-friendly information (Figure 2). In addition, ML algorithms can handle noisy or low-resolution biosensing data [22].



Aspect	Artificial Intelligence	Machine Learning	Deep Learning
Definition	A broad field of study that focuses on creating intelligent machines.	A subset of AI that enables computers to learn from data and make predictions or decisions.	A subset of machine learning that employs neural networks to learn hierarchical representations of data.
Approach	Involves the simulation of human intelligence to solve complex problems.	Relies on statistical techniques to enable computers to learn from data.	Utilizes neural networks with multiple layers to extract features and patterns from data.
Data Dependency	Relies on both structured and unstructured data to make informed decisions.	Depends on labeled and unlabeled data for training and testing.	Requires large amounts of labeled data to train complex models.
Feature Extraction	Can involve rule-based approaches or expert knowledge for feature extraction.	Automatically extracts features from data using algorithms.	Learns hierarchical representations of features from raw data without explicit feature
Complexity	Can range from simple rule-based systems to complex cognitive architectures.	Can handle moderate complexity tasks, depending on the size and quality of data.	Excels in handling high-dimensional and complex data, but requires significant computational
Applications	Widely applicable in various domains, such as healthcare, finance, and robotics.	Used in areas like image recognition, natural language processing, and recommendation systems.	Commonly applied in computer vision, speech recognition, and natural language processing.

Figure 2: AI vs Machine Learning vs Deep Learning.

Depending on the types of sensors, the raw sensed data is present in different forms, such as digital data files from electrochemical biosensors and image data files from optical sensors. An ML model can be designed based on datasets to efficiently process the data. In addition, raw sensing data often require various pre-processing methods to improve the performance of ML models and provide early warning when abnormalities are detected [23]. The accuracy and computation time of artificial intelligence models can depend heavily on data pre-processing. The accuracy of camera-based early detection of skin cancer has often been affected by image enhancement, image restoration, and hair removal to improve image quality and remove noise. In addition, preprocessing methods such as Savitsky-Golay smoothing, background subtraction, and min-max scaling were used to process surface-enhanced Raman scattering spectra (SERSS) [24]. The pre-processed data were fed into a CNN for further processing, which significantly increased sensitivity to metabolites or toxins. In addition, data pre-processing has also been applied to wearable devices for a location reminder system. In addition, a wearable wireless integrated interface was designed to classify gestures using surface electromyogram signals. The signals were pre-processed using a pseudo-wavelet pre-processor to remove noise caused by movement during use [25]. Denoised data represents a higher quality signal and will therefore require less processing time.

Machine Learning (ML) Algorithms Used in Biosensors

A biosensor is a device that detects and measures the presence of biological analytes and chemical analytes. Biosensors have traditionally been limited in their sensitivity, specificity, and adaptability. However, with the help of ML, these limitations can be overcome and biosensors can be more effective in detecting and monitoring diseases, pollutants, toxins, etc. Machine Learning (ML) is a subset of Artificial Intelligence (AI) that enables computers to process data to make predictions or make decisions. In the biosensors context, ML algorithms can extract more information from complex data generated by the biosensor, improve its accuracy, and automate it. One of the key benefits of ML for biosensors is its ability to process large data sets and extract meaningful information. ML algorithms are able to learn from large datasets and can identify patterns and correlations which may not be visible in traditional analysis methods. As a result, the accuracy and sensitivity of the biosensor can be improved. This is especially useful in applications that generate complex data. Another advantage of ML in biosensors is the ability to optimize biosensor performance. Biosensors have come a long way in recent decades, thanks to the development of nanotechnologies, signal amplification techniques and transducers. All biosensors, however, have irregular signal noise, and some rely heavily on antibody or protein acting as bio-receptors, resulting in short shelf life, poor selectivity and poor commercialization. ML algorithms can help to improve these parameters by optimizing electrode design, analyste selection, assay conditions, and other parameters to increase their sensitivity, selectivity, and selectivity. Biosensors may also be able to adapt better to changing conditions, as ML algorithms can learn from data and adapt to new situations. This can make biosensors more effective tools to monitor dynamic processes, such as the progression of disease or environmental changes. Therefore, researchers are looking for breakthroughs in other aspects to improve the performance of biosensors. The focus is on machine learning (ML)-based analysis of sensing data. ML can provide new strategies to overcome the challenges faced by biosensors, and it can also be a way for common biosensors to become intelligent biosensors that can automatically predict species or analyte concentration based on a decision-making system (Figure 3).

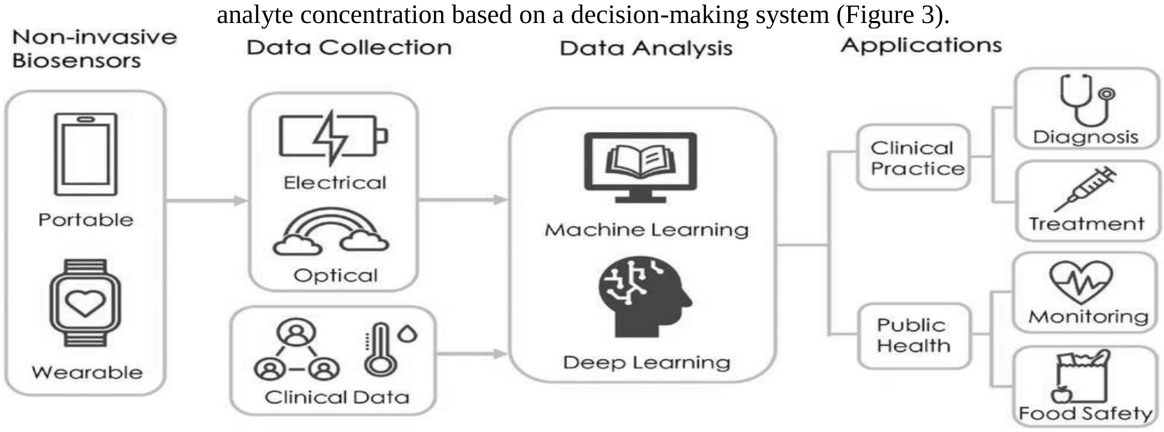


Figure 3. Basic procedures of ML-reinforced biosensors.

In recent years, there has been a huge increase in the number of advanced ML algorithms being developed for data processing. Some of these algorithms are: K-nearest neighbor (KNN) Support vector machine (SVM) Naive Bayes Decision tree (DT) Gradient boosted tree (GBT) Random forests (RF) Feed forward artificial neural network (FFANN) Recurrent neural network (RNN) Conceptual neural network (CNN) Others have not been fully studied yet [30]. Advanced ML methods are able to detect non-linear relationships within complex biological samples better than conventional approaches. This makes advanced ML methods a useful tool for solving urgent problems in biosensors. AI, ML and DL Relationship and Different ML Algorithms are shown in Figure 4.

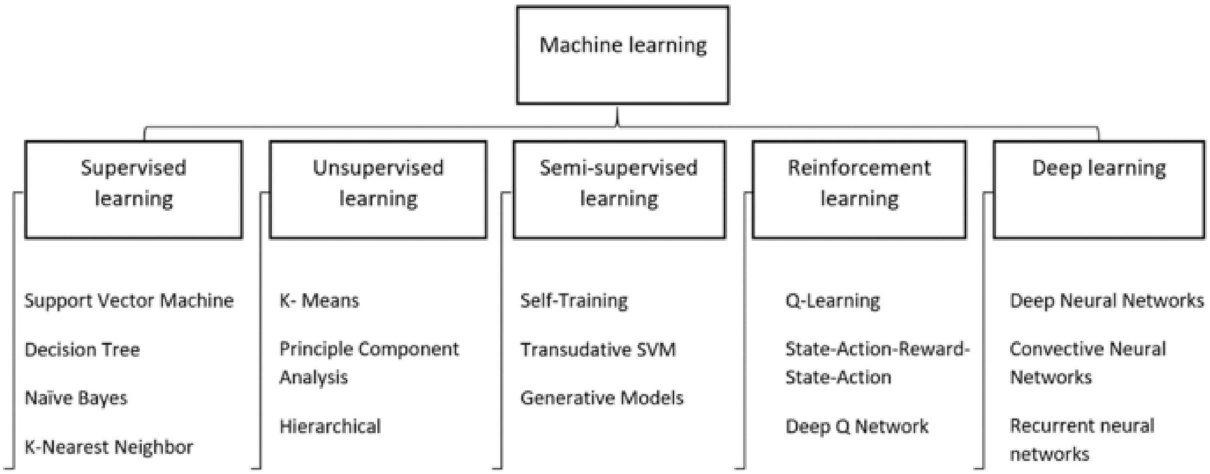


Figure 4. Different types of machine learning (ML) algorithms used in biosensors.

Supervised learning

Supervised learning is an ML algorithm in which input data is labelled and the algorithm is trained to infer output labels from the input data. Biosensors Supervised learning algorithms in biosensors are used to diagnose diseases, discover drugs, and monitor environmental conditions.[31]. Support vector machine (SVM) is one of the most commonly used methods for many supervised classification tasks, where the input is a set of n-dimensional data points, each accompanied by a true label. The goal of SVM is to find hyper-planes (generalizations of lines and planes to higher dimensional spaces) that can accurately separate these data points. For example, in 2D space this hyperplane would be simple. a line that divides a space into two subregions, each corresponding to a different class. These hyperplanes are defined by a set of points called support vectors. Support vector machine (SVM) and random forest (RF) are supervised learning algorithms that classify patient samples as "healthy" or "diseased" according to their biomarker levels [32]. SVMs are one of the most widely used supervised learning algorithms in biosensors because of their high-dimensional data handling capabilities and nonlinear relationship between input features. SVM is widely used in cancer detection, environmental monitoring and food safety applications. Random forest (RF) is another widely used supervised learning algorithm based on decision tree. RF is widely used in bioassays, such as bacterial contamination detection in food samples and cancer cell classification based on gene expression profile [33].

Unsupervised learning

Unsupervised learning, also known as unsupervised learning, is a type of machine learning that works with unstructured input data. It is designed to identify patterns or clusters in the data. Biosensors use unstructured learning algorithms to perform tasks such as predicting protein structure, analyzing microbial communities, and learning about gene expression patterns [34]. For example, protein structure prediction is a challenge in computational biology. Deep learning neural networks, for example, can be used to predict protein 3D structure based on amino acid sequences. ML algorithms have shown promising results in this area. In microbial community analysis, unstructured algorithms such as Principal Component Analysis (PCA) or hierarchical clustering can be used to identify microbial communities based on their DNA sequences. In gene expression analysis, an unstructured learning algorithm was used to cluster genes according to their expression profiles. Understanding gene expression patterns is essential for understanding cell processes and identifying drug potentials [35].

Reinforcement learning

Reinforcement learning, on the other hand, is a type of machine learning algorithm that interacts with the environment and receives rewards or punishments for its actions. In the case of bio sensors, reinforcement learning algorithms are used for self-optimization and control. For instance, in bio-optimization, reinforcement learning algorithms optimize bio-electrode design, bioanalyte selection, and bioassay conditions to increase bio sensor sensitivity and selectivity [37]. In bio-control, reinforcement learning algorithms control bio sensors in real-time to enable autonomous decisions based on sensor data [38].

Artificial Neural Networks (ANN)

One branch of machine learning that has received significant attention recently is called artificial neural networks (ANNs). These methods are loosely inspired by the inner workings of the human brain, but in reality these methods apply many highly non-linear and complex functions, aka neurons, to the input data in parallel. This complex nonlinear dynamics allows them to extract much more complex and useful feature representations from the raw data, leading to more useful representations and significantly better performance in many complex tasks. The learning process within such ANN models is actually to find the optimal parameters for the synaptic weights of neurons in order to obtain reasonable accuracy [39]. It is also necessary to mention that in most ANN architectures, more than one layer of neural operations are cascaded to solve more complex tasks, which gives them the name "Deep Learning models".

Convolutional Neural Networks or Deep Learning

A specific form of ANN is called a convolutional neural network (CNN). These architectures are specifically designed for image-based tasks such as image/video classification, object detection, tracking, recognition, etc., although they have been applied to other problems as well [40]. Unlike Feed Forward Neural Net (FFNN), these architectures use specially designed cells that use a convolution operation. More specifically, the learnable weights of a network are the parameters of a set of convolution kernels that are convolved with the input images or outputs of each layer. Such architectures were originally proposed for image focusing problems, mainly because they exploit the effect of spatial invariance in images as well as the importance of spatially adjacent features [40]. Deep learning is a machine learning algorithm that uses neural networks with multiple layers learn effectively from data. In the field of biosensors, deep learning algorithms have been instrumental in disease diagnosis, drug discovery, and image analysis [41]. For instance, in disease detection, CNNs (convolutional networks) can be used to classify X-rays, MRIs, and other medical images. Drug discovery can be predicted by deep learning algorithms based on chemical structures of compounds. Image analysis can be analyzed by deep learning algorithms for environmental monitoring, food safety, and more. [42].

Wearable biosensors with artificial intelligence support

In the development of wearable biosensing devices, the functions of the devices have expanded to include acquiring physiological information from users, wireless communication, data processing and storage, and providing an interactive user interface [43]. Wearable AI-enabled biosensors typically consist of sensing modules, wireless communication components, processors, memory devices, displays, wireless charging, energy harvesting components, and power supplies (Figure 5).

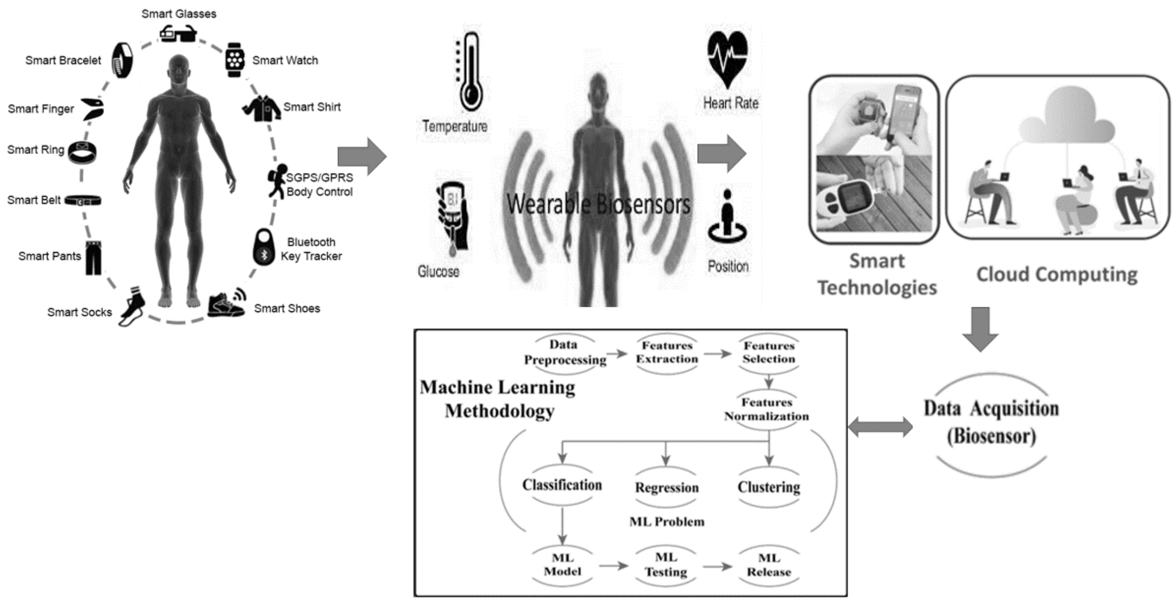


Figure 5. Different types of AI-assisted wearable biosensors.

Biosensors act as data acquisition units that collect biochemical or biophysical data from body fluids and convert them into signals that can be recognized by data acquisition and processing devices. Wearable biosensors can directly collect biofluids on the body surface and detect levels of health-related biomarkers [44]. A biosensor consists of a bioreceptors (i.e., antibodies, nucleic acids, or glucose oxidases) and a sensor that interprets physiological signals as optical, electrochemical or mechanical signals. Biosensors based on various biofluids could be integrated with a variety of wearable platforms, including wrist bands, contact lenses and electronic skin [45]. Wireless communication devices then transmit the data collected by the biosensors to personal smart reading devices or other terminals for processing. Current communication technologies potentially applied in wearable biosensors are Bluetooth, NFC and 5G mobile network. The raw sensed data is finally processed and stored on local devices or cloud servers where machine learning (ML) algorithms can be used to aid in diagnosis. The integration of the above components improves the availability of AI-enabled wearable biosensors, which represent a compelling alternative to invasive blood-based diagnostics [46].

Wearable Biosensing Device

In recent years, researchers have focused on the development of continuous, noninvasive, and real-time monitoring of various health-related biomarkers in biofluids, such as glucose, lactate, and ions [47]. Such sensors can be integrated with a variety of wearable platforms, including contact lenses for tear fluid analysis, wristbands, tattoos, electronic skin, and epidermal sensing patches for sweat fluid analysis and mouthguard salivary fluid analysis [48]. Notably, the non-invasive nature of biosensors implies an effective alternative to invasive blood-based diagnostics. Wearable sensors can now detect various diseases such as COVID-19, cancer, diabetes and dry eye syndrome [49]. In addition to recent research on wearable sensing techniques, other components that can be integrated into wearable devices have also been intensively investigated. For example, microfluidics provides a reliable way to collect body fluids and deliver fluids to the sensing sites of wearable biosensors [50]. Meanwhile, the integration of energy harvesting devices with wearable biosensors can extend the lifetime while maintaining light weight and small volume for wearing convenience. In addition, recent developments in flexible electronics enable the production of devices that are capable of being worn for long periods of time while maintaining the performance of the electronics. Recent advances in the fabrication of biosensors, microfluidic channels, self-powered devices and flexible electronics have also further enhanced the functions of wearable biosensors to enable non/minimally invasive, multiplexed real-time monitoring of physiological and pathological biomarkers [51].

Analyzing biosensing data using ML

ML algorithms can learn from existing biosensing data and analyze users' health status. ML can efficiently process high-dimensional biosensing data generated by wearable multiplexed sensors and find hidden patterns and relationships between data points. Powerful pattern recognition capability can help users interpret and understand collected biosensing data. In recent years, both non-neural and neural algorithms have been used in biosensors to process biomedical data to classify healthy and unhealthy users and quantify biomarker levels [52]. Biosensing Non-Neural Algorithms In recent years, several research papers have been published on the use of Non-neural Algorithms in Biosensing. Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Naive Bayes (NB), K-nearest Neighbors (kNN), Decision Tree (DT), and Random Forest (RF) [53]. LDA Directed ML Algorithm LDA predicts linear decision boundaries Probability estimation of input features Different biomarkers can be classified using LDA SVM Supervised Learning Algorithms SVM can be used for Classification, Regression, and Abnormality Detection of Raw Sensing Data. Performance of SVM depends only on the selection of kernel function (Linear, Polynomial, Sigmoid, and Radial basis Functions (RBF) [54]. Therefore, SVM can maintain its performance even for a problem with large dimensions, so it is suitable for processing multiplexed sensing data. Therefore, SVM has been applied in various biosensors such as glucose oxidase-based glucose sensing and nitrate sensing [55].

NB is a set of supervised learning algorithms used for probabilistic classifications based on Bayes theorem assumptions with strong naive independence between different features. Since the assumption greatly simplifies the problem, NB classifiers can work well with small amounts of training data [56]. kNN is a non-parametric algorithm used for classification and regression. The principle of kNN is to find a user-defined number (k) of training data points closest to a new data point and predict the output of the new data point. The distance can be calculated using Euclidean distance, Manhattan distance, maximum distance and Mahalanobis distance [57]. DT and RF are non-parametric directed ML algorithms for regression and classification. The principle of DT is to predict the values of the target variables by learning simple decision rules from the features of the input data set. The main advantage is that DT results can be interpreted and understood using tree visualization. Interpretability of prediction results is essential for quality control of wearable biosensors [58]. DT also shows that its cost is logarithmic in the number of training data points, which reduces computational cost and improves model efficiency in biosensing technologies.

Unlike the aforementioned non-neural algorithms, artificial neural networks (ANNs) are inspired by the structure of neurons in the human brain. ANNs can be divided into different categories based on network structures, including feedforward neural networks (FNNs), recurrent neural networks (RNNs), and CNNs [59]. Compared to other non-neural algorithms, the main advantage of using ANN is that it learns from a training dataset without any user-defined parameters. However, ANNs are not interpretable and explainable, so it is difficult to guarantee the performance and duration of problem solving, which becomes a significant drawback for ANNs for use in the medical field [60]. FNN has been used to diagnose lung cancer using exhaled breath analysis. The results showed a sensitivity of 83% and a specificity of 84%. In addition, RNN has been used to develop a health monitoring system for diabetes patients to monitor blood glucose, heart rate, and blood pressure [61]. The RNN model predicted the blood glucose level and showed the highest performance among the other tested algorithms [62]. Recent research on multiplexed biosensing technologies using artificial intelligence has already demonstrated high accuracy and reliability in detecting biomarker levels and associated diseases. The implementation of artificial intelligence in the medical field can significantly reduce the cost of treatment and improve the accuracy of diagnosis. Future research should focus on adaptive learning and interpretable models. With adaptive learning, the AI model will be able to learn from the environment.

Recent advances in artificial intelligence-enabled wearable biosensors

Wearable AI biosensors coupled with smartphone-based sensing systems are effective platforms for continuous health and fitness monitoring. Researchers have begun to integrate energy harvesting techniques and wireless communication into artificial intelligence-enabled wearable biosensors. Artificial intelligence-enabled wearable biosensor applications provide a chance to develop a more personalized healthcare and telemedicine system.

A smartphone-based biosensing system

The worldwide popularity of smartphones has led to a growing interest in smartphone-based biosensing systems. Since most commercially available smartphones carry additional hardware components such as wireless communication, mobile processors, cameras, and audio ports, users can control wearable biosensors and receive biosensors in real time. The benefits of using smartphone-based biosensing systems have been realized and have begun to play a vital role in AI-enabled biosensing systems for processing, storage, sharing, user interface, and cloud connectivity of health data [63]. Data collected by biosensors are transmitted to smartphones or other platforms for data processing. In real-world environments, wireless data transmission is often required to be integrated with wearable devices. However, due to the power limitation of wearable devices, it is more advantageous to integrate low-power wireless communication technology with wearable devices. With energy-efficient wireless data transmission, streaming biosensing data can be sent to data storage and processing devices. In addition, by applying wireless communication technologies, artificial intelligence-enabled wearable biosensors can increase flexibility and add new devices to build a wearable artificial intelligence biosensor network.

Plasmonic sensor for cancer detection

One-way plasmonic sensors can be used for cancer detection through surface-enhanced Raman spectroscopy (SERS). SERS is a powerful technique that can identify specific molecular compositions based on their unique vibrational spectra. By integrating plasmonic nanostructures, such as gold or silver nanoparticles, with biological samples, the SERS sensitivity can be significantly increased [64]. In cancer detection, plasmonic SERS sensors can be used to identify cancer-specific biomarkers present in body fluids such as blood or urine. These sensors can be designed to selectively bind to cancer biomarkers, allowing their detection at extremely low concentrations. By analyzing the Raman scattering of bound biomarkers, plasmonic SERS sensors can provide accurate and rapid cancer diagnosis information [65]. In addition, plasmonic sensors can also be used to detect circulating tumor cells (CTCs), which are cancer cells that have broken away from the primary tumor and entered the bloodstream. Plasmonic sensors can be designed to capture and detect CTCs based on their unique molecular and physical properties. This enables non-invasive monitoring of cancer progression and treatment response [66]. Overall, plasmonic sensors offer a promising technology for cancer detection. Their high sensitivity, specificity and ability to analyze complex biological samples make them a valuable tool in the fight against cancer. However, further research and development is needed to optimize the performance and translate these sensors into clinical applications.

Biosensing for patient monitoring

Biosensing in patient monitoring refers to the use of biological, sensing, and data analysis techniques to continuously or periodically track patient health outcomes [67]. Biosensors are devices that collect physiological data in real-time, often through the use of a wearable device or implantable device. This allows healthcare professionals to track patient health, identify anomalies, and make clinical decisions [68]. Monitoring patients using biosensitivity is a major improvement over traditional methods. Biosensors enable healthcare providers to capture real-time, dynamic readings of vital signs, markers, and other vital signs. [69]. This comprehensive understanding of the patient's state of health allows early detection of any changes or deviations from normal values. Continuous monitoring is particularly useful in the treatment of chronic diseases, as it provides valuable insights into disease progression, response to treatment and overall patient well-being.

Biosensors used in patient monitoring can detect a variety of vital signs, including heart rate, blood pressure, body temperature, respiratory rate, and oxygen saturation [70]. Biosensors can also detect biomarkers that are important for the management of conditions like diabetes, heart disease, kidney disease, and infectious diseases (e.g. hormones and enzymes) [71]. Biosensing works by interacting with the patient's body. It detects and converts biological signals into quantifiable electrical, optical or chemical outputs [72]. The data collected by a biosensor is extremely valuable to healthcare providers. With the use of sophisticated algorithms, data analytics and machine learning, clinicians can identify patterns, trends and anomalies in biosensing data to gain insights into a patient's health [73]. Biosensing data can then be integrated into electronic health records (EHRs) and clinical information to create a complete patient profile, allowing for personalized medicine and personalized treatment plans [74]. This can lead to improved patient outcomes and improved overall healthcare outcomes. Biosensing-based patient monitoring is not limited to medical facilities, as it can also be performed remotely and in the home environment. Wearable biosensors, including smart watches and fitness trackers, allow individuals to continuously monitor their health parameters. This promotes self-awareness and proactive health management [75]. In addition, remote patient monitoring allows healthcare providers to monitor patients from afar, reducing the need for frequent hospital visits and increasing patient comfort and convenience. The benefits of using biosensing for patient monitoring are numerous. It makes it possible early detection of deteriorating health conditions, early intervention and adaptation care. In addition, it increases patient safety, lowers healthcare costs, and improves patient outcomes. Biosensing technology leads to proactive and preventive healthcare by enabling continuous monitoring that can detect subtle changes that could indicate the beginning of a health problem before symptoms appear. As biosensing technologies advance, patient monitoring will become increasingly advanced, convenient and seamlessly integrated into daily routines.

Futuristic biosensors for Point of Care (POC) diagnostics

For diagnostic purposes, point-of-care (POC) can be defined as a quick, inexpensive, and efficient process that is performed close to the patient's environment. The integration of biosensors with wireless capabilities via Bluetooth, Wi-Fi, and GPS has facilitated the proximity of the professional healthcare professional and the home patient [76]. The sensor is connected to a readout circuit and amplification channels along with a microcontroller for sensing and generating information from a remote source. Power consumption is a limitation for such devices, and self-powered devices are generally designed so that once the device is implanted, it is impractical to charge the implanted device. The goal of POC diagnostics is to rapidly initiate medication or prognostic treatment where laboratory equipment is less or unavailable. In developing and underdeveloped countries, facilities are much less distributed than per unit of individuals. Therefore, POC diagnostics with biosensors as the core is emerging as a significant protocol along with advances in digitization. In addition, the development of carbon nanotubes, graphene metal nanoparticles, improved the selectivity of the POC diagnostic tool [77]. The programmable bio-nanochip (p-BNC) system is another biosensor platform with learning capacity. It is a "biology digitization platform" in which the sample produces an immunofluorescence signal on agarose bead sensors corresponding to a small amount of the patient's sample, which is further optically extracted and adjusted for antigen concentrations. The essential components for p-BNCs are microfluidic cartridges, software for automated data analysis, a portable analyzer, and embedded mobile health interfaces [78]. In addition, to include fluid transfer, optical recognition, image exploration, and user interface, a compact analysis tool that speaks to a general framework for acquiring, preparing, and overseeing clinical information has been built [79]. POC-based applications can be further classified as lab-on-a-chip, labeled, label-free, wearable nanomaterials, and wireless [80]. Detection mechanisms for wearable devices are electrochemical, calorimetric and optical. Conductive ink on a textile screen-printed electrode and smart tattoos and patches are able to sense a small number of microfluids as biopatterns on the epidermis of the skin [81]. "Lab on a chip (LOC)" is a replacement for complex pathologies and heavy machines in which the biomarker is sensed using a micro- and nanotransduction mechanism. These mechanisms include fluorescence intensity measurement, absorbance-based spectrometry, surface plasmon resonance, chemiluminescence, interferometry, amperometry, voltammetry, impedance, conductometric, thermal, acoustic waves, paper-based microfluidic devices, and lateral flow immunoassay [82]. Lab-on-a-chip and microfluidics are robust contenders to supply the necessary hardware to these electrochemical reagents and biosensors. A microfluidic system built using polydimethylsiloxane using soft lithography has various limitations such as cost inefficiency and limited availability, since the introduction of paper-based 3D wax printing technologies such as multi-jet lab-on-a-chip modeling has gained so much appeal at a very low cost. time span. Other techniques for optical, mechanical, and electrical biosensing modes are described in the literature within label-free and labeled detection for micro- and nanosensing. For the quantitative detection of CRP, a microfluidic system is introduced by implementing a chemiluminescence immunoassay [83]. This LOC microfluidic platform with portability, quantification and automation features creates a significant strategy for POC diagnostics.

Multiplex point-of-care testing (xPOCT) is the simultaneous testing of different analytes for disease from a single sample [84]. Multiplex capabilities for POC testing can be grouped as a paper-based system, an array-based system, a bead-based system, and a microfluidic multiplex system with detection techniques lying between optical and lateral flow. The development of user interface devices such as smartphones and smart watches with such technologies has also opened the future space for xPOCT [84]. The most prominent machine learning algorithms for futuristic biosensors and various issues related to the integration of biosensors with wireless functions via Bluetooth, Wi-Fi and GPS for POCs were investigated. Real-time monitoring of a specific patient makes it easier to diagnose the patient in a timely manner. Compiling the interpretation of results using machine learning and data analysis approaches is understood to be quite efficient and to support clinical decision making [85]. These parameters are key components for assembling size-efficient and composite smartphone-based devices. The goal of POC diagnostics is to rapidly initiate medication or prognostic treatment where laboratory equipment is less or unavailable. The Internet of Things reduces or eliminates active human intervention in remote and hard-to-reach places [86]. Soon, it is also likely that biomarkers of hematocrit, oxygen saturation, HbA1C, lipids, infection and inflammation, which are signs of volume overload or dehydration, can also be integrated into AI technology. In addition, a new twist in this field is a non-contact or pseudo-touch biosensor that is used to diagnose diseases by reading physiological activities running deep mind algorithms. Nowadays, scientists are quite interested and involved in the development of new, smart and advanced devices to invent more specific, sensitive and stable biosensors for theranostic purposes. Integrated AI tools combining mechanics, biology, chemistry, engineering, etc. are the requirement of the current scenario to combat typical diseases and environmental problems.

Key challenges and the way forward

Despite increasing progress over the past few years, there are still a number of significant hurdles to overcome for AI biosensors for IoT-based applications. With EHRs and cloud storage, data allows for detailed patient profiles and personalized care.[87]. Although the analysis of wearable sensor data presents some challenges, innovative techniques and visualization methods are constantly being developed to effectively address them. Wearables and patient monitoring are expected to experience significant growth and development in the coming years. Sensor technology is one of the key areas of development, where advances in sensor technology are expected to lead to more advanced and smaller-scale biosensors that can detect a wider variety of biological molecules with greater precision and energy efficiency [88]. The integration of multiple biosensors in a single wearable device is a major obstacle to comprehensive health monitoring, which provides a comprehensive view of an individual’s health and allows for tailored treatment plans. Combining data from multiple sensors, modalities, and data analysis techniques will inform and support better decision-making. Real-time feedback and interventions will become increasingly easy, enabling wearable devices to continuously monitor health parameters and provide immediate alerts or interventions. For commercial applications, flexible bioelectronic materials are a key component [89]. The human body and its internal organisms are naturally elastic and flexible. In this case, the integration of electronics into platforms made of flexible material is necessary. Flexible bioelectronics are advantageous for adapting the human body and organs (such as skin, eyes, and muscles) with low mechanical tissue damage and less adverse effects after long-term use [90]. Medical artificial intelligence biosensors will play a key role in the development of key technologies in the future with the help of nanotechnology. They will continue to pursue miniaturization, scalability, low power consumption, low cost, high sensitivity, multi-functionality, safety, non-toxicity and degradability. Another problem is that most ML-enhanced biosensors currently lack adaptive learning capabilities. Biosensors can learn from their surroundings through adaptive learning, and not just depending on manually entered training sets. Unlike a non-adaptive system, an adaptive model continuously improves and optimizes by learning from the environment [91]. This can reduce the likelihood of catastrophic errors and erroneous results that a single fixed model can cause. Building an intelligent sensor system that relies on huge datasets and algorithms is a significant hurdle for a data processing and storage platform. In recent years, cloud computing has been used to process sensor signals because it offers superior computing power and data storage. The integration of cloud and biosensors is nothing new, especially for monitoring applications where the volume of data is constantly growing over time. Connecting many sensors directly to the cloud is sometimes too expensive and slow due to the exponential growth of the number of sensors. Edge computing has thus been introduced in recent years. Instead of a single data center, edge computing enables data processing on dispersed edge devices. It benefits from great computational efficiency, fast network processing, low cost, and more. Biosensors are therefore likely to make use of this cutting-edge technology [92]. Machine learning algorithms will enable more precise predictions for personalized medicine while providing strong data protection and privacy safeguards. Wearable biosensors combined with telehealth and remote monitoring will enhance access to healthcare and facilitate early detection and treatment, particularly for patients in remote settings. These future perspectives reflect how biosensors and patient monitoring will revolutionize healthcare practice and set the stage for a more interconnected and data-driven health system.

Conclusion and future work

The impact of biosensors on healthcare, the environment and biotechnology is far-reaching. Wearable biosensors play an important role in diagnosing diseases, providing personalized medicine and monitoring the environment. Biosensors are particularly useful in the context of continuous physiological data collection for remote health monitoring and personalized care. The use of artificial intelligence in biosensors is gaining increasing attention in the healthcare industry for various purposes. AI-based methods are being adopted in the healthcare industry, where low-cost, intelligent, and adaptable methods are impacting areas such as clinical decision support, diagnostics, prevention, telehealth, public health policy, and clinical recommendations. Machine learning algorithms have played a major role in enhancing biosensor performance. By automating data analysis, pattern recognition, and prediction, these algorithms have greatly improved the accuracy, sensitivity, and adaptability of biosensors. They also made it possible to fine-tune biosensor properties, overcoming bottlenecks and extracting valuable information from large data sets. Biosensing algorithms are used for a variety of purposes, including diagnosing diseases and monitoring environmental conditions. These algorithms can be supervised or unsupervised. To summarize, the use of ML algorithms in biosensors has tremendous advantages that automate the cumbersome and complicated process of extracting, processing, and analyzing data that is generated by biosensors. More user-friendly machine learning technologies such as Auto ML, clinical AI, patient-centric AI, and explainable AI are needed to strengthen the trust of healthcare stakeholders and make machine learning an integral part of everyday clinical practice. Artificial intelligence can only help healthcare professionals and improve lives, and in no way can AI replace the human touch that is the essence of every field. AI and doctors should work together to maximize benefits for patients. Given the vast amount of data and computing power available today, we expect an increasing role for AI and biosensors in clinics to augment or assist healthcare professionals and reduce their workload. Looking further ahead, AI and ML will bring unlimited possibilities for high-accuracy data collection in the next generation of various sensor devices such as medical sensors and biosensors.

Acknowledgements

The author would like to acknowledge Prof. Hari Murthy for his supervision and Christ University, Kengeri campus, Bangalore for providing the resources to write the current paper.

Declarations

Funding

No external funding was obtained for the purpose of the study.

Availability of Data and Materials

Materials required for the current review article were previously published peer review articles which have been cited in the text and references.

Ethics Approval

Not applicable.

Consent for Publication

Not applicable.

Competing interests

Author declare that they have no conflicts of interest relevant to the content of this review. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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