Chapter 1
Computational Intelligence for Brain Tumors Detection

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Abstract Recently, computational intelligence (CI) techniques have become efficient intelligent tools for brain tumor detection. It has become one of the major research subjects in medical imaging and diagnostic radiology. In the area of processing the brain images, computer-aided diagnosis (CAD) systems are basically relied on different CI techniques in all its stages to implement a smart consultation system that can help the radiologists by providing a second opinion that can assist in detection and diagnosis of brain tumors. This paper presents a comprehensive and up-to-date research in the area of digital medical imaging covering a wide spectrum of CI methodological and intelligent algorithm. The paper discusses the current research of the CI techniques for developing smart CAD systems. We present two applications for a hybrid intelligent technique for automatic detection of brain tumor through MRI. The technique is based on the following CI methods: the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed-forward back-propagation neural network to classify inputs into normal or abnormal.

1.1 Introduction

Magnetic resonance imaging (MRI) is an imaging technique that plays a vital role in detection and diagnosis of brain tumors in both research and clinical care for providing detailed information about the brain structure and its soft tissues. The image-processing techniques can provide great help in analyzing the tumor area. Computer-aided detection (CAD) has been developing fast in the last two decades.

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The main idea of CAD is to assist radiologists in interpreting medical images by using dedicated computer systems to provide 'second opinions.' The current research reveals that the CAD systems of human brain MRI images are still an open problem [1, 2].

On the other side, AI and CI offer robust, intelligent algorithms and smart methods that can help to solve problems in a variety of healthcare and life sciences areas [3–6]. This paper presents some of the CI techniques for managing and engineering knowledge in digital computer-aided diagnosis (CAD) systems. Some applications of the author and his colleagues that have been carried out in last years are discussed. The paper is organized as follows: Sect. 1.2 presents the computational intelligence paradigms. Section 1.3 presents the subareas of the intelligent of healthcare informatics. Section 1.4 discusses the applications of deep learning technique in health informatics. In Sect. 1.5, we discuss the medical imaging techniques for human brain. Section 1.6 presents our applications of brain tumors diagnosis using CI techniques, and then, we conclude in Sect. 1.7.

1.2 Computational Intelligence Paradigms

Computational intelligence (CI) is the study of intelligent computer algorithms that improve automatically through experience. CI aims to enable computers to learn from data and make improvements without any dependence on commands in a program. This learning could eventually help computers in building smart models for specific task for prediction purpose [6–8]. Figure 1.1 shows the inherently interdisciplinary field of research of CI. From the figure, it can be seen that CI includes the following disciplines: neurobiology, information theory, probability, statistics, AI, control theory, Bayesian methods, physiology, and philosophy.

Figure 1.2 shows the computational intelligence paradigms and models from intelligent computing and AI perspectives [9–19].

(a) Cognitive computing: This model is based on cognitive sciences (human memory, languages, vision, stress, learning, and sleep phenomena)

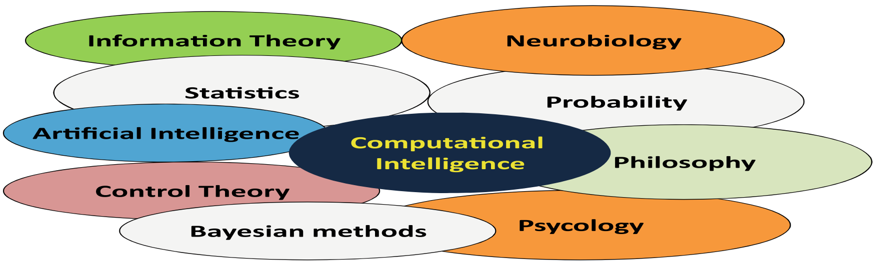


Fig. 1.1 Interdisciplinary field of research of CI

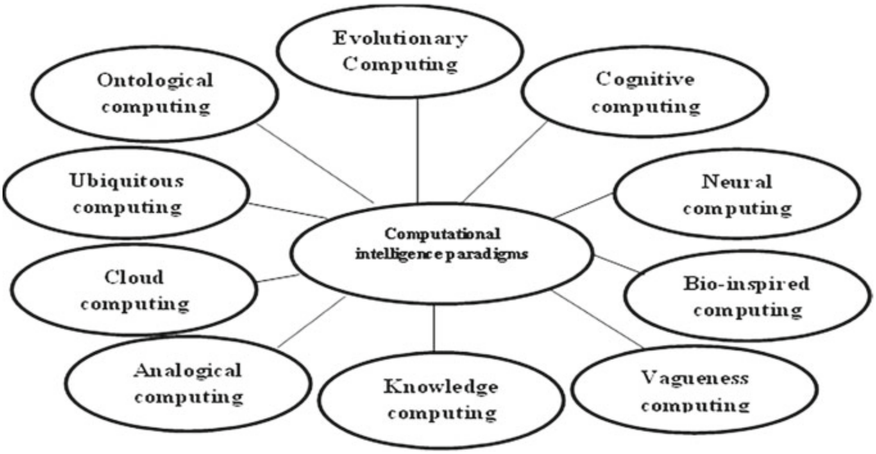


Fig. 1.2 Computational intelligence paradigms

(b) Neural computing: This is based on neuroscience, biological sciences, and mathematics
(c) Bio-inspired computing: This is based on life sciences (biology and medicine)
(d) Vagueness computing: This is based on fuzzy logic theory and rough sets
(e) Knowledge computing: This is based on knowledge engineering issues (management, discovery, acquisition, and modeling)
(f) Analogical computing: This is based on case-based reasoning methodology
(g) Cloud computing: This is based on distributed processing and Internet of things (IoT)
(h) Ubiquitous computing: In this, model computing is made to appear anytime and everywhere
(i) Ontological computing: This is based on the ontological engineering concepts
(j) Evolutionary computing: This is based on simulated annealing, swarm optimization, and ant colony.

1.3 Computational Intelligence Applications in Intelligent Health Informatics

Figure 1.3 shows the main and subareas of the intelligent health informatics. From the figure, it can be seen that it is a multidisciplinary field of research and covered many digital healthcare areas, namely dental, neuro, biological, medical, nursing, and clinical. From the informatics perspective, each are composed of many fields of research, e.g. the medical informatics contains, knowledge engineering, medical imaging, expert systems, robotic surgery, education, learning, and training [20–22].

In the last years, various computational intelligence techniques and methodologies have been proposed by the researchers in order to develop digital healthcare systems

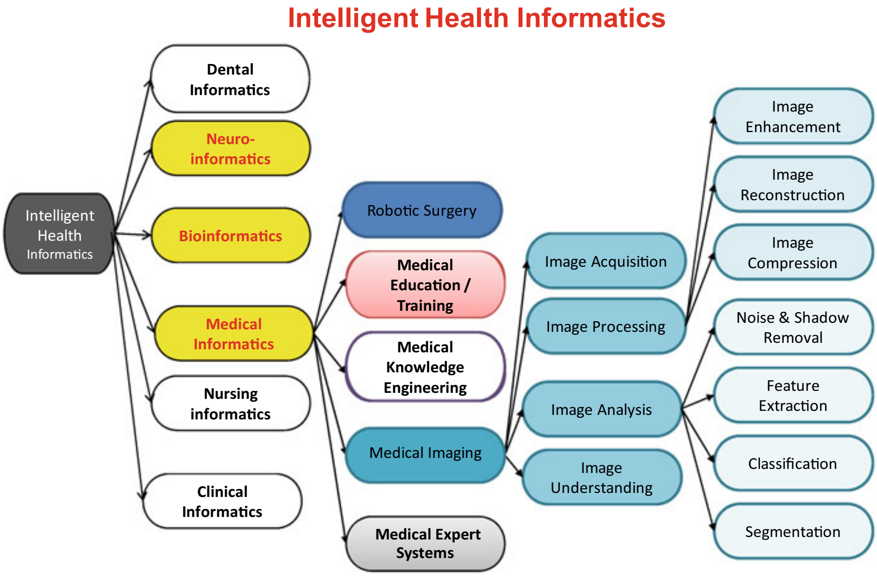


Fig. 1.3 Intelligent healthcare informatics

for different medical and healthcare tasks. These systems are based on the knowledge engineering paradigms and artificial intelligence (AI) concepts and theories. Many types of such systems are in existence today and are applied to different healthcare domains and tasks.

CI is successfully used on a wide variety of medical problems and data. Medicine is largely an evidence-driven discipline where large quantities of relatively high-quality data are collected and stored in databases. The medical data are highly heterogeneous and are stored in numerical, text, image, sound, and video formats. In addition, CI techniques are also used to modify medical procedures in order to reduce cost and improve perceived patient's experience and outcomes.

From the medical informatics point of view, medical data includes [9, 10, 12]:

(a) Clinical data (symptoms, demographics, biochemical tests, diagnoses and various imaging, video, vital signals, etc.), (b) logistics data (e.g., charges and cost policies, guidelines, clinical trials), (c) bibliographical data, and (d) molecular data.

On the other side, bioinformatics concerns with biological data, conceptualizes biology in terms of molecules, and applies CI techniques to understand and organize the information associated with these molecules on a large scale [14, 15]. Bioinformatics encompasses analysis of molecular data expressed in the form of nucleotides, amino acids, DNA, RNA, peptides, and proteins. The huge amount and breadth of biological data requires development of efficient methods for knowledge/information extraction that can cope with the size and complexity of the accumulated data.

There are numerous examples of successful applications of CI in areas of diagnosis and prevention, prognosis, and therapeutic decision making. CI algorithms are used for the following tasks: (a) discovering new diseases, (b) finding predictive and therapeutic biomarkers, and (c) detecting relationships and structure among the clinical. CI contributes to the enhancement of management and information retrieval processes leading to development of intelligent (involving ontologies and natural language processing) and integrated (across repositories) literature searches. Moreover, applications of CI in bioinformatics include the following areas of research: (a) microarray analysis, chromosome and proteome databases, modeling of inhibition of metabolic networks, (b) signal analysis (echocardiograph images and electroencephalograph time series), and (c) drug delivery, information retrieval, software for pattern recognition in biomedical data.

1.4 Deep Learning Paradigm in Health Informatics

Deep learning is a subarea of CI covering a spectrum of current exciting research and industrial innovation that provides more efficient algorithms to deal with large-scale data in healthcare, recommender systems, learning theory, robotics, games, neurosciences, computer vision, speech recognition, language processing, human–computer interaction, drug discovery, biomedical informatics, act [23–25]. DL is a branch of AI covering a spectrum of current exciting research and industrial innovation that provides more efficient algorithms to deal with large-scale data in many areas (see Fig. 1.4).

In the last decade, with the development of artificial neural networks, many researchers have tried to develop further studies using DL methods. DL studies are investigated in popular areas to illuminate the paths of researchers working in DL Tables 1.1, 1.2, 1.3, and 1.4 and to summarize the different DL methods and applications of health informatics.

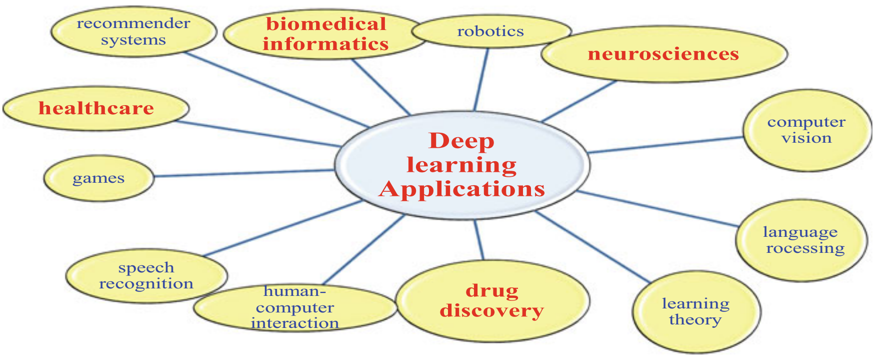


Fig. 1.4 Deep learning (DL) applications

Table 1.1 Deep learning methods and applications for bioinformatics

Application	Input data	DL method
Cancer diagnosis Gene selection/classification Gene variants	Gene expression Micro RNA Microarray data	Deep autoencoders Deep belief network Deep neural network
Drug design	Molecule compounds	Deep neural network
Compound–protein interaction RNA-binding protein DNA methylation	Protein structure Molecule compounds Genes/RNA/DNA sequences	Deep belief network Deep neural network

Table 1.2 Deep learning methods and applications for medical informatics

Application	Input data	DL method
Prediction of disease Human behavior monitoring Data mining	Electronic health records Big medical dataset Blood/laboratory tests	Deep autoencoders Deep belief network Convolutional neural network Recurrent neural network Convolutional deep belief network Deep neural network

Table 1.3 Deep learning methods and applications for public health

Application	Input data	DL method
Predicting demographic info Lifestyle diseases Infectious disease epidemics Air pollutant prediction	Social media data Mobile phone metadata Geo-tagged images Text messages	Deep autoencoders Deep belief network Convolutional neural network Deep neural network

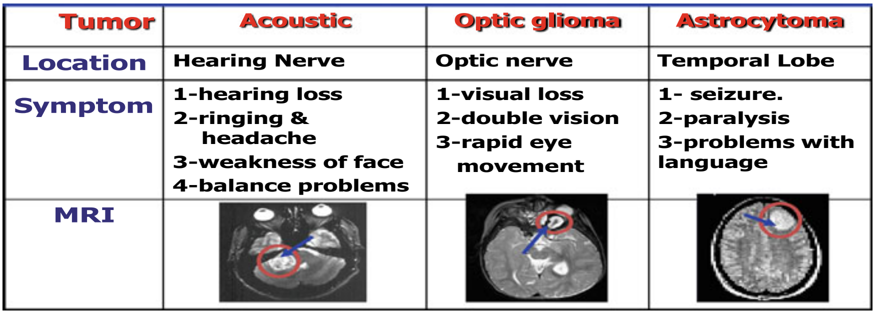
1.5 Medical Imaging Techniques for Human Brain

1.5.1 Medical Aspects

A brain tumor is a mass or growth of abnormal cells in the brain. Many types of brain tumors exist (see Fig. 1.5). Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in the brain (primary brain tumors), or cancer can begin in other parts of the body and spread to the brain (secondary, or metastatic, brain tumors). The growth rate as well as location of a brain tumor determines how it will affect the function of nervous system. Brain tumor treatment options depend on the type of brain tumor as well as its size and

Table 1.4 Deep learning methods and applications for pervasive sensing

Application	Input data	DL method
Anomaly detection Biological parameters monitoring	EEG ECG Implantable device	Deep belief network
Human activity recognition	Video Wearable device	Convolutional neural network Deep belief network Deep neural network
Hand gesture recognition Obstacle detection Sign language recognition	Depth camera RGB-D camera Real-sense camera	Convolutional neural network Deep belief network
Food intake Energy expenditure	Wearable device RGB image Mobile device	Convolutional neural network Deep neural network



Tumor	Acoustic	Optic glioma	Astrocytoma
Location	Hearing Nerve	Optic nerve	Temporal Lobe
Symptom	1-hearing loss 2-ringing & headache 3-weakness of face 4-balance problems	1-visual loss 2-double vision 3-rapid eye movement	1- seizure. 2-paralysis 3-problems with language
MRI			

Fig. 1.5 Some types of brain tumors

location. Tables 1.5 and 1.6 show applications of deep learning methods of medical imaging as well as the well-known brain imaging techniques (BIT), respectively.

1.5.2 Magnetic Resonance Imaging (MRI)

Brain MRIs have three types: T1, T2, and PD which differ in the contrast characteristics of the brain tissues. These three types have three orientations which are axial, corona, and sagittal. All these types are interpreted by radiologists, physicians,

Table 1.5 Deep learning methods and applications for medical imaging

Application	Input data	DL method
3D brain reconstruction Neural cells classification Brain tissues classification Alzheimer/MCI diagnosis	MRI/fMRI Fundus images PET scans	Deep autoencoders Convolutional neural network Deep belief network Deep neural network
Tissue classification Organ segmentation Cell clustering Hemorrhage detection Tumor detection	MRI/CT images Endoscopy images Microscopy Fundus images X-ray images Hyperspectral images	Convolutional deep belief network Convolutional neural network Deep autoencoders Group method of data handling Deep neural network

Table 1.6 Well-known brain imaging techniques

No.	Brain imaging technique
1	Computed tomography scan
2	MRI brain sagittal and coronal MRI scans
3	Positron emission tomography (PET) scan
4	Single positron emission computed tomography (SPECT) scan
5	Functional magnetic resonance imaging (fMRI) scan
6	Electroencephalography scan
7	Magneto encephalography scan

and researchers for diagnosing brain tumors and putting a treatment. Also, for the research purpose, a number of datasets are available online for research use [26].

1.5.3 General Methodology of Brain Images Processing

Based on our comprehensive study of the published literatures [26], one can conclude that the general methodology of brain images processing consists of seven processes, namely (a) image acquisition and preprocessing, (b) segmentation of ROI, (c) feature extraction and selection, (d) dimensionality reduction, (e) classification of the selected ROI, (f) performance evaluation, and (g) interpretation by the expert radiologists. Figure 1.6 shows the general methodology of brain image processing.

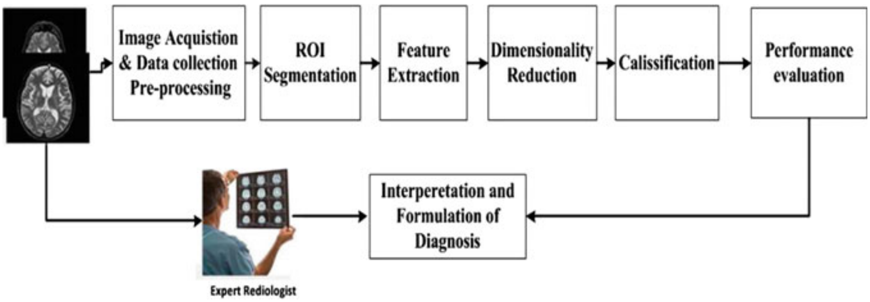


Fig. 1.6 General methodology of brain image processing

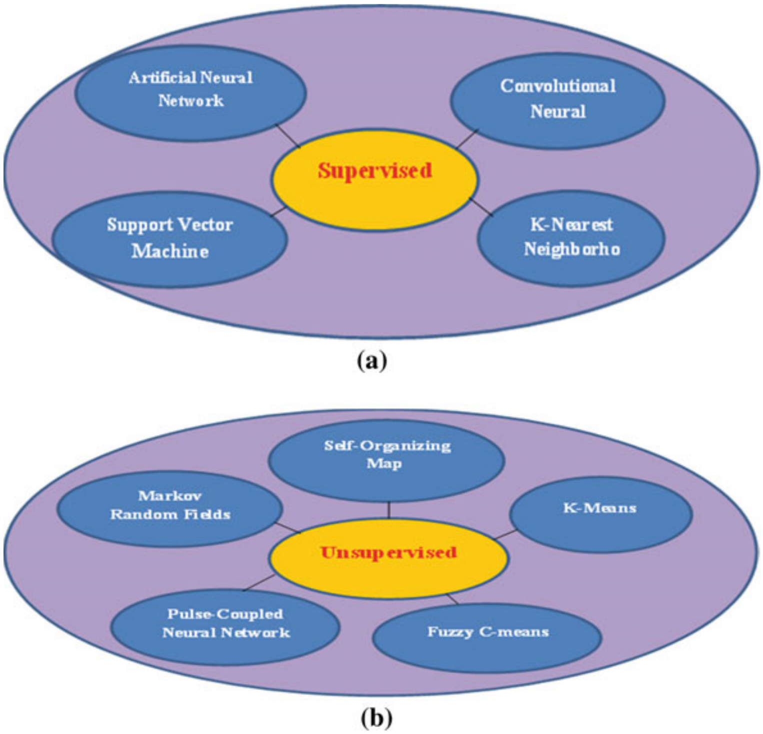


Fig. 1.7 **a** Different supervised CI techniques for the image segmentation. **b** Different unsupervised CI techniques for the image segmentation

1.5.4 CI Techniques for Segmentation and Classification Processes

Figure 1.7 shows the different supervised and unsupervised CI techniques for the image segmentation. For more technical information about these techniques, see Refs. [27–30]. For classification process, see Refs. [31–36].

1.6 Brain Tumor Diagnosis Using CI Techniques

1.6.1 1st Application: Developing CAD Systems for Brain Tumor Diagnosis

This study concerned with developing a CAD system that can process the brain MR images for detection and diagnosis of different brain tumors using several computational intelligence techniques. Commonly, the implementation of any CAD system for classification of brain tumors based on brain MRIs involved the following three stages: (1) segmentation, (2) feature extraction and selection, and (3) training/testing of the classification model

In this study, two types of CAD systems are implemented.

(A) For the first type of CAD system, three CAD systems with several models are presented. The three CAD systems included three stages: segmentation, feature extraction and selection, and classification. For segmentation process, K-means and fuzzy C-means techniques that have been used separately. While for feature extraction and selection processes, gray-level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT) integrated with principal component analysis (PCA) have been used separately.

(B) The second type is to differentially diagnose cognitive normal (CN) brain from Alzheimer's disease (AD) brain subjects using brain MRIs from two real online datasets of brain MRIs. This study is based on linear discriminate analysis (LDA) classifier.

Extracting the features from the input brain MRIs of the two datasets used is done for each dataset separately using DWT integrated with PCA for reducing the number of features to avoid classification complications and reduce the computation time and costs.

The developed system is tested using two different datasets obtained from online datasets of real human brain MRIs. The performance of the system proved its efficiency and reliability in the problem which it is used for according to different performance measures.

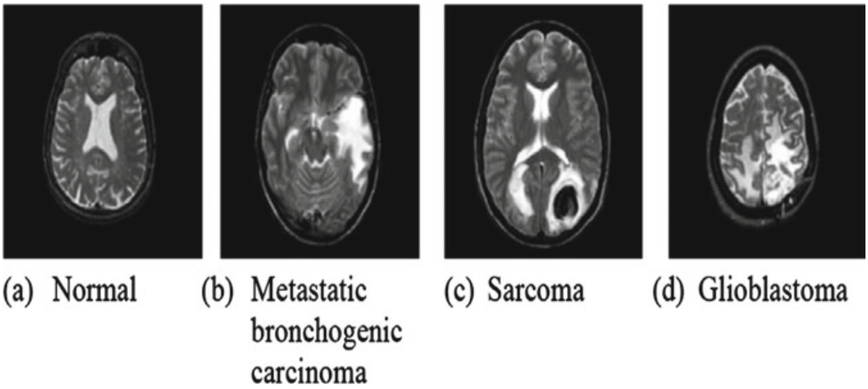


Fig. 1.8 Sample of brain MRIs' dataset

1.6.2 2nd Application: Classification Using Deep Learning for Brain Tumors

In this application, we used DL neural network for classifying a dataset of 66 brain MRIs into four classes, e.g., normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors (see Fig. 1.8). The classifier was combined with the discrete wavelet transform (DWT) and principal components analysis (PCA). The evaluation of the performance was quite good over all the performance measures.

We can summarize the main features of this study as follows:

1. The methodology combines the discrete wavelet transform (DWT) with the deep neural network (DNN) to classify the brain MRIs into normal and three types of malignant brain tumors: glioblastoma, sarcoma, and metastatic bronchogenic carcinoma.
2. The architecture of this developed system resembles the convolution neural network (CNN) architecture but requires less hardware specifications and takes a convenient time of processing for large-size images (256 × 2563—The developed DNN classifier shows high accuracy compared to traditional classifiers).

1.7 Recommendations and Conclusions

1.7.1 Recommendation

From our comprehensive analysis, one can recommend the following recommendations:

(a) The cooperation between physicians and AI communities is essential to produce efficient computing systems for medical purposes. The physicians will have more information to deliver a better service and dynamic guidelines to improve quality and reduce risks.

(b) The industry of intelligent medical decision support systems is a promising area of research for developing successful telemedicine projects.

(c) Mobile devices can feed real-time medical data directly to patients and doctors via secure computing networks and IoT. The web-based and IoT medical systems can enhance the online education/learning/training processes.

(d) The use of ICT technologies also improves the quality of patient care and reduces clinical risk. At the same time, the patient will be part of the healthcare process, having more information about diseases and access to his/her electronic health record.

(e) The pharmaceutical industries can get more accurate information about drug´s effects and supply chain delivery systems.

(f) Public health authorities can get more accurate information and develop dashboards to make better and fast decisions.

(g) Hospital management benefits from a more updated meaningful data. This data is used by management systems to deliver key performance indicators (KPI).

1.8 Conclusions

AI technologies and techniques play a key role in developing intelligent tools for medical tasks and domains. This paper analyzes the main paradigms and applications of the computational intelligence (CI) in health care from the artificial intelligence perspective. CI offers potentially powerful tools for the development a novel digital healthcare system. The variety of such technique enabling the design of robust and efficient intelligent healthcare systems. CI techniques (e.g., CBR, data mining, rough set, and ontology) can cope with medical noisy data, subsymbolic data, and complex structure data. In addition, CI offers intelligent computational methods for accumulating, changing, and updating medical knowledge in IHS, and in particular learning mechanisms that will help us to induce knowledge from medical information or data. The key to the success of such systems is the selection of the CI technique that best fits the domain knowledge and the problem to be solved. That choice depends on the experience of the knowledge engineers. On the other side, the development of such systems is a very difficult and complex process that raises a lot of technological and research challenges that have to be addressed in an interdisciplinary way.

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