Chapter 9
A Comprehensive Review of Wireless Medical Biosensor Networks in Connected Healthcare Applications

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Abstract The development of the hardware platform, as well as the underlying software, led to the emerging Internet of Healthcare Things (IoHT). The demand for remote healthcare continuous monitoring systems using limited resources and biosensors has increased. This paper provides a comprehensive review of the wireless medical biosensor networks in Connected Healthcare Applications. The main aim is to provide a basic overview of WMBNs and to discuss current achievements, particularly applications concentrating on remote patient monitoring for the elderly and chronically ill. A detailed examination of WBSN architecture, challenges, healthcare applications, and their needs is necessary to fulfil the scientific notion of WMBN. Following that, the main critical features of the WBSN are discussed, including data gathering, fusion, telemedicine and remote patient monitoring, rehabilitation and therapy, biofeedback, assisted living technologies, risk assessment, and decision making. It also offers insight into machine learning techniques and their applications in medical environments.

Keywords IoT · WBSN · Data reduction · Patient risk assessment · Decision making energy efficiency

9.1 Introduction

Over the last years, an increasing amount of interest was focused upon the wireless body sensor networks (WBSNs) due to their vast, innovative, accurate and simultaneous applications of monitoring in various areas, which include healthcare, sport training and fitness, social interactions, and monitoring industrial workers. People are getting increasingly aware of the importance of health-care in their daily lives as

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the standard of living rises and the population ages. Wearable health monitoring (WHM) can be defined as a new technology which allows for continuous ambulatory monitoring of potions for recording the vital sign about their body and health without causing undue discomfort or interfering with their daily activities when they're at home, work, or other exercise-focused locations, or in a clinical setting. The technical WHM device designs have been focused on four major areas: reliability and safety, low power consumption, ergonomics, and comfort.

The smart WHM systems can be provided in different forms skin- touch devices, implantable devices as well as another wearable tiny devices and were used to monitor the vital signals regarding body and health body activity and location On the other hand, the agreement level of (WHM) devices by end employer is low, in order to the data treatment technologies applied in the WHM devices or systems can't manage data gathering by the set of the sensors composite in a system through the phase of data preprocessing, origin of discriminative and salient characteristics, and data identification in the status of the body activity. In the present day, the clinicians usually perform the diagnoses and classification of the diseases, according to the information that has been obtained from many physiological sensor signals. Nonethe-less, the sensor signal could be vulnerable easily to specific interference or noise cases and as a result of the large individual variation sensitivity to various physiological sensors might vary as well. Which is why, multiple sensor signal fusion is necessary for providing more reliable and robust decisions.

The principal contribution of this paper is to introduce a comprehensive show of Wireless Medical Biosensor Networks in connected healthcare applications. This review covers the background of the Wireless Body Sensor Networks, their applications, and the principal challenges of network. The data collection, data fusion, local emergency detection, and decision making about of the patients situation investigated. The machine learning applications in smart cities are explored.

This paper is set up as follows: The Wireless Body Sensor Networks (WBSNs) are presented in the next section. Section 9.3 introduces the architecture of WBSN. The biosensor is given in Sect. 9.4. The WBSN applications are illustrated in Sect. 9.5. The main challenges of WBSNs are shown in Sect. 9.6. Section 9.7 presents the Early Warning Score (EWS). The data gathering is given in Sect. 9.8. Section 9.9 introduces data fusion in WBSNs. Telemedicine and remote patient monitoring are investigated in Sect. 9.10. Section 9.11 demonstrates the decision making. Section 9.12 shows energy consumption. Section 9.13 explores machine learning techniques and their applications in smart cities. Finally, the conclusions are indicated in Sect. 9.14.

9.2 Wireless Body Sensor Networks (WBSNs)

The WBSNs had set up as follows an inexpensive resolution allowing the continuous control of the physiological and physical parameters of the patient body. A lot of research has been made and is still being made in the design of medical accurate invasive and noninvasive sensors and the design of comfortable wearable health monitoring systems. Firstly the most commonly employed sensors in WBSNs. capture physiological parameters including vital signs and physiological signals as well as physical parameters related to body movement. In additionally to the discussion of the differences of several commercially available wearable sensor nodes on the market [1]. Having health related data being continuously collected leads to a palette of body sensor network (BSN) applications. A particular focus is given to healthcare applications given that it is the main focus of this thesis. All types of population can benefit from BSN healthcare applications, starting from toddlers to elderly, depending on the monitoring phenomenon of interest. Furthermore, diverse monitoring tasks can be achieved such as event detection, prediction, diagnosis etc.

Thus a discussion about these tasks and depict them is provide as a function of three different dimensions: the type of user, the type of processing and the monitoring location However, BSN healthcare applications should meet a set of requirements in order to achieve user satisfaction, perform as desired, have an impact on people's life and ensure continuity, especially that WBSNs have limited resources, are subjected to interference as well as faulty measurements and that are dealing with sensitive medical data [2].

In the previous years, the entire world has been facing an growing number of patients and illnesses. Moreover, The relationships between humans and animal led to the introduction and prevalence of new types of viruses and unknown ailments such as covid-19. Consequently, this will increase health observation and evaluation a complex task for hospitals and medical staff. In addition, the connected healthcare applications are overcoming some significant obstacles such us keep the power of the biosensor devices to guarantee as much a time period of monitoring as possible for the patients, and speeding up the discovery of the patient's state sending it to a medical expert so they can make an appropriate conclusion.

9.3 The Architecture of WBSN

A WBSN include the biosensor nodes and a coordinator, The former is deployed on a person's body. They may be either implanted inside the human body or placed on it. They continuously sense physiological signals, vital signs, an example of physiological signals include ECG, EEG and PPG etc. Whereas an example of vital signs includes the RR, HR, temperature, BP and oxygen saturation etc. The acquired data is periodically and wirelessly transmitted to the coordinator of the network [3]. The latter can be any portable device close to a person's body such as his/her smartphone or PDA. Its role is to manage the network and perform the fusion of the collected data. Thus, emergencies, abnormal events as well as the continuous follow-up of the person's health condition can be ensured by the coordinator. Moreover, it can provide the person advice, reminders and take action in emergency situations such as call the doctor. The collected data as well as results of the process of fusion are sent

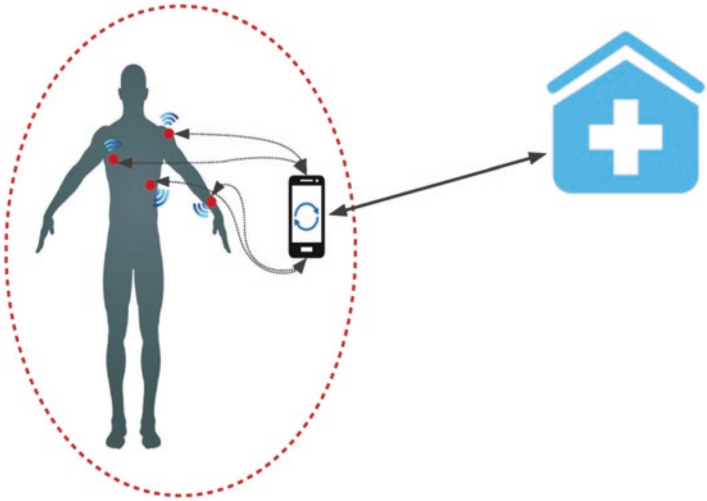

Fig. 9.1 WBSN architecture [3]

by the coordinator to the medical center (healthcare experts, doctors) where further processing can be made [3].

The main motivations for using the WBSN are (1) reducing the energy consumed by the biosensor devices make ensure the patient receives the longest possible monitoring and (2) fast detection of the patient's urgency and sending it to the medical professionals to provide the best decision to save their lives. (3) monitoring and tracking the patient's situation Whenever he wants, from anywhere, the patient can give professionals remote access to patient data (Fig. 9.1).

9.4 Biosensor

Biosensors are miniature, lightweight, low power, limited-resources and intelligent sensor nodes that sense, process and transmit human physiological parameters such as the ECG, the heart rate, the body temperature, the body movement etc. Figure 9.2 illustrates the components of a wireless biosensor node. It is composed of three units powered by a battery: the sensing, the processing and the transmission units.

All three units require power for performing tasks. However, the transmission has been viewed as the most power-hungry of tasks. The unit of sensing includes a sensor and an ADC, converting the analog signal that is sensed with a certain frequency (Nyquist-Shannon), to a digital signal.

The latter is given to processing unit (i.e. memory and processor) where the algorithms of processing are run. In addition to that, the processor regulates the transmission and sensing units and it changes and/or activates their status based on applications and utilized protocols [4].

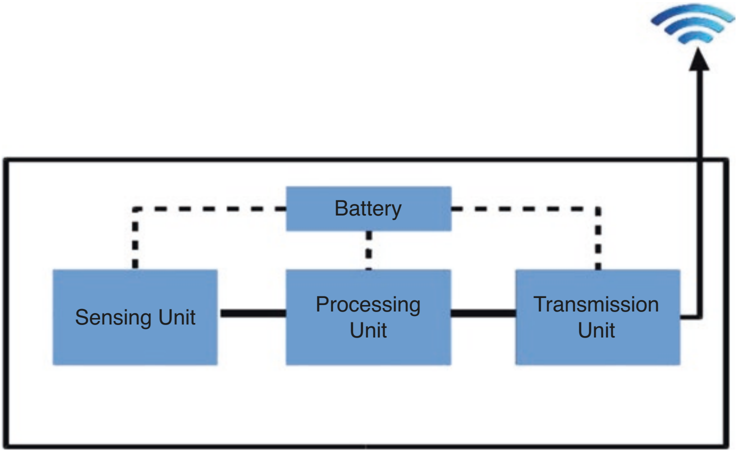

Fig. 9.2 The components of a biosensor node [4]

9.5 WBSN Applications

These applications are comprehensive for multiple areas such as health care, assistance to the elderly and provision response to emergency case [5] an overview of potential medical applications will be presented in this section.

- **Telemedicine and Remote Patient Monitoring**
  Increasing cost of medical care and old age in the world's population leads to a major development in the telemedicine network for the purpose of providing many medical services. Telemedicine uses an integrated medical system and modern communication techniques to enable the delivery of a remote patient care service and also provides the possibility for health professional in the world such as physicians, scientists and others to take care of more patients. In this case, the patient can remain under the continuous monitoring of the doctor under normal physiological conditions without affecting the daily activities and at the lowest cost. WBSNs are able to supply constant monitoring for the biomedical parameters and failure detection in the devices when it occurs, as well as early detection of emergencies. Such patient monitoring systems will be more secure, more compatible and inexpensive [5].
- **Rehabilitation and Therapy**
  Aim of rehabilitation application is permitting for sick people after leaving the hospital to recover their functional abilities and return to normal condition by convenient treatment Rehabilitation is a dynamic operation designed for correction any wrong behavior by using the available facilities to arrive the optimal state. In order to reach a person with a brain stroke to the highest level of stability, the movement of the patient during rehabilitation period should be constantly monitored and corrected. Thus, patients' movement tracking becomes necessary in the scheme of rehabilitation [5].

- **Biofeedback**
  Biofeedback indicates to the possibility of measuring biomedical activity and potential medical parameters and returning them to the user in order to allow him to modify his biological activity and control it for the purpose of enhancing his health. It is beneficial for controlling certain conditions and for non- voluntary human body functions such as blood pressure plus migraines. The devices of biofeedback can involve those designed for monitoring the human heart functions, breathing apparatus, brainwaves and others [6].
- **Assisted Living Technologies**
  Aging in the world population and the high cost of formal healthcare institutions as well as the tendency of some individuals to live independently all this led to an expansion of innovative living techniques for an independent and secure aging. These applications use house automation to enhance living and preserve an independent style for life. Actually, supported living techniques have been used as an alternative for older people, people with special needs and disabilities persons who cannot be independent and the same time do not need health care all the time.

  The ambient health sensor network can obtain the bio parameters of the environment of living and then send them to a centralized station due to medical constant monitoring system. The health of these people can be guessed by knowing the blood pressure, heart rate, etc. These systems could be linked to a medical center for the purpose of emergency response or sudden changes (if the parameters deviate from the physical range) [7].

9.6 Main Challenges of WBSNs

- Reliably – the major problem is to ensure that information reaches is intended destination in reliable manner. Many factors contribute to the reliability of wireless body sensor network, including stable software programing, dependable wireless communications between nodes sensor and efficient processing in every sensor node.
- Biocompatibility – for sensors node that directly interact with patient body, the shape, size and materials are limited. Packaging the sensor in biocompatible materials is the solution.
- Portably – the size and Wight of the sensors node employed in wireless physiology measuring device must be tiny and light Wight, whether they are placed on or swallowed.
- Privacy and security – the major security concerns include eavesdropping, identity spoofing and disclosure of personal information to the unauthorized persons. It is possible to be secure improved by incepting data, privet data must be

safeguarded against unauthorized access "Consented data acquisition, proper data storage, secure transmissions, and integrity of the data and authorized data access are vital areas for developing software or hardware solutions" [8].

- Light-weight wireless communication protocols have to be able to handle self-organization networks (include security features) as well as data gathering and routing.
- Enrage aware communication nodes should transmit at allow power level to permit. The nodes bargain to reduce their transmission power, an emerge-were protocol is required.

9.7 Early Warning Score

The healthcare doctors at the hospital use the National Early Warning Score (NEWS), a physiological scoring system, to assess each patient's condition and determine how best to treat instances with high risks. This system of scoring uses six physiological measures that presented in Fig. 9.3 [9]. The key benefit of NEWS is how easily it can calculate the patient's overall risk using the appropriate scores for each type of sensor. The NEWS can assess the patient's condition by evaluating the sensed values from various biosensors [10, 11].

9.8 Data Gathering

Data collection is a method of gathering and measuring data, that are collect from several source of information so as to supply answers to pertinent questions [7].

The process of gathering, measuring, and evaluation of the correct information for the study, utilizing approved established processes has been known as the data collection. According to the obtained facts, a study could evaluate the hypothesis. Despite the subject of study, the collection of data is typically the first and most important stage in the process of the research. For the dialysis, the different methods to the data acquisition are utilized in various disciplines of study, relying on the information needed [7].

The most significant aim of data gathering is collecting the information-rich and accurate data for the statistical analyses so that the data-driven study decisions could be made. There are two type of data collection: primary data and secondary data, the primary data are un processed data that have been obtained for the first time. The secondary data represents the information that was gathered and tested already [12].

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Level of Consciousness				A			V, P, or U

Fig. 9.3 NEWS

9.9 Data Fusion

Currently, developing intelligent algorithms for a variety of tasks in healthcare applications has been attracting the research community. Hence, the treatment and processing of the collected data is an important aspect in WBSNs. For instance, data fusion in WBSNs allows to combine, to correlate and to associate physiological data and medical information coming from one or multiple biosensor nodes in order to achieve accurate situation assessments about the monitored person. Particularly, multi-sensor fusion has been gaining an ever-increasing interest driven by its potential in ensuring a unified picture about the health condition of the patient. However, several challenges exist in WBSNs, especially that the collected data is subject to noise, interference and faulty measurements, thus leading to the fusion of imperfect and inconsistent data.

Furthermore, real-time fusion and good accuracy, which are two important aspects in healthcare applications, should be satisfied by multi-sensor fusion approaches.

The Data fusion is multilevel operation that deals with associations, correlations, combination of the data and information from multiple as well as single sources for achieving the identity estimations, refined position, and complete timely evaluations of the situations, threats in addition to their relevance [13].

The following definition for Multisensor fusion enables to obtain a unified image and a globalized view of the system by combining information from several sources [2, 14].

There are three different data fusion approaches based on the processing architecture are identified: distributed, centralized and hybrid. The centralized method depends on a fusion center where all processing is carried out. A distributed method is adopted when the sensor nodes perform independent processing on the data they have captured and transmit the results to a fusion node. In this case, the fusion node executes a global analysis based on the results sent by all the sensor nodes [15, 16].

Finally, hybrid fusion concerns approaches where the sensor nodes only perform pre-processing and/or perform partial lightweight computation on the collected data in a distributed approach fashion while a central node fuses the gathered data and performs high-level fusion [17].

9.10 Telemedicine and Remote Patient Monitoring

In clinical uses, multiple devices placed on the bodies of the patients are being used to sense their vital signs. These devices continuously transmit each signal they have detected to the Gateway. Every period, the gateway collects massive observed data. Therefore, before sending the data to the gateway, each device must reduce the data. Data cleaning at the sensor devices can reduce cost and maximize system longevity. Additionally, it can lower the amount of data that is received at the Edge gateway to make it easier to analyze and provide an accurate assessment of the patient's situation.

NEWS claims that the devices only transmit measures with results greater than 0 to the healthcare experts. The data of the patients' normal state won't have been sent to gateway. It is obvious that less time will be spent periodically checking on the patient's condition and sending data to the gateway. This issue can be resolved by determining the relationships between the detected data per period and then send them to the gateway.

9.11 Decision Making

After receiving the readings of the biosensor nodes that executing the emergency detection algorithm, the Edge gateway achieves the fusion for the readings of biosensor nodes to provide meaningful information about the situation of the patient health.

This health condition of the patient is utilized to assess the health risk of the patient and then take the appropriate decision. The Edge gateway transmits the taken decision and the collected data to the experts in the medical center. The Edge gateway collects the first readings of biosensor nodes at the beginning of each period, then each time t receives reading from appropriate biosensor k, it computes its updated score US. Finally, the Edge gateway calculates the aggregated score AS for the whole biosensor nodes using their updates scores. For example, if the Edge gateway only receives the scores of the biosensor nodes HR, RESP, and ABPsys at the time t, it calculates the updated score for them. Then, it uses the last saved updated score of the remaining two biosensor nodes BLOODT and SpO_2. Finally, it computes the aggregated score.

9.12 Energy Consumption

This model can be characterized as the design and analysis of mathematical representation of the WBSN for studying the effects of the alteration of the parameters of the system. The behavior of this model represents a function of its parameters [18]. The reduction of power that is consumed in the communication by the wireless sensor nodes may be highly effective, due to the fact that radio transceiver is a component with maximum power consumption. The wireless sensor node is comprised of three components that are powered by battery: the sensing, the processing and the transmission units. All those three units need power for performing their tasks. The energy consumption of this thesis was evaluated based on typical power consumption concerning wearable node, where 1 energy unit equals 152 J: the task of the sensing consumes 6 J, the task of processing consumes 24 J, transmission task (TX) consumes 60 J and receiving task (RX) consumes 62 J [19] (Fig. 9.4).

9.13 Machine Learning Applications in Smart Cities

The goal of a smart city is to maximise the efficient use of limited resources while also improving residents' quality of life. To develop a sustainable urban existence, smart cities used the Internet of Things (IoT). In smart cities, IoT devices such as sensors, actuators, and smartphones create data. The data created by smart cities is submitted to analytics in order to obtain insight and uncover new information for increasing the smart cities' efficiency and effectiveness. Several works are focused on the machine learning in the internet of health and things [20–24]. In this section, some machine learning methods are presented [25].

9.13.1 Convolutional Neural Network (CNN)

The mathematical technique 'convolution' is used in the convolutional neural network (ConvNet) displayed in Fig. 9.5. The processing of numerous convolution applications that run simultaneously is referred to as "convolution" in this context.

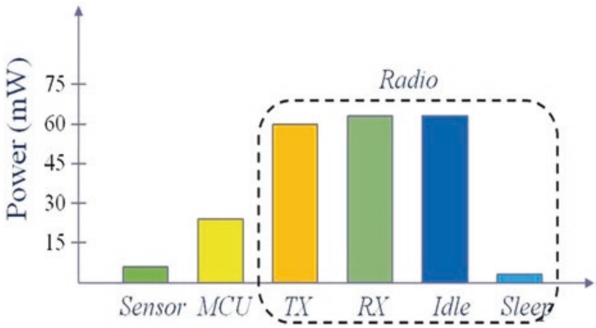

Fig. 9.4 Typical Power Consumption in Wearable Nodes [19]

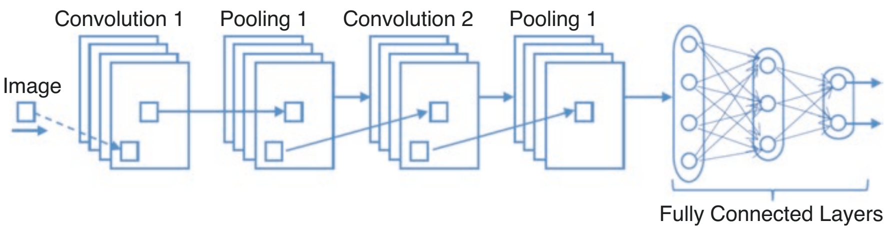

Fig. 9.5 The CNN

It is a particular linear transformation action in its levels that substitutes convolution for conventional matrix multiplication. The 1st parameter is called the input, the 2nd parameter is called the kernel, and the output is called the feature map, according to TheConvNet.

Whereas the input is a matrix of data, the kernel is an array of variables. These two matrices are known as tensors because the input and kernel parts should be kept independently. ConvNet's main inspiration is based on three factors: sparse interactions, parameter sharing, and equivariant representation. The kernel is smaller than the input because to the sparse interaction, and parameter sharing is used in a model. Equivariant representations imply that when the input modified, the output would likewise change [26].

The ConvNet components are divided into two layers: left and right. The left layer is made up of a limited number of complicated layers, each of which has many stages. These stages are also known as the input stage, output stage, and numerous hidden stages, with convolutional, pooling, fully connected, and normalising hidden layers being the most common. There are three steps in a pooling layer: The first stage involves running a series of convolutions one after another to produce a collection of linear activations. Each linear activation is carried out in the second step using function of activation. The pooling function is used in the third stage to affect the output of the following layer. Because it may utilise lower pooling units than detector units, pooling enhances the network's computational and statistical efficiency while also reducing the amount of storage needed to hold the parameters [26].

9.13.2 The RNN (Recurrent Neural Network)

It is efficient network that provides a succession of learning [27]. RNNs are temporal state-structured dynamical systems. They're rather powerful, and they're used in a variety of temporal processing situations and digital applications. Both the Hopfield and Cohen Grossberg models use a kinetic basic feature to hold data, and serves as an associate memory respectively for storing knowledge and finding solutions to optimization problems, are two common RNN models. The RNN is divided into two types: global and local. Local RNN tight feed forward connection organised using dynamic neuron models, whereas global RNN applies the connection between the neurons as feed forward. The time-delayed and simultaneous RNNs are two static time models for RNNs. First of which is taught to minimise error of prediction and the 2nd is learned to create broad approximation function skills [28]. In contrast to the shallow RNN, the deep RNN has numerous hidden layers (see Fig. 9.6).

9.13.3 The DRL (Deep Reinforcement Learning)

The DRL algorithm works in the environment to take action with the purpose of maximising rewards and improving the learning algorithm's efficiency [29]. The reinforcement learning block diagram is shown in Fig. 9.7.

9.13.4 Support Vector Machine

SVM one of the common tools of supervised machine learning, it is commonly utilized for the efficient classification. The SVMs demonstrate high accuracy of the classification with many applications, like the object detection, speech recognition, bio-informatics, image classification, medical diagnosis, and so on [30]. The supervised machine learning is typically composed of 2 fundamental stages, learning/training phase and classification phase. The training phase of the SVMs constructs a model to be utilized to classify any testing data which has been based upon the Support Vectors (SVs).

Support Vectors have been identified from training data-set throughout the process of the training, to be utilized then in the phase of the classification for the prediction of proper class of input testing data. The SVMs showed high rates of the classification accuracy, as they outperform other common algorithms of classification in a wide range of the applications and cases [31, 32]. There is a growing interest for the exploitation of the SVMs in several of the embedded systems of detection and different applications of image processing.

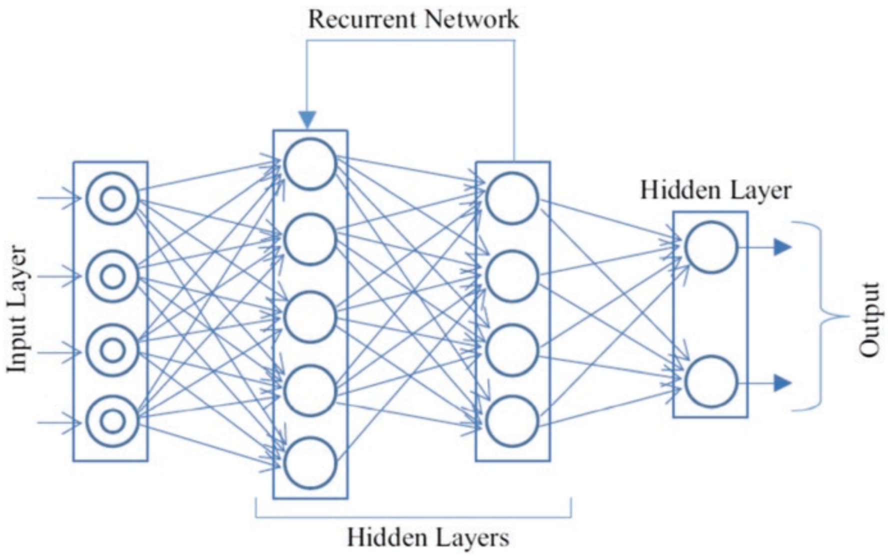

Fig. 9.6 Deep RNN

Fig. 9.7 Reinforcement learning

SVM represents a powerful algorithm for machine learning, showing high precision in various problems of classification [33]. The SVMs are based upon the theory of decision boundary, efficiently differentiating between 2 different data sample classes. There are two main phases in this model of supervised learning, training/learning and classification phases. In phase of training, a trained model is advanced with the use of input training data-set, where a decision boundary has been formed from optimal separating hyper-plane which optimally separates the data samples of those 2 classes. SVs represent data samples which lie on decision boundary, and they have been defined in the phase of the training and are utilized after that for the tasks of the classification in classification stage.

The reason for using the SVMs in machine learning The SVMs are utilized in some applications such as the hand-writing recognition, face detection, intrusion detection, gene classification, e-mail classification, and in web pages. It is a reason for using the SVM in machine learning. It has the ability of handling the classification as well as the regression on the linear and the nonlinear data. An additional reason for using the SVMs is due to the fact that they have the ability of finding complex relationships between one's data without needing to perform many transformations on their own. It is one of the best options in the case of working with smaller data-sets having tens-hundreds of thousands of the features. Usually, they find more precise results in comparison with other algorithms due to their capability in handling small, complex data-sets [34]. Below is a set of advantages and disadvantages for utilizing the SVMs.

9.14 Conclusions

The rapid development of the Internet of Things (IoT) has led to increasing advancements in the healthcare industry. The development of the hardware platform, as well as the underlying software, led to the emerging Internet of Healthcare Things (IoHT). The demand for remote healthcare continuous monitoring systems using limited resources and biosensors has increased. In Connected Healthcare Applications, this study presents a detailed assessment of wireless medical biosensor networks. The main goal is to present a fundamental introduction of WMBNs and to highlight recent advances, with a focus on remote patient monitoring for the elderly and chronically ill. To fulfil the scientific idea of WMBN, a detailed investigation of WBSN architecture, problems, healthcare applications, and their demands is required. The WBSN's primary important elements are then covered, including data collection, fusion, telemedicine and remote patient monitoring, rehabilitation and therapy, biofeed-back, assisted living technologies, risk assessment, and decision making. It also gives an overview of machine learning techniques and how they're used in medical settings.

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