Smart Healthcare Using ML and Cognitive Radio Technologies

Subjects: Computer Science, Artificial Intelligence

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The rapid technological advancements in the modern world bring the attention of researchers to fast and real-time healthcare and monitoring systems. Smart healthcare is one of the best choices for this purpose, in which different on-body and off-body sensors and devices monitor and share patient data with healthcare personnel and hospitals for quick and real-time decisions about patients' health. Cognitive radio (CR) can be very useful for effective and smart healthcare systems to send and receive patient's health data by exploiting the primary user's (PU) spectrum.

Keywords: smart healthcare ; spectrum sensing ; optimizable tree ; machine learning ; cognitive radio

1. Introduction

In the current technologically fast-paced world, people are facing many health-related issues and concerns. Therefore, it is the need of time for quick and reliable healthcare and monitoring systems. Smart healthcare is one of the remedies to address health-related issues and patient care remotely in real-time scenarios. Smart healthcare has gained the attention of researchers and industries dramatically in recent years [1][2][3][4]. Smart healthcare can make it very easy and convenient for medical personnel to share their information and suggestions on real-time data of the patient's medical conditions and history in a short time. The electroencephalogram (EEG)-driven secure and reliable cognitive authentication system provides a solution to fix the security and privacy problems for an IoT-based healthcare system [5]. The effectiveness of existing diabetic foot ulcer (DFU) techniques can be enhanced by using a sensor-based remote patient monitoring (RPM) healthcare system [6]. The early detection of human health issues is very important for the better provision of cures. Different sensors in the IoT-based health system collects health-related data for the early detection and real-time monitoring of human health [7]. Cognitive radio (CR)-based smart healthcare is one of the most popular and important research areas nowadays. Hybrid optical camera communication (OCC) and Bluetooth low energy (BLE) are used to make an efficient smart healthcare system [8]. The system ensures that patients' real-time electrocardiogram (ECG) data are transmitted to a remote monitoring system in an efficient way. The smart healthcare system can also be beneficial for providing maximum advantages of smart medicine to patients at their door step by exploiting the CR technology. Smart medicine uses different artificial intelligence (AI) techniques to process the patient's health data on a micro level, even at the patient's genetic level, and prescribes relevant treatments [9][10][11]. Cognitive sensors in CR-based smart healthcare continuously sense the available spectrum to transmit and share the patients' data with the remotely placed server via CR base station(s) or a fusion center. An architecture of a CR-based smart healthcare system can be visualized in **Figure 1**. Different monitoring wireless sensors are attached to the human body. These sensors monitor the human body parts for which they are placed and collect the real-time data of the respective parts. These monitoring sensors are capable of performing spectrum sensing. Once they find a free spectrum, they share their collected data with a remotely placed fusion center or data server. Other components of the smart healthcare system, such as hospitals, ambulance services, pharmacies, and doctors' clinics, are also equipped with CR technology and are connected to the server. When the monitoring sensors on the human body share their data with the server, these components also receive those data simultaneously through the server. Then, according to the level of health condition based on the sensors' data, the respective component of the CR-based smart healthcare system responds to the patient and provides immediate and real-time advice and precautions.

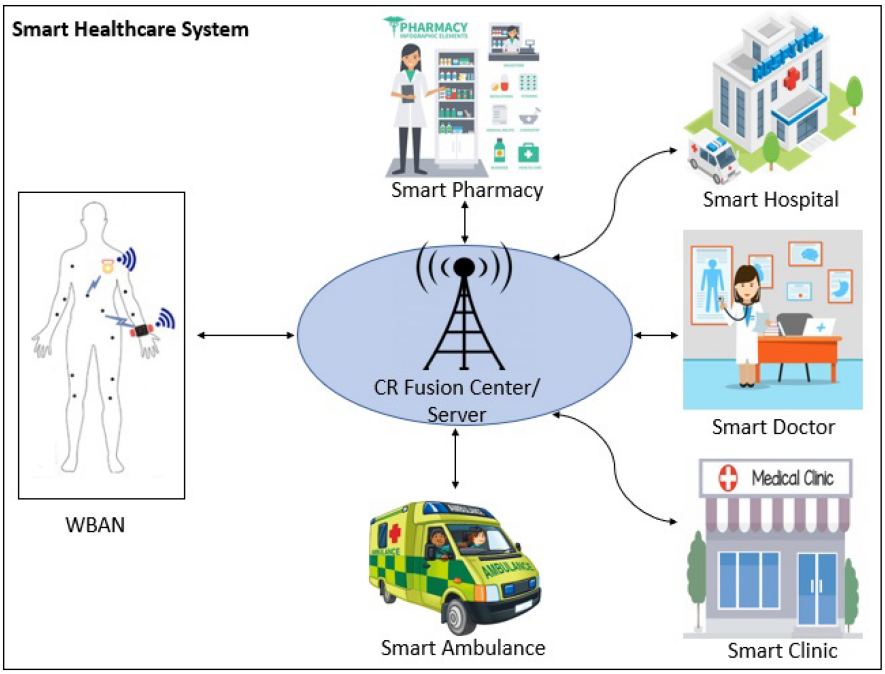

Figure 1. Cognitive radio-based smart healthcare system.

There has been significant growth in the consumption of wireless spectrum bands in the past couple of decades. Cognitive radio (CR) has been under rigorous research to overcome spectrum scarcity and underutilization [12]. Application areas of cognitive radio can be smart healthcare systems, disaster relief, military and defense, emergency scenarios, industry, transportation and communication, internet of things (IoT), wireless body area networks (WBANs), and many more [13][14][15]. The throughput of the cognitive radio-enabled unmanned aerial vehicle (CR-UAV) is enhanced by jointly designing the UAV trajectory and resource allocation [16]. High data rates and minimal end-to-end routing delays in CR-based IoT communication are achieved by using a reinforcement learning (RL)-based routing approach [17]. The energy harvested communication protocol is a good approach to optimize the throughput of the UAV-assisted CR system [18]. A Q-learning-based dynamic spectrum access is considered in three different access scenarios, such as orthogonal multiple access (OMA), underlay spectrum access, and non-orthogonal multiple access (NOMA), to utilize the spectrum resources intelligently in the cognitive industrial internet of things (CIIoT) [19]. The fair and cooperative medium access control (FC-MAC) protocol enhanced the performance efficiency of the heterogeneous CR-based vehicular ad hoc network (VANET) [20][21].

The most important part of cognitive radio technology is spectrum sensing. The role of this part is to sense the spectrum and detect unused or free channels with the help of secondary users (SUs). From its beginning, researchers have been researching the development of different methods for spectrum sensing. Various methods have been proposed by the researchers. Energy detection, cyclostationary feature detection, and matched filter [22] are the most commonly used methods of spectrum sensing. The probability of detection ($\mathscr{P}d$) and probability of false alarm ($\mathscr{P}f$) are among the important parameters used in spectrum sensing. A high value of $\mathscr{P}d$ and lower value of $\mathscr{P}f$ are always required to avoid interference by SUs to PUs. There exists a trade-off between the optimal sensing time and spectrum hole utilization in cognitive radio networks [23]. A solution of an optimization problem maximizes the spectrum utilization efficiency of secondary users by considering the different possible communication scenarios of SUs in CRN [24]. Sampling controlled block orthogonal matching pursuit (SC-BOMP), schemes of wideband compressive spectrum sensing (CSS) provided the high sensing accuracy of CRNs in real time [25]. A convolutional neural network (CNN) obtained high spectrum detection accuracy under different noise models in CRN [26]. One of the main purposes of smart healthcare systems is to provide health-related facilities to people remotely. In smart healthcare systems, most of the monitoring devices and nodes share their data with remotely placed servers or physicians through a wireless medium, but spectrum allocation for new wireless services and applications is a big challenge for authorities.

2. Smart Healthcare Using Machine Learning and Cognitive Radio Technologies

A smart healthcare system refers to the integration of advanced technologies, such as robotics and IoTs, data analytics, and intelligent algorithms of AI and ML, into the healthcare industry to improve patient care, streamline processes, and enhance overall efficiency of system. The efficient use of modern technologies can make smart healthcare systems

superior and robust over the conventional healthcare systems. Smart healthcare systems can encompass a wide range of advanced technologies and concepts as shown in **Figure 2**.

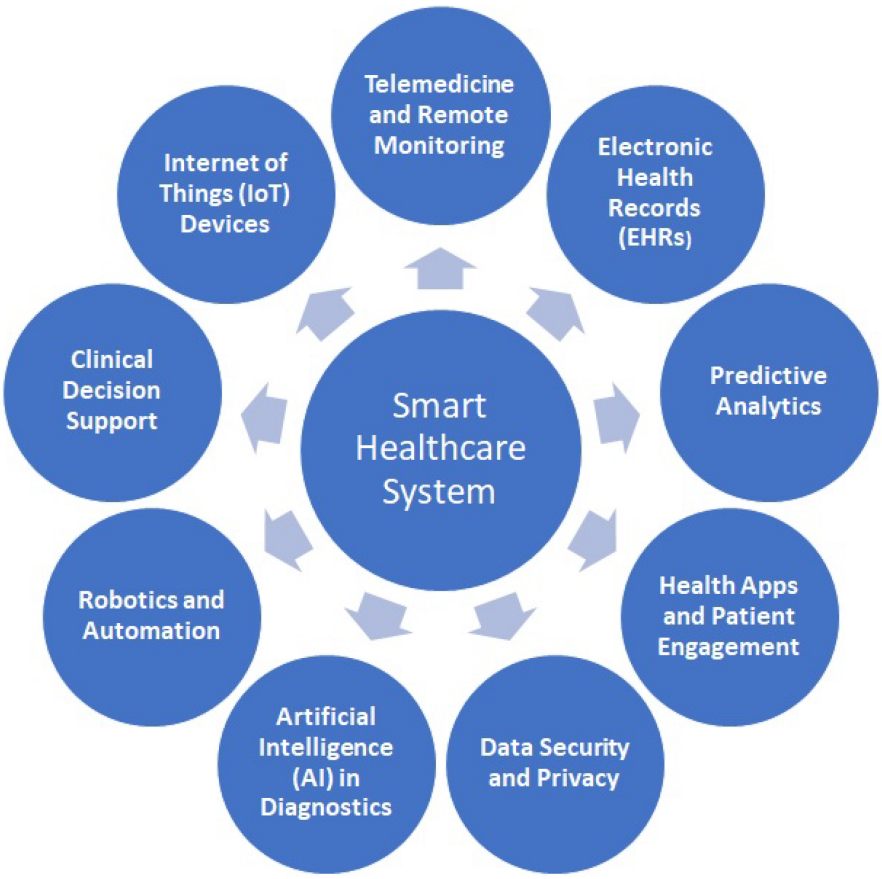

Figure 2. Advanced technologies as integral parts of smart healthcare system.

Data storage and the management of patient health records collected by monitoring devices have significant importance in an efficient smart healthcare system. Healthcare professionals can access patient health record through EHRs. EHRs ensure better care coordination between the patients and their physicians to reduce chances of errors in the treatment [27]. Telemedicine and remote monitoring in smart healthcare system help patients to consult and seek medical care advice from their physicians remotely. Monitoring devices regularly monitor health metrics and send real-time data to physicians for proactive intervention [28][29]. Different wearable health monitoring devices in the IoT-based smart healthcare system collect data of patients' health condition to provide personalized healthcare recommendations [30][31]. Smart healthcare systems can offer clinical decision support to healthcare professionals by providing evidence-based treatment recommendations and alerts about potential drug interactions or allergies. Robotic technologies can assist in surgeries, medication dispensing, and other medical tasks, enhancing precision and reducing the risk of human error [32]. Advanced data analytics and machine learning can predict disease outbreaks, patient needs, and trends. This helps healthcare providers to allocate resources effectively and make informed decisions. AI-based algorithms can be used to process medical images for faster and more accurate diagnosis of cancer or other diseases [33]. Mobile applications can encourage patient engagement by offering tools for medication reminders, exercise tracking, and lifestyle management. These applications can also provide access to health information and educational resources. As healthcare systems become more connected and reliant on data, robust security measures are essential to protect patient privacy and sensitive medical information. Smart healthcare systems are integrated with emergency services to provide real-time location data and medical information during emergencies, enabling faster and more effective responses. Analytics can help hospitals and healthcare facilities to optimize resource allocation, such as staff scheduling and bed availability, leading to improved patient flow and reduced wait times [34]. Comprehensive patient care also requires that different healthcare systems and devices can communicate and share data seamlessly with each other.

An efficient and successful smart healthcare system can be designed by incorporating machine learning and cognitive radio with it [35][36]. Smart healthcare devices and systems must be spectral and energy efficient while they are assisted by cognitive radio [37][38]. Spectrum utilization and energy harvesting protocols can make WBANs more convenient and efficient in smart healthcare systems and applications [39]. A patient-centric heterogeneous smart healthcare network predicts the patients' health condition by employing different machine learning algorithms, including decision tree [40]. Data security and the timely evaluation of patients' data in smart healthcare is the most important factor. A novel data

encryption solution has made medical data transmission secure between CR-based devices and systems in a smart healthcare network [41]. 5G and 6G technologies have high bandwidth and data rates; therefore, these technologies can have a key role in the development of smart healthcare systems for the betterment of humanity. A comprehensive review on 5G and advanced technologies-based smart healthcare solutions is given in [42].

A very famous research area in computer science is machine learning that aims to create algorithms and software which can train and test the system for different data sets of interest and act intelligently while they are introduced to new information [43]. Machine learning techniques and algorithms are also used widely in the development of modern technologies, such as image processing, computer vision, speech recognition, and object (face, text, posture, and people) detection in robotics [44][45]. Considering the effective use of machine learning in other areas of science and technology, the healthcare system can also take advantages of ML to transform conventional healthcare systems into smart healthcare. The dream of smart healthcare systems can become true by adapting ML and CR technologies in such a way that sensing and monitoring devices in the healthcare system can adapt their parameters according to the dynamic radio conditions for real-time data transmission and processing. A deep learning (DL)-based convolutional neural network (CNN) model showed good performance for detecting the movement of a fractured ankle after surgery [46]. Machine learning (ML) has been used extensively over the years to predict and decide the spectrum availability in CRNs. In [47], the authors used support vector machines (SVMs) for joint spectrum sensing and spectrum allocation to network dynamics-aware IoT devices. The cost-effective and energy-efficient spectrum detection of real-time signals in a CRN is performed by using SVM, decision tree (DT) and KNN [48]. Different ML and DL techniques and algorithms, including decision trees, are used to predict human emotions that are positive, neutral, or negative from the EEG signals [49]. Decision tree classifier with other ML classifiers [50] are used for predicting the free spectrum. A decision tree-based energy efficient protocol has made it possible for decease detection in mobile healthcare network [51]. The efficiency of health-monitoring systems can be increased by the privacy-preserving decision tree (PPDT) classification scheme [52]. Three tree-based algorithms—random forest (RF), gradient boosting (GB), and extra trees (ET)—are used to examine the importance of several aspects of medical staff engagement in healthcare organizations [53]. A novel segment-based cognitive radio vehicle ad hoc network (CR-VANET) architecture can solve the spectrum scarcity problem by using fuzzy and naïve Bayes algorithms [54]. KMeans, AND and OR spectrum-sensing techniques are used to compare their performance in CRNs [55]. Q-learning-based spectrum sensing adaptively allocates the multimedia data over multiple spectrum holes [56]. A decentralized RL resource allocation scheme improves the spectrum utilization [57]. Ref. [58] provides the solutions to different spectrum sensing challenges by using different supervised and unsupervised machine learning algorithms. An intrusion of unauthorized data during cooperative spectrum sensing (CSS) can be avoided by K-medoids and mean-shift data fusion methods [59]. A comparison of several machine learning techniques, including K-nearest neighbors, naive Bayes, random forest, SVM, etc., for spectrum sensing is presented in [60].

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