Chapter 1

Introduction to smart healthcare and the role of cognitive sensors

Smith K Khare, Asif Manzoor Khan, Varun Bajaj and G R Sinha

Artificial intelligence, deep learning, and machine learning technologies have greatly facilitated the upgrade of healthcare systems. Implantable sensors, wearable cognitive devices, and portable monitoring systems have enabled the acquisition and analysis of physiological data from anyone, anytime, anywhere. Furthermore, advancements in the Internet of Things (IoT) have facilitated the healthcare transition from face-to-face consulting to telemedicine. Cognitive sensors offer a way to monitor an individual's activities and biological and physiological traits. These sensors offer a wide range of applications in brain–computer interfaces, human activity recognition, diagnostic and decision tools for brain disorders, and analysis of human physiology. This chapter introduces a framework for smart healthcare systems, summarizes state-of-the-art smart healthcare systems, the role of cognitive sensors for health monitoring, an overview of applications using cognitive sensors, challenges in implementing smart healthcare, and the security challenges of smart healthcare systems. This chapter also aims to explore the current challenges in existing healthcare systems and future directions for advancing healthcare technologies with an integration of the Internet of Things and cognitive sensors.

1.1 Introduction

The word 'smart' has recently gained massive popularity in various fields. This word has evolved to follow a lightning progression in the research of technology development with simplistic procedures, tremendous information in terms of data, speed in decision-making, efficient power consumption, and secured systems [1]. The building of an intelligent system has contributed to almost every area, including innovative schools, intelligent transportation, smart campus, smart healthcare, and many more [1]. The intelligent system, in simple words, is a combination of the physical world composed of many sensors, actuators, algorithms, calculations, and

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decision-making. These components are information technology elements integrated with day-to-day objects and data networks, making the system intelligent and efficient. Smart healthcare is one such element or application area of these smart environments. Cognitive sensor data analytics combined with smart healthcare play an essential role in cognitive healthcare systems. A cognitive sensor enables timely detection of severe brain disorders and provides a way to improve the brain–computer interface. This chapter provides an overview of three critical components which are listed below:

(i) Introduction of smart and secure healthcare systems;
(ii) Elements of cognitive sensors;
(iii) Broad application areas and decision-making tools for sensor data analytics.

The remainder of this chapter is organized as follows. Section 1.2 provides an overview of smart healthcare systems along with critical components and security components. Section 1.3 covers different types of cognitive sensors along with application areas and data analytics stages, and finally, section 1.4 covers a conclusion of the study.

1.2 Smart healthcare

Health is a lack of illness, but also, it is characterized by a combination of mental, social, and physical well-being. People need good health for a happy and better life, a principle component of human life. The lack of medical experts, nurses, and physicians, outdated health services, a poor standard of living, and an ideological gap between the people of urban and rural areas are responsible for global health issues. The increase in informatization in today's era has resulted in the advancement of scientific theory and technologies. There is a rapid transition from traditional medicinal solutions to digitized solutions from abundant data. Intelligent and innovative health are not just mere words. Multi-level changes from low to high-level information has resulted in overall development. Low-level information can be routine activities, dietary habits, standard of living, etc. In contrast, high-level information comprises data acquired from body sensors, medical history, environmental factors, and family history. Technology advancement has resulted in caring from disease-centered treatment to patient-centered treatment, generalized to personalized management, clinical to regional health management, from disease level diagnostic treatment to preventive healthcare treatment [2] (figure 1.1).

1.2.1 Idea of smart healthcare

The concept of intelligent healthcare was first coined from the 'Smart Planet', introduced in 2009 by IBM. The Smart Planet was composed of embedded types of sensors that acquire data as multi-level information, denoising the data to make it free from artifacts. The artifact-free data is transmitted over channels using the Internet of Things (IoT), followed by information processing over the cloud using supercomputers, which then results in decision-making [3]. Similarly, smart

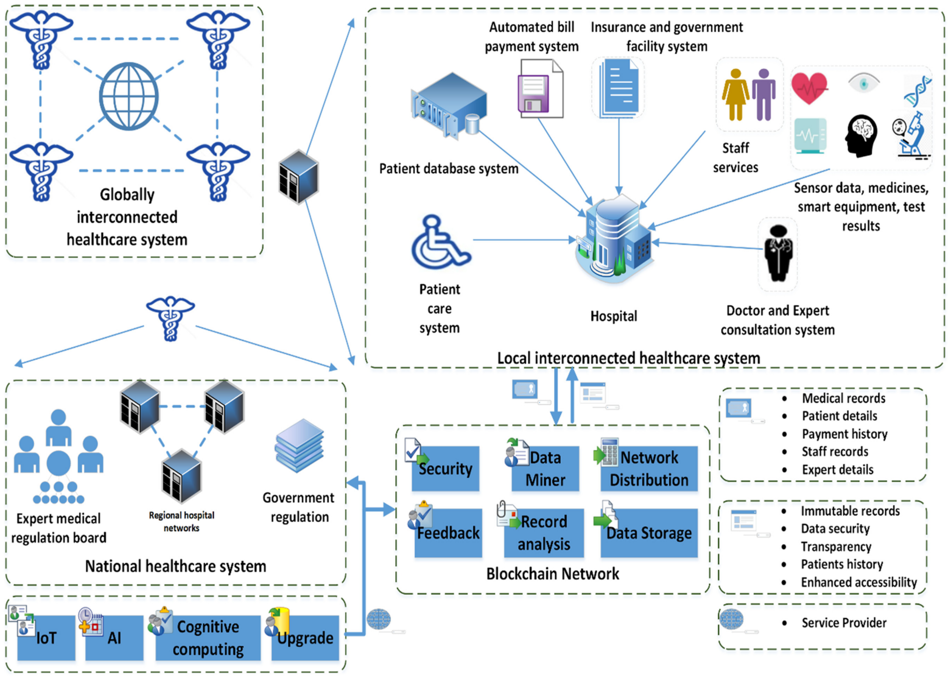

Figure 1.1. Broad overview of a smart and secure healthcare system.

healthcare integrates different parties for a targeted healthcare issue. To realize this, smart healthcare takes data from the sensors connected to various human body vitals using wearables and transfers the data from mobile to dynamically integrated networks for data analytics and decision-making using artificial intelligence (AI) algorithms. In simple words, smart healthcare is transitioning from treatment after disease diagnosis to the tracking of vitals to prevent it from occurring.

1.2.2 Technologies of smart healthcare systems

Competent healthcare consists of data acquired from multiple sensors with different parameters. The data can be an individual's habits, diet, activities, and type of work, as well as the data relating to vital organs like the heart, brain, muscles, etc [4]. Multiple biosensors record this data from the vitals in electrical activities, imaging techniques, or other techniques [5]. The next component of smart healthcare includes multiple participants like medical experts, nurses, patients, research institutes, and hospitals. Smart healthcare is an entire world composed of multi-dimensional data analytics for monitoring and preventing diseases, early diagnosis and timely treatment of diseases, intelligent data management, decision-making for individuals' good health, and new medical research breakthroughs. The elements of biotechnology combined with the IoT, modern mobile technologies, digital electronics, big data, and AI are the building blocks of intelligent healthcare, constituting the overall development of medical technologies. Assistance to the patients or individuals is offered by monitoring and analyzing data from multiple wearables and offering medical facilities through virtual assistance [4].

In contrast, from the medical expert's perspective, data is monitored remotely through a smart clinical decision support system. Based on the output of this system, assistance is provided to improve diagnostic services. Doctors use different integrated and multifunctional information platforms, including electronic healthcare records, laboratory management systems, picture and video communication systems, etc. Hospitals and research institutes use wireless services, including technologies like radio-frequency identification and the IoT for managing the supply chain, integrated data accumulation services, and high-performance computing for decision-making. Smart healthcare systems also assist medical experts in robotic surgery and tele-solutions in providing precise and accurate surgical operations. From a nurse's perspective, continuous monitoring, robotic assistance, and monitoring sensor data remotely can improve patient care. Finally, the use of AI, machine learning (ML), and big data analysis to screen drug data enables the identification of suitable subjects for testing and evaluation. Therefore, through continuous data analysis using advanced technologies, smart healthcare provides intelligent, low-cost, efficient, and low-risk solutions for medical assistance through telemedicine, fruitful use of medical resources, secured data transfer, and accurate surgical operations for a healthier society [5].

1.2.3 Status of the applications in smart healthcare systems

The applications and services of smart healthcare systems are mainly categorized into three parts: individual and family users, regional institutes, and scientific research centers (e.g. hospitals and universities). The critical application areas of smart healthcare systems are explained in the following sections.

1.2.3.1 Treatment and diagnostic assessments

Technological advancement, the rapid growth of ML and AI, and intelligent robotic technology have facilitated smart and innovative treatment and diagnosis of acute diseases. High-performing artificial intelligence has improved and achieved results for acute illnesses like cancer, hepatitis, COVID, and other types of healthcare abnormalities. Today, robotic and AI solutions have surpassed the accuracy of clinical experts, researchers, and doctors. Deep and ML-based automated computer-based clinical decision support systems have taken pathology and image-based detection to the next level. One example in this series is the clinical decision support system provided by IBM Watson (capable of delivering minute detailing of literature and clinical data). With a clinical support system, doctors offer early detection and diagnosis of various disorders, which reduces the probability of misdiagnosis, and provides timely medication [7].

1.2.3.2 Intelligent health management

The number of chronic diseases reported annually is rising worldwide [8]. Chronic diseases are incurable, slow, long for disease advancement, and costly to treat [9].

Health management through traditional healthcare systems and a doctor-centered approach are incompatible, incapable, and error-prone, with a rapid increase in cases. The new healthcare system offers automated patient monitoring, analysis of health data, and medical intervention of healthcare data. It also automates patient health data management through applications and information platforms. The advancement in data analytics has also facilitated the integration of data from multiple sensors to provide hierarchical health management systems using decision support systems. In addition, mobile platforms use wearable data to provide economical healthcare solutions, reduce medical errors, and provide ease of communication between a user and medical experts.

1.2.3.3 Virtual assistant

Virtual assistance is the analytics of big data as an information source and provides user-assisted or desirable output after evaluation through some algorithms and learning from past experiences. It uses expertise and understanding of scenarios to finish various tasks. Virtual assistance is crucial in bridging the gap between patients, nurses, doctors, and research institutes in the healthcare environment. The use of virtual assistance from a hospital or research institute perspective can facilitate saving workforce and medical resources efficiently to cover the need of doctors and patients simultaneously. From a doctor's perspective, virtual assistance helps to provide critical information to the patients and assists the patients with efficient medical procedures, thereby providing the best solution with minimal use of resources and time. On the other hand, from the patient's point of view, virtual assistance can significantly help track changes in the sensor data analytics in terms of abnormal body behavior and enable them to seek medical services more efficiently and conveniently [10].

1.2.3.4 Prevention and monitoring of diseases

Conventional healthcare diagnostic procedures are manual in terms of involving medical and scientific experts to collect data and make analyses. This includes data collection, comparison of healthcare records per the defined standards of the authorities, and providing the observed findings [11]. These manual, time-consuming, error-prone, and data-dependent techniques make the system inaccurate and slow. As a remedy, a smart healthcare system and analytics of various sensor data can be an effective solution. The smart disease analytics model acquires data from smart apps and wearable devices. The acquired data is uploaded to the cloud through wired or wireless networks. The efficient signal analytics and ML models with some efficient algorithms analyze the data and make real-time predictions to provide support through short message services [12]. These systems are updated to track the changes in decision-making or assist with the change in data.

1.2.3.5 Smart hospitals

The concept of intelligent hospitals is composed of three elements which are family or individuals (service seeker), doctors and nurses (service provider), and hospitals/research institutes (service infrastructure). Smart hospitals are information and technology-dependent, integrating IoT and data from various sensors [13]. The services provided by smart hospitals include services to patients, services to management, and services to the doctors/staff. The benefits to patients can be digital data monitoring, robotic assistance, innovative pharmaceutical services, and smart/secure payment services. The services to medical staff include smart assistance through digital platforms like computer-based decision-making, help through automated robots, and computer-based drug assistance to patients. Similarly, digital management of staff, intelligent tracking of biological instruments, digital drug management, and advanced services are provided by infrastructure management.

1.2.3.6 Drug discovery

The increasing amount of data, development of AI, and multi-disciplinary collaboration make drug research and development a prominent area. The traditional approach for drug discovery includes target screening, drug research and discovery, recruiting subjects for trials, clinical trials, results in analysis, and decision-making. The traditional methods are manual, slow, biased, and error-prone. However, automated screening of subjects, analysis of effects, and results using AI not only enhances discovery results but also expedites the research process. AI and ML not only provide an effective solution but also ensure robustness by auto-updating the parameters and features based on the addition of data from different races and countries [14].

1.2.4 Security of smart healthcare systems

All computer-based technologies are affected by a fear of security concerns. Similarly, serious security threads can also attack and affect intelligent healthcare systems. Healthcare systems are associated with critical data related to the health status of an individual. If cyber-attackers or individuals attack such data, it might modify crucial information, which may have life-threatening effects. Taking into account the importance of data, if necessary measures are not taken, vulnerabilities in the system could enable hackers to steal important information. In addition, continuous monitoring, rigorous auditing, and periodic updates are required to keep the system safe and secure [15]. The integrity, availability, authorization, confidentiality, non-repudiation, and authenticity of the system must be fulfilled to secure it (figure 1.2).

Alongside the security aspects mentioned earlier, some issues are also required to be addressed [16]. A minor breach in the security of an intelligent system could claim a life of an individual or affect multiple patients (figure 1.3). The following aspects are also required to be taken into consideration such as:

- routing attacks;
- location-based attacks.

In routing-based attacks, denial of services (DoS) is critical and can affect the security of healthcare systems and patient data. Many services are demanded or requested with unknown traffic to slow down or disable the benefits to patients and

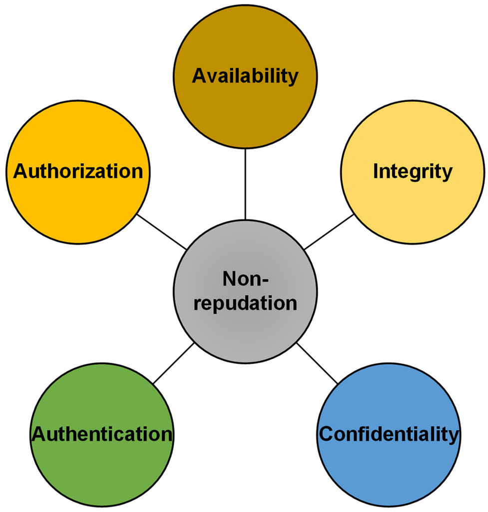

Figure 1.2. System requirement for a secure environment.

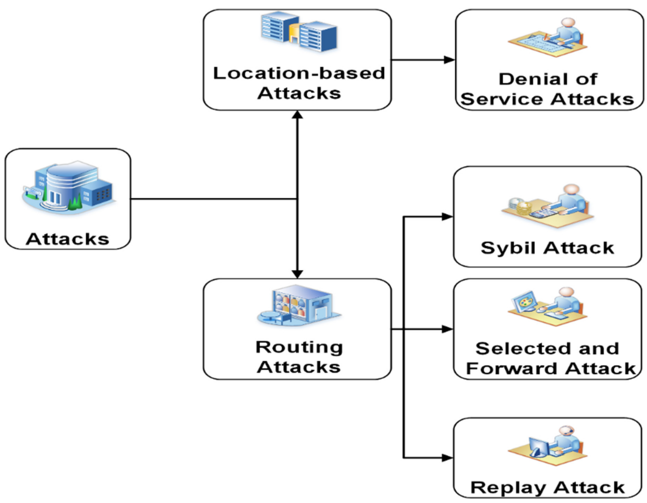

Figure 1.3. Types of attacks in a smart healthcare system.

hospitals. In DoS, patients may gain access to information without any authentication. It also enables attackers to send false information about the patients resulting in misdiagnosis, fraudulent emergency calls, and wrong treatment. A pictorial example of DoS is shown in figure 1.4(a).

Location-based attacks are categorized into Sybil attacks, replay attacks, and forwarding attacks (figure 1.4(b)–(d). During Sybil attacks, an attacker uses a fake ID to communicate with other nodes in the network. It destroys the identity of the nodes obtained while communicating and replicates the counterfeit nodes.

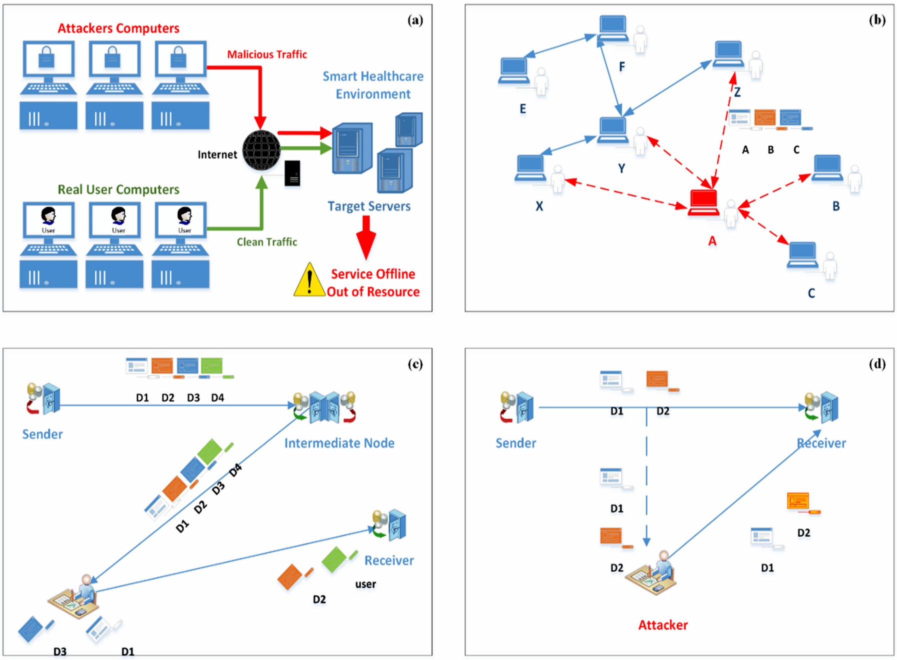

Figure 1.4. Exemplary illustration of various attacks: (a) denial of services attack, (b) multiple ID Sybil attack, (c) drop selected packets and forward attack, and (d) replay attack.

In a replay attack, an attacker gains access to a healthcare system, capturing the network information and sending it to the receiving node with the claim of being an original or authenticated user.

The forwarding or a gray hole attack is a particular type of black hole attack. During forwarding attacks, access is gained to multiple nodes that behave like a normal node. Information is dropped in terms of packets and attempts are made to send new packages with the wrong information. This is one of the most dangerous attacks; harmful to the medical healthcare systems or patients seeking treatment.

The above threats are malicious to the healthcare system, and demand an urgent solution. The steps following can mitigate these security threats.

1. Timely update of the hashes and the certificates.
2. Periodical conduction of secure booting.
3. Secured authentication.
4. Strong and secure communication and routing protocol.
5. Devices with end of life capabilities.
6. Efficient and secured storage of certificate and keys.
7. Update of firmware, devices, and applications.
8. Voice, facial, handprint, and fingerprint scanner.
9. System with durability, flexibility, stability, uniqueness, and universal characteristics.

1.3 Cognitive sensors

The human brain is one of the crucial organs in the body. It is the central control module of the body that coordinates activities like memory creation, physical activities, emotional sensation, and hormone secretion. Analogous to the electronic computer system, neurologists consider the brain a biological computer responsible for reasoning, problem-solving, creativity, and capturing and storing external information [17]. It combines about 100 billion neurons and 1000 billion support cells. These cells and neurons communicate through electrochemical reactions to generate a pattern as per the changes occurring in the brain providing information about neurological states [18]. These patterns are studied to develop a real-time brain–computer interface (BCI) system and detect brain disorders.

1.3.1 Types of cognitive sensors

Multiple techniques have been developed over time to access brain patterns. These are categorized as blood flow based and electrical activity based methods. The blood flow based plans include computerized tomography (CT), magnetic resonance imaging (MRI), functional MRI (fMRI), and positron emission tomography (PET). These are based on the fact that cerebral circulation and neuronal processing are correlated. Electrical activity based approaches overcome these limitations since electric waves are quick and direct measures of brain activity. Electroencephalography measures the electrical activities of the brain, magneto-encephalography measures magnetic activities of the brain, and the brain activity in fNIRS is measured by using near-infrared light.

1.3.1.1 Computed tomography

Hounsfield was the first to coin the prototype of the CT scanner in 1969. It is also known as x-ray CT, utilized by archeologists, biologists, radiologists, neurologists, and other scientists to study and analyze a targeted area by generating cross-sectional images [19]. CT scans use x-rays to show the brain's structure, with details such as blood perfusion (plates a and b). The perfusion generates two-dimensional images that are often low in resolution. Over time, significant improvement in CT scans have been achieved. Different variants of CT scans have been developed to generate high-resolution images that enable deeper investigation of brain regions. High-resolution CT requires high radiation drug dose but results in the production of high-resolution images. Micro-CT can produce a spatial resolution of about 1–100 μm. Three-dimensional ultrasound CT is another advancement with high-resolution 3D proofs for identifying various abnormalities and disorders.

The risk of CT is minimal. However, if produced by a more significant number of scans, this slight risk may result in serious public health issues. The radiation from a CT scan increases the risk of cancer [18]. The CT scan technique is especially more likely to cause cancer in children than in adults. As per the study, the chances of developing brain tumors and leukemia increase after exposure to CT radiation [20].

1.3.1.2 Positron emission tomography (PET)

The PET scan technique is a functional nuclear medicine technique used to display the total concentration of the labeled radioactive elements in the body with clear images. The PET scan measures the emissions from radioactive materials called radiotracers injected into the bloodstream. The tracers are labeled with fluorine-18 (F-18), nitrogen-13 (N-13), oxygen-15 (O-15), and carbon-11 (C-11) [21].

The amount of radioactive dose injected during PET is the same amount as used in a CT scan. The typical duration to obtain a PET scan is about 10–40 min. The positron emission data is computer-processed to produce two- or three-dimensional images showing the distribution of chemicals throughout the brain. A cyclotron produces positron-emitting radioisotopes, which are utilized to label chemicals [19]. The PET scan is a powerful tool for diagnosing non-curable brain disorders like schizophrenia, Parkinson's, and Alzheimer's, and in addition, to identify local neurofunctional changes by voluntary movements and tactical movement of the human body.

1.3.1.3 Magnetic resonance imaging

Magnetic resonance imaging (MRI) is a non-invasive visualization to study the anatomy of the human brain and other vital human organs. The MRI technique provides excellent fine resolution of the gray and white matter of the brain [19, 22]. The different variants of MRI are gradient and spin echo, magnetic resonance angiography, susceptibility and diffusion-weighted, and functional MRI (fMRI). The advantage of MRI is that it is radiation-free compared to other imaging variants like PET and CT scans. During MRI studies, a strong magnetic field is produced by magnets. The magnetic field results in hydrogen ions alignment in the targeted portion. The spin echoes of these ions produce images by the computer system. In addition, it is also possible to get time-series data from the fMRI. MRI and fMRI have been widely used to detect brain infections, CNS tumors, brain disorders, and spine infections.

1.3.1.4 Functional near-infrared spectroscopy

In preterm newborns undergoing intensive care, fNIRS was first utilized to monitor the proper supply of nutrients and oxygen to the brain [23]. It was first used with a single channel measurement. fNIRS is a non-invasive neuroimaging technique that maps measurement of brain tissue concentration. It assesses variations in blood oxygenation levels in various brain regions, revealing the areas of the brain employed for various cognitive tasks. Through the use of fNIRS, the color of light reflected back from the skull is measured.

It is becoming more commonplace to examine infant brains using this method because it is absolutely secure. Using this method to measure brain activity carries no risks. Additionally, fNIRS provides better spatial and temporal resolution than EEG and fMRI, respectively. Furthermore, although fNIRS' spatial resolution is less precise than fMRI's, it nevertheless allows for the localization of activity patterns to certain cortical areas. When examining the quickly developing brains of young infants and children, such knowledge is essential.

1.3.1.5 Magnetoencephalography

Magnetoencephalogram (MEG) signals measure the brain's magnetic field variations that capture neuronal activities [24]. The spatial resolution of magnetoencephalography is much better than that of electroencephalography. Due to the excellent spatial resolution provided by an MEG, it has been widely accepted in detecting brain disorders and stroke identification. The technological advancement has also improved spatial resolution to another level because of source location techniques and an increased number of sensors (i.e. more than 250 channels). The main difficulty in capturing the brain's neuronal activities using an MEG is the strength of signals generated by an MEG of order pT (which is about 100 times less than that of the Earth's magnetic field) [24]. However, the minute magnetic field generated by neuronal processing is measured by a highly sensitive magnetic field meter called a superconducting quantum interference detector, due to which an MEG recording is possible. Digital advancement has proved magnetoencephalography to have a unique feature in the assessment of stroke motor rehabilitation. The quantitative magnetoencephalography technique has also shown a significant breakthrough in brain disorder and stroke assessment. However, MEG-based research was started very late, requiring further exploration for stroke assessment and brain disorder detection. In magnetoencephalography, a specific magnetically shielded room is needed to avoid the effect of external magnetic noise on the brain-generated magnetic field. This limits MEG utility to real-time aspects like BCI systems. In addition, magnetoencephalography requires bulky and costly equipment.

1.3.1.6 Electroencephalography

The other technique based on electrical activity extensively used for assessing brain patterns is an electroencephalogram (EEG) record [25]. The measure of electrical activities of the brain's nerve cells of the scalp is measured by an EEG. The advantages of an EEG include short time constants, function in realistic environments, and simple and inexpensive equipment. EEG signals study various neurological states in the form of electrical activities. During an EEG recording, sensors placed at the appropriate location on the scalp can reveal crucial information about the changes in the brain. EEG electrodes are placed over the head of subjects using the 10–20 electrode positioning system [26]. It is an internationally standardized system which records spontaneous EEG. The recorded EEG signal has amplitude in the micro-volts (μV) range, and frequency variation falls in the range of 0.5–60 Hz [25]. The recording of an EEG provides excellent temporal resolution of rapid brain activities, but it comes with a cost of limited spatial resolution due to a limit on electrode placement [24]. The technological advancement in EEG acquisition has facilitated up to 256 electrodes or channels. An EEG signal consists of several base frequencies or rhythms, which reflect certain behavioral, diagnostic, therapeutic, and neuropsychiatric states of the brain [25]. The base frequencies of an EEG are categorized into the following frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–60 Hz) [25]. EEG signaling facilitates portable, low-cost, non-invasive, non-radioactive, and real-time solutions for acquiring neural activity [27]. This attracts researchers across the globe to investigate changes in the brain from EEG signals for various physiological conditions and neurological brain disorders [28, 29].

1.3.2 Applications of cognitive sensors

The data from cognitive sensors are composed of images or time-series changes in brain activities. The data from the sensors are utilized to detect various brain abnormalities and activities. Detection of these sensors' instantaneous changes in the brain has provided therapeutic and technical advancements. The revolution in healthcare has been possible due to these minute changes in brain variation detectors, resulting in the detection and diagnosis of various brain disorders such as epilepsy (seizure), Parkinson's disease, Alzheimer's disease, schizophrenia, attention deficit hyperactivity disorders, tumor detection, and many more [30, 31].

The increasing rate of neurological disorders has a high economic burden on patients and their families. One person in every three individuals is affected by some neurological condition in their life [32]. Over the past three decades, there has been a 40% increase in deaths due to neurological disorders and still counting [33]. A survey conducted between 1990–2016 suggests that in 2016, about 276 million people had disability-adjusted life-years due to neurological disorders [33], among the second highest causes of death globally. The incidence of neurological disorders in males was higher than in females [33]. The number of deaths and disability-adjusted life-years was highest due to stroke, migraine, Alzheimer's disease and other dementias, and Meningitis. Epilepsy ranked fifth among all, whereas Parkinson's disease was at 11th position [33]. According to The Pan American Health Organization, in 2019, more than half a million deaths were accounted for due to neurological conditions, of which 40% included male (213 129) and 60% were female (320 043) [34]. About 32.9 deaths per 100 K population (age-standardized), including 33.1 and 32.2 deaths per 100 000 population in men and women [34]. Years of life lost due to premature mortality (YLL) were 7.5 million (3.5 and 3.9 million YLLs in men and women, respectively).

In contrast, years lived with a disability were about 8.2 million, including 3.1 and 5.1 million males and females [34]. Most brain disorders are incurable, but their symptoms develop over time and timely detection and proper medication may provide vital solutions to prevent or reduce the advancement of symptoms. Therefore, there is an urgent need for an accurate and automated decision-making model for the timely detection and diagnosis of these neurological disorders. In addition, these neurological disorders severely affect the motor imagery abilities of individuals, making it difficult for them to carry out daily activities. Therefore, efficient and accurate detection of physiological conditions like the detection of emotions, motor imagery tasks, sleep stages, drowsiness, and mental states play a crucial role in developing the brain–computer interface (BCI). The development of a BCI using physiological states not only helps in technological advancements but also provides ways to make the individual affected by different accidents partially independent. However, detecting neurological conditions directly from raw images and time-series signals is difficult due to instantaneously varying signals. Therefore, analysis of these images and signals using different tools can extract hidden representative information to enable decision-making (figures 1.5 and 1.6).

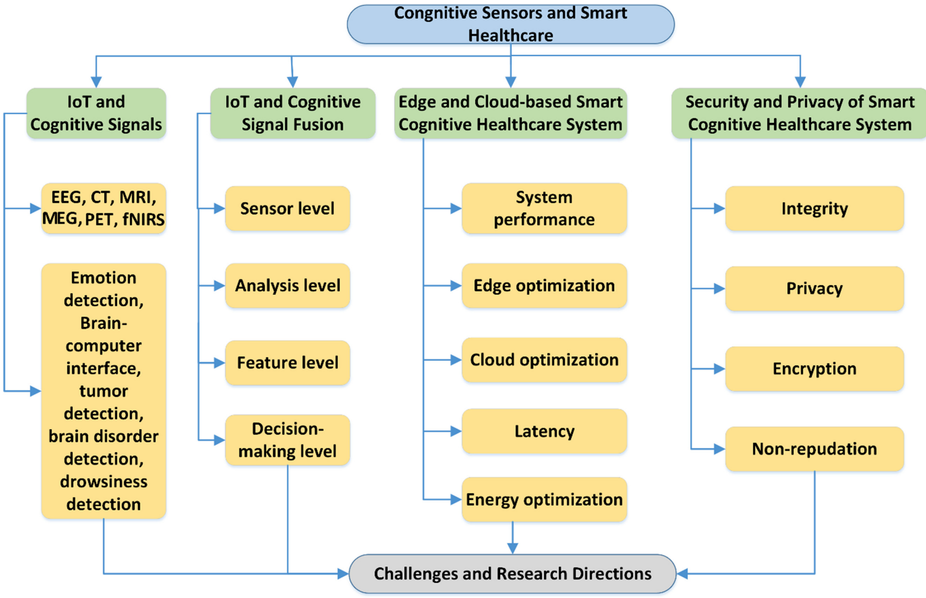

Figure 1.5. Direction and challenges of various levels of cognitive sensor data analytics.

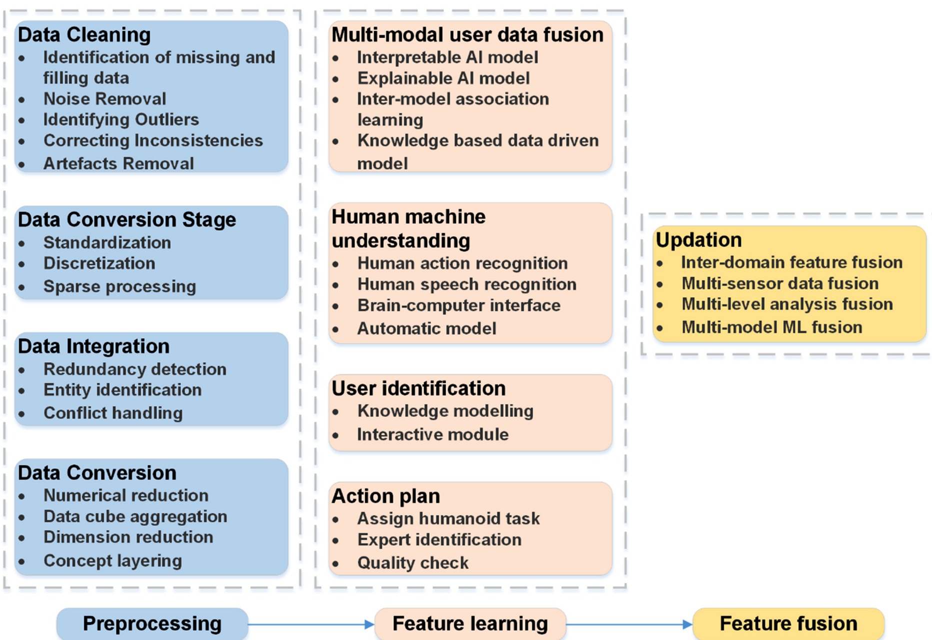

Figure 1.6. Overview of multi-level cognitive sensor feature fusion.

1.3.3 Analysis of cognitive sensors' data

Analysis plays a crucial role in identifying critical information hidden in the data acquired from cognitive sensors. Various types of analysis of the image and time-series data are required to find relevant information. Image and signal processing are crucial in removing different kinds of artifacts and noise from the image and time-series data. Over time, various tools have been developed for analyzing and classifying this data. A brief introduction to some of the available techniques is listed and discussed below.

1.3.3.1 Time-domain analysis

Order statistics, principal component analysis, independent component analysis (ICA), and optimum allocation sampling (OAS) are all elements of the time-domain analysis used to evaluate different features [35]. The statistical features used for analysis and classification of brain states using cognitive sensors' data involve evaluation of mean, standard deviation (STD), temporal mean, quartile, skewness, and kurtosis. But direct extraction of such features may not provide distinctive characteristics for classification. OAS converts a long-length non-homogenous cognitive data sequence into a homogenous sequence and has also been used for the analysis and classification of cognitive signals. ICA has been extensively used to lower the dimensionality of the signals. It decomposes multi-dimensional time-series signals into statistically independent components. The utility of ICA has been found extensively in feature extraction, artifacts removal, and channel selection [36].

1.3.3.2 Frequency-domain analysis

This analysis involves transforming signals into the frequency-domain to analyze spectrum, energy, and power. The estimation of the data spectrum is achieved with two types of techniques:

(a) Non-parametric analysis methods, (b) parametric analysis methods. The frequency-domain analysis done using non-parametric methods is also known as a classical method. Power spectra are obtained from autocorrelation sequences using Fourier transforms [37]. In this category, the Welch method is used for the estimation of the power spectrum. However, the non-parametric methods lead to the leakage of spectral components due to which researchers shift their interest to the non-classical or parametric methods. Non-classical methods or parametric methods are employed to evaluate spectral content. One such type of non-classical method is autoregressive model coefficients. The wavelet transforms, fast Fourier transform (FFT), and Walsh transforms have been explored for analyzing the frequency components of the signals [38].

1.3.3.3 Filtering and non-linear analysis

Filtering techniques have also been used for the analysis of cognitive signals. Filters have been designed to obtain different spectral components, rhythms, and features to extract important information from the sensors' data. Non-linear analysis involves techniques like the largest Lyapunov exponent, fractal dimensions

(Higuchi, Kolmogorov, and Katz), correlation dimensions, and Hurst exponent [37]. The chaotic measures have been studied to check the variability and predictability of cognitive signals. In addition, evaluation of recurrence quantification analysis, minimum redundancy and maximum relevance, and magnitude squared coherence estimate have also been explored. The approximate entropy, sample entropy, Renyi's entropy, wavelet entropy, spectral entropy, fuzzy entropy, permutation entropy, Tsallis entropy, Kolmogorov–Sinai entropy, higher-order spectra entropies, recurrence quantification analysis entropy, Karskov entropy, Shannon entropy, sure entropy, and neg-entropy are suggested for exploring the variability and predictability of cognitive sensors' data [39].

1.3.3.4 Non-stationary decompositions

The decomposition technique is a powerful tool used for the analysis and classification of sensors' data. It splits the signals into multi-components providing the characteristics of a signal. These multi-components are used for feature extraction and further for classification purposes. Discrete wavelet transform (DWT) and wavelet packet decomposition (WPD) decompose a finite time signal into sub-bands (SBs). It is obtained by scaling and shifting operations on the mother wavelet [40]. In DWT decomposition, an appropriate number of decomposition stages are defined. The test signal passes through the high-pass and low-pass channels simultaneously in the first stage, followed by down sampling. The output of each stage represents two components or coefficients: detail (D) and approximation (A). The approximation (A) part is further decomposed following the same process as the previous stage. The procedure continues until defined levels of decomposition are achieved. WPD is an extension of DWT in which the detail coefficients D are also decomposed along with approximation coefficients [40]. This variation produces a different number of components for both decompositions. For the J-stages, DWT produces $J + 1$ set of components, whereas WPD generates $2J$ set of components [40]. Advanced versions of DWT have also been developed, which are tunable Q-factor wavelet transform [38, 41, 42], rational dilated wavelet transform [28], dual complex wavelet transform, and flexible analytic wavelet transform which uses an iterative filter bank structure [43]. Empirical mode decomposition decomposes the signal into instantaneous amplitude and instantaneous frequency components [44]. The sub-signals represent the combination of amplitude and frequency-modulated components called intrinsic mode function. Empirical wavelet transform builds adaptive wavelets capable of extracting amplitude and frequency-modulated components from a signal [45]. Separating the distinct modes is the same as segmenting the Fourier spectrum and applying some filtering to each detected support, which represents the capability to extract and classify statistical features. A signal can be divided into several modes using variational mode decomposition. VMD determines the relevant bands and adaptively estimates the bandwidth of modes, due to which it has gained wide acceptance [46, 47].

1.3.3.5 Time–frequency analysis

Time–frequency (TF) analysis describes how the spectral content of a signal varies with time. Time–frequency representations (TFRs) are divided in two main classes:

linear and quadratic techniques [48, 49]. Linear TFRs work on the linearity principle (i.e. if a signal $x(t)$ is a linear combination of some signal components, then the TFR of $x(t)$ is also a linear combination of the TFRs of individual signal components [48]). Two important linear TFRs are: short-time Fourier transform [35] and wavelet transform [50]. In quadratic TFRs, the variants of Wigner–Ville TFR have obtained the most attention. The Wigner–Ville distribution (WVD) TFR attains a good tradeoff between times versus frequency resolution [30, 50, 51]. The WVD has better resolution than linear TFRs but suffers from cross-term interference.

1.3.3.6 AI-based decision-making

AI is the emulation of human intelligence in devices that have been designed to behave and think like humans. The ability to reason and take actions that have the best likelihood of reaching a certain objective is the ideal quality of AI. The idea that computer programs can automatically learn from and adapt to new data without the aid of humans is referred to as ML, which is a subset of AI. Deep learning algorithms, which are the subset of ML, allow for this autonomous learning by ingesting vast quantities of unstructured data, including text, photos, and video. In short, AI is a bigger domain of which ML and DL are the subsets as shown in figure 1.7.

With the advent of intelligent healthcare, ML has gained much traction in medicine and is very effective. It improves service delivery, makes it faster, gives healthcare facilities the ability to reach singularity, and improves the productivity of medical staff by reducing the time and effort to do things. Additionally, it supports patients' efforts to guard their money against pointless purchases. An illustrative classification of various machine learning modalities is shown in figure 1.8. Ml techniques like the support vector machine (SVM), decision tree, ensemble class of classifiers, k-nearest neighbor, and artificial neural network models have

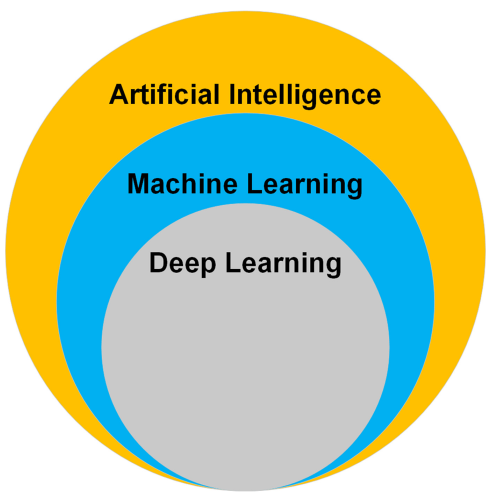

Figure 1.7. Classification of AI, ML, and deep learning.

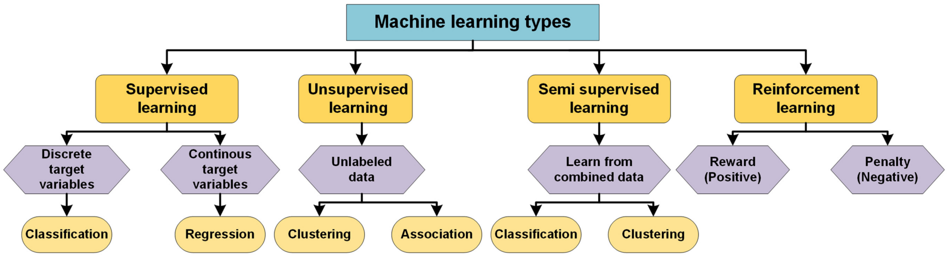

Figure 1.8. Classification of machine learning techniques.

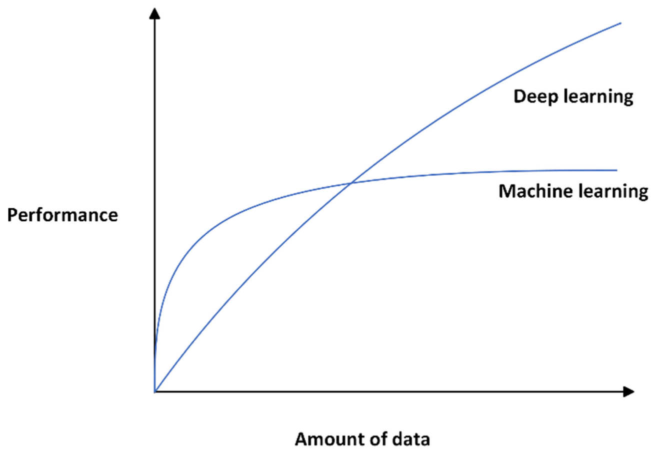

Figure 1.9. Exemplary performance comparison of ML and deep learning techniques versus amount of data.

significantly contributed to healthcare informatics [52]. These networks are able to not only classify whether an individual has some abnormalities or not but also successfully predict the risk of disease development from various day-to-day parameters. However, with the advent of technology, the amount of data has risen multifold. This rapid increase in the amount of data has limited the performance of traditional ML techniques to some saturated level. Therefore, deep learning techniques have recently grabbed a lot of attention in data analytics in almost every field. The biggest advantage of deep learning technology is that with the increase in input data, the system's performance is improved drastically with more illustrative model parameters, as shown in figure 1.9. This technological and data advancement has shifted the data analytics domain from ML to the deep learning era [53]. The deep learning modalities are so diverse and broad that they can be used as a single component to discriminate or generate the domain information, but also, in combination with these discriminative and generative data analytics, take smart healthcare data analysis to the next level. Figure 1.10 provides a brief overview and taxonomy of the recent deep learning techniques.

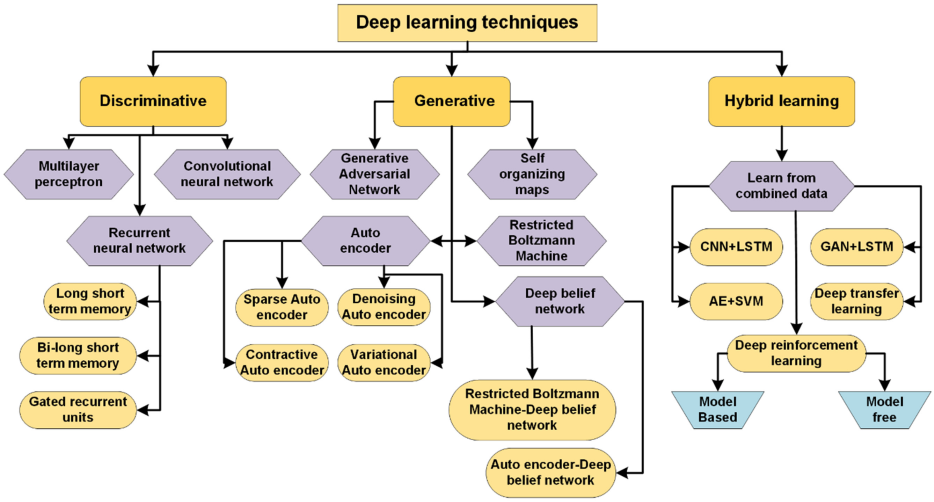

Figure 1.10. A taxonomy of DL techniques.

1.4 Conclusion

The issues of smart healthcare and cognitive sensors are solved using technology and regulation, which are two sides of the same coin. The first side of technology can be inoculated by maturity, scalability, and stability of the related technologies through updates and upgrades. In addition, we require interpretable and explainable analysis of the big underlying data to achieve maximum performance and compatibility for different sensors, devices, and platforms. Lastly, stable data transfer, integrity, security, and authenticity can be maintained by the use of blockchain techniques. Regulation of the proposed systems can be achieved through seeking expert suggestions from relevant fields and industrial goals. As the technologies are associated with healthcare systems, the developed solutions must provide:

- self-management;
- privacy of individuals and their data;
- timely and appropriate medical services which are cost-effective and result oriented.

To sum up, smart healthcare should improve overall system efficiency, reduce research time, provide timely and accurate medical aid, reduce service costs, and have a safer environment. In terms of cognitive sensors, a standard protocol must be designed for a particular brain-related issue. The solution must be secure to acquire the users' data, must be able to produce accurate interpretation with minimal human intervention, and provide effective and timely medical treatment. There exists a lot of challenges in the current healthcare system about the rapid and lightning advancements in technological development, especially in the field of AI, differences in the opinions of patients, doctors, experts, researchers, and healthcare industries, lack of global standards, and versatile studies of the topic including various parameters like geographical locations, race, and varying medical standards.

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