CHAPTER

Machine learning in expert systems for disease diagnostics in human healthcare

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Arvind Kumar Yadav[a], Rohit Shukla[a], and Tiratha Raj Singh[b]

Department of Biotechnology and Bioinformatics, Jaypee University of Information Technology (JUIT), Solan, Himachal Pradesh, India[a] Centre of Excellence in Healthcare Technologies and Informatics (CHETI), Department of Biotechnology and Bioinformatics, Jaypee University of Information Technology (JUIT), Solan, Himachal Pradesh, India[b]

Chapter outline

1 Introduction

Good health is an important aspect of quality of life, as nothing is more valuable, and new technologies are continually leading to tremendous advances in healthcare. The definition of healthcare is the improvement of health through prevention, treatment, and inspection of diseases (Toli and Murtagh, 2020). Accurate diagnosis is essential for medical treatment and decision-making, but it can be difficult to identify a specific disease from the stated symptoms of a patient, due to the inexact information

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provided. Thus the main job in medical diagnosis is to use expert logical reasoning to make decisions. Physician control is an effective solution for diagnosis and treatment, but it is costly. Artificial intelligence (AI) seems particularly well suited for this application (Davenport and Kalakota, 2019).

A smart healthcare system for disease diagnostics can be developed using a combination of AI, Internet-of-Things (IoT), information and communication technology (ICT), along with Big Data and good decision making (Chui et al., 2017; Panigrahi and Singh, 2017). The shortage of medical personnel in the healthcare sector is a current major challenge (Liu et al., 2016), but smart healthcare systems can be developed using the available health data with increased computational power by applying AI (Shukla et al., 2021). A smart healthcare system can assist in optimizing the financial and social impact of health services having insufficient medical personnel (Du and Sun, 2015; Momete, 2016).

An expert system (ES) is a common application of AI. It is a combination of computer-based programs that employ specific information and knowledge from several human experts to resolve specific problems. An expert system basically includes a knowledge base that has stored information and a set of rules that are applied to the knowledge base to make a particular prediction (Godfrey et al., 2011; Li and Shun, 2016). This type of intelligent knowledge-based system can provide self-diagnosis to individuals. Such a self-diagnosis mechanism is still very important for early diagnosis and treatment. The most important functions of the expert system are a flexible user interface, good data representation, inference, and rapid outcomes. Results can include greater accuracy and reliability, cost savings, and minimal errors. Expert systems also have some drawbacks, such as lack of human "common sense," no effect of environment change, and no response in exceptional cases.

Expert system development has gained much attention from researchers in recent decades for medical decision-making. Expert systems can support novice medical practitioners in urban areas and, more specifically, in rural and remote areas. They are also helpful for doctors who use them to identify diseases and suggest suitable treatment options. The expert system also provides the facility to store images, sound, and videos related to disease symptoms (Ali and Saudi, 2014). The expert system appeared in medical diagnosis applications in the 1970s, when the MYCIN expert system was developed for the identification of diseases caused by bacteria. Since then, many expert systems have been used for the identification of various human diseases and are being referred to by medical practitioners globally (see Table 1).

Table 1 Comparison of developed expert systems for human disease diagnostics.

Method used	Disease Diagnosed	Input	Reference
Rule-Based Expert System	Influenza	The patient data from Bangladesh collected by the influenza specialists, consultants, and disease symptoms	(Hossain et al., 2014)
	Memory loss	Disease symptoms	(Hole and Gulhane, 2014)
	Viral infection	Disease symptoms	(Patel et al., 2013)
	Diabetes	Lab test results, ketone, disease symptoms, obesity, age, family history	(Geberemariam, 2013)
	Endocrine disease	Disease symptoms	(Abu-Naser et al., 2010)

Table 1 Comparison of developed expert systems for human disease diagnostics—cont'd

Method used	Disease Diagnosed	Input	Reference
	Dehydration Viral or allergic conjunctivitis	Disease symptoms	(Patra et al., 2010)
	Ear problem diagnosis	Disease symptoms	(Abu-Naser and Al-Nakhal, 2016)
	Lower back pain	Disease symptoms	(Abu-Naser and Aldahdooh, 2016)
	Food disease	Disease symptoms	(Abu-Naser and Mahdi, 2016)
	Urination problems diagnosis	Disease symptoms	(Abu-Naser and Shaath, 2016)
	Breast cancer	Disease symptoms	(Abu-Naser and Bastami, 2016)
	Skin disease	Disease symptoms	(Abu-Naser and Akkila, 2008)
	Male infertility	Disease symptoms	(Abu-Naser, 2016)
	Mouth problem	Disease symptoms	(Abu-Naser and Hamed, 2016)
	Shortness of breath in infants and children	Disease symptoms	(AbuEl-Reesh and Abu Naser, 2017)
	Rheumatic	Disease symptoms	(El Agha et al., 2017)
	Genital problems in men	Disease symptoms	(Abu-Naser and Al-Hanjori, 2016)
	Genital problems in infants	Disease symptoms	(Naser and El Haddad, 2016)
Fuzzy Expert System	Hypertension disease	Body mass index, age, gender, heart rate, and blood pressure	(Abdullah et al., 2011)
	Liver disorders	Data collected from the trusted database, 6 entrance parameters of liver disorders	(Neshat et al., 2008)
	Hepatobiliary disorders	Disease symptoms	(Mitra, 1994)
ANN-Based Expert System	Heart disease	Disease symptoms	(Ajam, 2015)
	Parkinson disease	Disease symptoms	(Avci and Dogantekin, 2016)
Knowledge-Based Expert System	Cardiological disease	Disease symptoms	(Bursuk et al., 1999)
	Chest pain	Data collected from laboratory examinations, narrative texts describing the patient's condition, and chest X-ray images	(Ali et al., 1999)
	Bronchial asthma	Disease symptoms	(Prasad et al., 1989)

Continued

Table 1 Comparison of developed expert systems for human disease diagnostics—cont'd

Method used	Disease Diagnosed	Input	Reference
	Eye disease	Disease symptoms	(Ibrahim et al., 2001)
	Brain diseases	Disease symptoms	(Ayangbekun Oluwafemi and Jimoh Ibrahim, 2015)
	Spine disease	Disease symptoms	(Ghazizadeh et al., 2015)
	Neck pain diagnosis	Disease symptoms	(Abu-Naser and Almurshidi, 2016)
	Stomach pain	Disease symptoms	(Mrouf et al., 2017)
	Ankle disease	Disease symptoms	(Qwaider and Abu Naser, 2017)
	Hypertension in pregnancy	Disease symptoms	(Gudu et al., 2012)
	Oncology	Disease symptoms	(Shortliffe, 1986)
	Chest pain in infants and children	Disease symptoms	(Khella, 2017)
	Rickets diagnosis	Disease symptoms	(Al Rekhawi et al., 2017)
	Hair loss diagnosis	Disease symptoms	(Nabahin et al., 2017)
	Teeth and gum problems	Disease symptoms	(Abu Ghali et al., 2017)
	Ear disease	Disease symptoms	(Abu-Naser and Abu Hasanein, 2016)
	Nausea and vomiting problems	Disease symptoms	(Abu Naser and El-Najjar, 2016)
Adaptive Neuro-Fuzzy Inference System	Breast cancer	Disease symptoms	(Fatima and Amine, 2012)

The amount of biomedical data is exponentially increasing and such data contain essential patient information related to diversified medical conditions (Singh et al., 2018). These datasets can provide significant hidden information if important patterns latent in the data can be extracted. This information can serve as a medical diagnostic tool to identify particular diseases (Ali and Saudi, 2014). Medical knowledge can be effectively extracted by analyzing data using various machine-learning techniques, such as genetic algorithms, (Ghaheri et al., 2015) neural networks (Lundervold and Lundervold, 2019), decision trees(Ahmed et al., 2020), and fuzzy theory (Arji et al., 2019; Sweidan et al., 2019).

These machine-learning techniques can also be helpful in automating expert systems for medical diagnosis. The aim of this chapter is to present an overview of the research and development of expert systems in the field of medical diagnosis, with the specific application of machine learning. We have provided specific case studies along with their respective algorithmic procedures, to elaborate the typical use of expert systems for diagnosis of human diseases, which include cancer and Alzheimer's disease.

2 Types of expert systems

There are various classes of expert systems. Several of the most prominent classes are described in the following paragraphs.

Rule-based expert system: The simplest form of AI is represented by the rule-based system. The rules are used as knowledge representation, for the coding of knowledge into the system, (Grosan and Abraham, 2011) as the rules can advise what to do under various conditions. The rules in the expert system can be added in the form of a simplistic model based on IF/THEN statements.

Knowledge-based expert system: The knowledge-based expert system uses information for the decision-making process. A knowledge-based system uses a knowledge base that consists of expert experience and applies a set of rules in particular conditions (Arbaiy et al., 2017).

Fuzzy expert system: Membership functions and fuzzy rules make up the fuzzy expert system. These functions and rules are applied on datasets. This system takes in numbers as an input query and the job is performed by the fuzzy inference engine (Yager and Zadeh, 2012).

Artificial neural network (ANN)-based expert system: The ANN is widely used for pattern recognition and regression analysis. It is an interconnected group of artificial neurons that uses a mathematical model connectionist approach for computation (Fatima and Pasha, 2017).

3 Components of an expert system

Expert system software consists of different components (Ghazizadeh et al., 2015). Some basic components are represented in Fig. 1 and described in the following paragraphs.

User interface: The user interface is the part that establishes the communication between the user and the expert system. It provides various facilities to users such as graphical interfaces, menus, etc., to establish communication. The interface must be able to represent the internal decision to the user in an understandable form. In the development of an expert system, various personnel including users, knowledge engineers, domain experts, and maintenance personnel are involved with the user interface.

Knowledge base: This is domain-specific information obtained from a human expert or experts and stored. Sets of rules, logic, frames, and semantic nets are used to represent the information, or knowledge. The knowledge base holds the heuristic knowledge and factual knowledge. The factual knowledge is widely shared and available knowledge from textbooks and journals. The heuristic knowledge is more experimental, more judgmental, and more difficult to collect accurately. It is the knowledge of good judgment and good practice. The achievement of a truly expert system relies on the comprehensiveness and accuracy of its knowledge base.

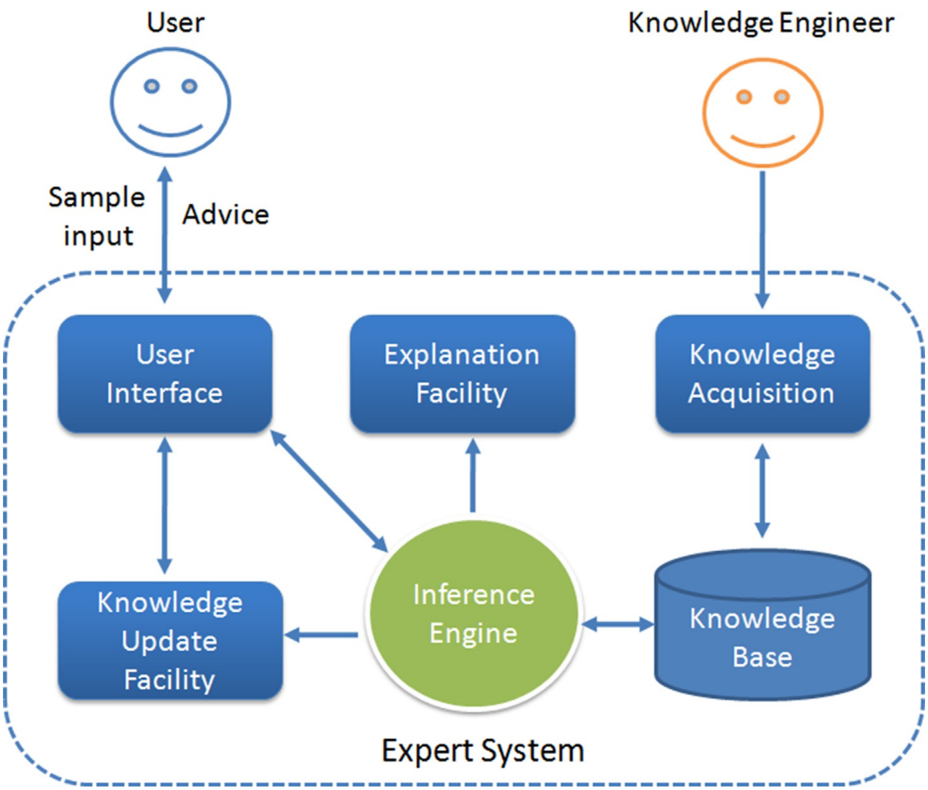

FIG. 1

The basic architecture of a typical expert system.

Inference engine: This engine performs the specific task requested, using the rules and given inputs. The main job of the inference engine is to arrive at a final decision using the forest of rules. It employs two main approaches, forward chaining and backward chaining.

Knowledge acquisition: This is the process of building a knowledge base. In knowledge acquisition, various techniques are used, such as protocol analysis, observation, interviews, etc. Collecting information is required to construct the knowledge pool.

Explanation facility: This component is helpful in explaining the reasoning process behind a recommendation made by an expert system. The explanation facility provides details about final or intermediate solutions and additional data needed. Here users can find answers to the basic question of how and why the server arrived at a conclusion or decision. Users can change the editor, if they are not satisfied with the explanation of the present reasoning. It has little flexibility in usage terms.

Knowledge engineer: This is a person who can design, build, and test expert systems. The knowledge engineer asks other people about their experience and knowledge and finds solutions to problems. Thus the knowledge engineer discovers the reasoning methods and implements the rules in the expert system and is also responsible for modifying, updating, and testing the expert system (Kumar, 2019).

4 Techniques used in expert systems of medical diagnosis

Current expert systems are composed of special software environments and are known by several names. The variations of the medical expert system depend upon their complexity. Expert systems produce situational and patient-specific suggestions. Different types of information are used by the ES to make decisions. Some techniques used in expert systems are discussed in the following paragraphs.

AI programs: AI programs are used by the computer to understand and implement the reasoning process. These programs attempt to mimic human reasoning, thinking, and mechanisms of learning, and, by combining all these things, to build a computational model that provides intelligent behavior and actions. AI uses both theoretical research and technology to build a model that can be implemented as a computer program. In the medical field, AI is used to build systems and tools to improve healthcare (Amisha et al., 2019; Esmaeilzadeh, 2020; Datta et al., 2019). The mechanisms and languages of AI are very costly and difficult to understand. AI can also be very hard to apply and incorporate among and within other information systems.

Machine learning (ML): ML is a field of AI that solves problems by computational methods with the help of a learning process (Frank et al., 2020). The main aim of ML research is to model human learning. Based on several criteria such as learning strategy, knowledge representation, or field of application, ML methods can be categorized (Réda et al., 2020). In ML, the main methods are genetic algorithms, neural networks, instance-based learning, analytical learning, and inductive learning. ML has been used in the diagnosis of various diseases, including acute appendicitis (Godfrey et al., 2011; Li and Shun, 2016), dermatological disease (Patra et al., 2010), thyroid disease, (Ghazizadeh et al., 2015) and female urinary incontinence, (Arbaiy et al., 2017) and in the detection of bacterial pneumonia by using X-ray reports. (Abu-Naser and Al-Nakhal, 2016) The main applications of ML are in data mining and knowledge acquisition. Knowledge acquisition is a very important method in the development of expert systems, because it is needed to extract the knowledge from experts. By applying various ML methods, data mining allows nearly automatic knowledge acquisition (Fatima and Pasha, 2017).

Data mining: This is the process of discovering information and hidden patterns in data. Data mining is also known as knowledge discovery by ML and AI societies. In recent decades, information technologies have been frequently used for disease diagnosis to assist doctors in decision-making activity. (Joshi and Joshi, 2013) Today, a huge amount of complex data is generated by the healthcare sector on an everyday basis. To extract valid and important information from this voluminous data, data mining is used to understand the patterns in the data. In this process, suitable data is retrieved from different data sources, and then cleaned before knowledge discovery, in which the data are evaluated based on quality criteria (Fig. 2). Finally, data mining is used for the prediction and evaluation of diseases (Durairaj and Ranjani, 2013). In the healthcare sector, data mining is a promising field with major significance for better understanding the medical data. Data mining techniques are used in medical diagnostics for various diseases, including diabetes (Kazerouni et al., 2020), stroke (Panzarasa et al., 2010), cancer (Weli, 2020), Alzheimer's disease, (Panigrahi and Singh, 2012; Panigrahi and Singh, 2013) and cardiovascular diseases. (Ayatollahi et al., 2019)

Decision tree: Decision tree is the most commonly used classification method and is used to solve complex problems. It consists of nodes and branches and presents the knowledge structure in the form of a tree (Lopez-Vallverdu et al., 2012). The path to be followed is defined by the evaluation of

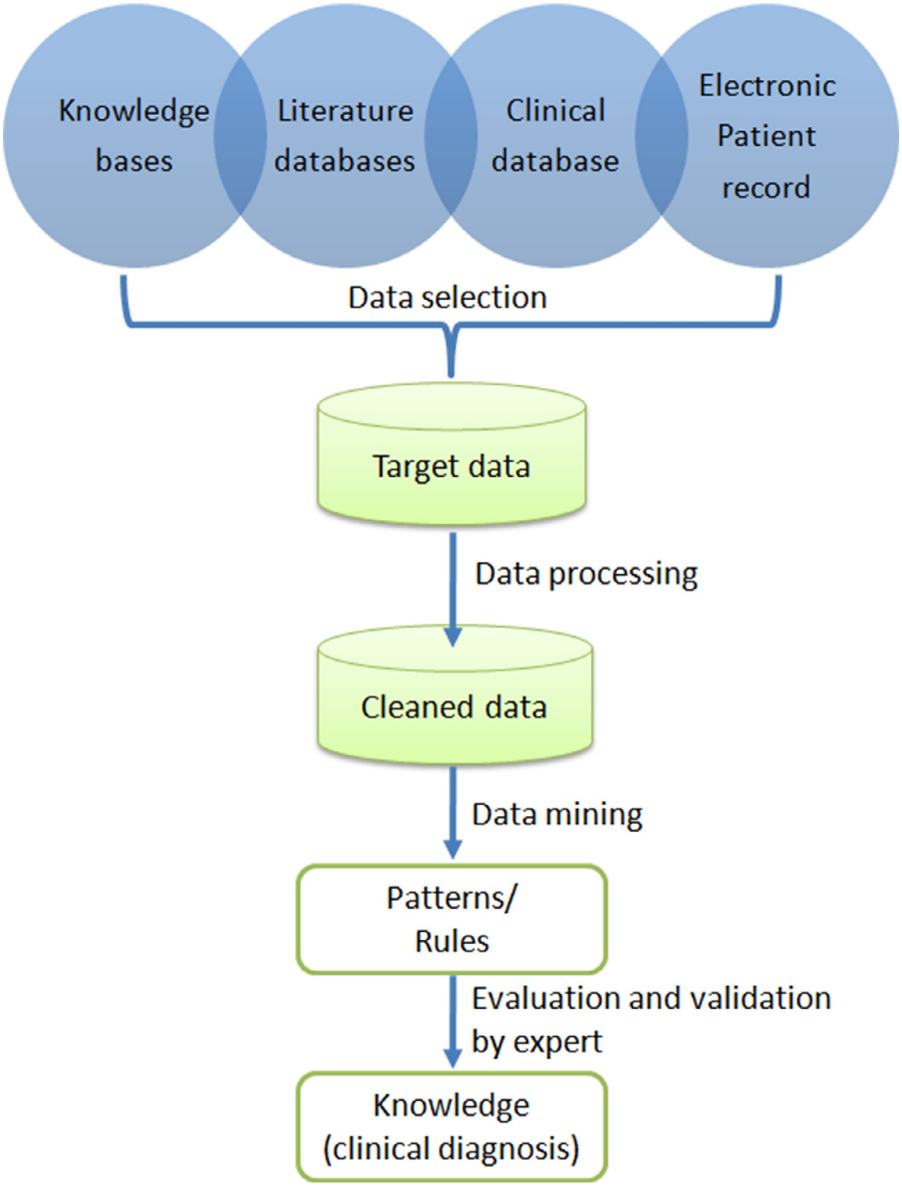

FIG. 2

Outline of the data mining process in medical diagnosis.

each node in the tree attributes. In this method, classification is carried out by the root node routing until the leaf node is reached. Decision tree models are best for data mining as they are simple to interpret and integrate, and have comparably better accuracy in many applications (Kumar and Singh, 2017; Lavanya and Rani, 2011).

Neural network: This method mimics the logic of the human brain. In neural networks, neurons and nodes are the basic components. The neural network has an input layer, one or many hidden layers, and a single output layer (Fig. 3). The neurons are connected with the network and help to decide the final output (Abiodun et al., 2018). The neural network is a widely used technique in the field of healthcare, used to diagnose various human diseases such as cancer (Shahid et al., 2019), heart disease (Reddy et al., 2017), and others.

Genetic algorithm: The genetic algorithm (GA) is a methodology involving an adaptive optimization search. For a heuristic search, GA supports Darwinian natural selection and genetic systems biology. The fundamentals of genetic algorithm techniques are designed to simulate the process in natural systems required for evolution (Uyar and Ilhan, 2017). The genetic algorithm has been very effective in the screening and diagnosis of several diseases (Ghaheri et al., 2015). Various medical diagnostic methods have been developed using GA for prediction of diseases such as cancer (Mansoori et al., 2014; Pereira et al., 2014), anemia (Wang, 2016), heart disease (Uyar and Ilhan, 2017), tuberculosis (Elveren and Yumuşak, 2011), and epilepsy (Kocer and Canal, 2011).

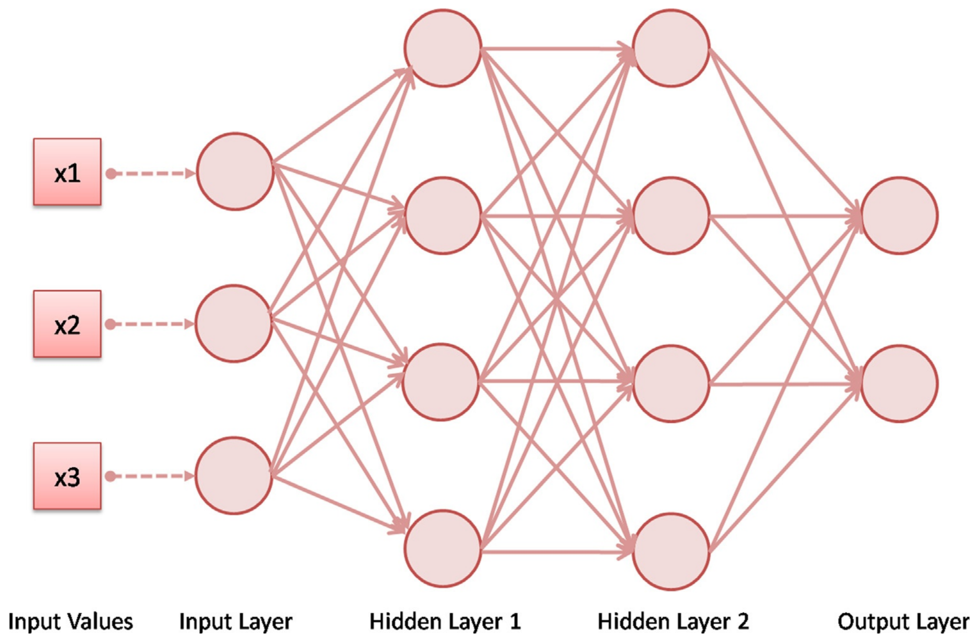

FIG. 3

The architecture of neural network with two hidden layers.

5 Existing expert systems

A tabular compilation of the existing popular expert systems developed for a myriad of human diseases is provided in Table 1. These expert systems are based upon standard methodologies followed, such as rule based, fuzzy, ANN based, knowledge based, and adaptive hybrid.

6 Case studies

Specialized case studies on human diseases such as cancer and Alzheimer's disease are provided with rule-based and fuzzy-based expert systems, respectively. General descriptions, flow diagrams, internal procedures, algorithmic details, and standard measurements are provided in later sections.

6.1 Cancer diagnosis using rule-based expert system

Cancer is caused by uncontrolled cell proliferation in various organs. There are numerous clinical appearances and treatment methods available for cancer. Cancer is still an important health issue and a leading cause of death globally, despite advancements in modern medicine. There are many types of cancers, classified on the basis of their origin from tissue.

A web-based expert system was developed by Başçiftçi and Avuçlu that uses a reduced-rule base to diagnose cancer risk using patient symptoms (Başçiftçi and Avuçlu, 2018). This method can be used for breast cancer, lung cancer, kidney cancer, and cervical cancer. In this expert system, 13 determinant risk factors are used for the diagnosis of cancer types. Two examples are given here, showing how this expert system determines the cancer types on the basis of the 13 risk factors.

First (Renal cancer)	Second (Breast cancer)
If **1.** Have a certain hardness or bloody discharge in the breast end (in women) is Yes and **2.** Coughing up blood constantly is Unimportant and **3.** Excessive weight is Unimportant and **4.** Taking long-term dialysis treatment >4 h is Unimportant and **5.** Smoking is Unimportant and **6.** Age > 50 is Yes and **7.** Hypertension >140 mmHg is Unimportant and **8.** Have you given birth (in women) is Yes and **9.** Have cancer in relatives is Unimportant and **10.** To give birth to her first child after age 30 is Yes and **11.** The existence of vaginal bleeding is Unimportant and **12.** Unexpected abnormal and bad-smelling vaginal discharge is Unimportant and **13.** Pelvic pain and have spotting is Unimportant - Then the patient has renal cancer from symptoms of cancer	If **1.** Have a certain hardness or bloody discharge in the breast end (in women) is Unimportant and **2.** Coughing up blood constantly is Unimportant and **3.** Excessive weight >100 is Yes and **4.** Taking long-term dialysis treatment >4 h is Yes and **5.** Smoking is Unimportant and **6.** Age > 50 is Unimportant and **7.** Hypertension >140 mmHg is Yes and **8.** Have you given birth (in women) is Unimportant and **9.** Have cancer in relatives is Yes and **10.** To give birth to her first child after age 30 is Unimportant and **11.** The existence of vaginal bleeding is Unimportant and **12.** Unexpected abnormal and bad-smelling vaginal discharge is Unimportant and **13.** Pelvic pain and have spotting is Unimportant – Then the patient has breast cancer from symptoms of cancer

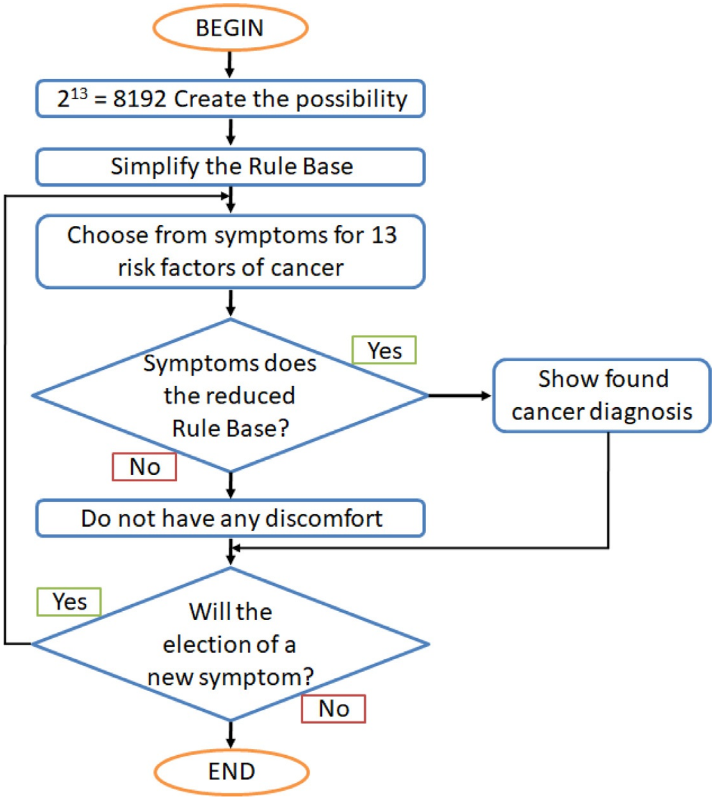

FIG. 4

The process flow chart of reduced rule-based application.

After performing the diagnosis using this approach, simplification of the rule-based method was carried out from all possibilities. After simplification, the expert system predicted the same results as the previous one. Diagnosis performed with the reduced-rule based system took less time. The overall process used in the reduced-rule based expert system is represented in Fig. 4.

Başçiftçi and Hatay developed a similar expert system using a reduced-rule based system by applying simplified logic functions for diabetes prediction (Başçiftçi and Hatay, 2011). In this study, they used a dataset for type 1 diabetes, type 2 diabetes, and gestational diabetes. Three datasets were downloaded from data 1 (http://www.cormactech.com/neunet/download.html), data 2 (https://www.webarchive.org.uk/wayback/archive/20180516221802/http://www.gov.scot/Publications/2003/01/16290/17629), and data 3 (http://lib.stat.cmu.edu/S/Harrell/data/descriptions/diabetes.html). The accuracy rate was observed as 97.13%, 96.5%, 98.26%, and 97.44% for diabetes patients, type 1 diabetes patients, type 2 diabetes patients, and diabetes with pregnancy, respectively.

6.2 Alzheimer's diagnosis using fuzzy-based expert systems

The neurological disorder called Alzheimer's disease (AD) is characterized by the two major hallmarks of β-amyloid plaques and neurofibrillary tangles (NFTs). It mainly occurs after the age of 65 and the identification of this disease in the initial stage is a critical task (Shukla et al., 2019; Shukla and Singh, 2020). AD is divided into various stages, including mild cognitive impairment (MCI), severe AD, etc. At the beginning of the disease, no critical symptoms appear, while after 5 years, when symptoms do appear, the disease has completely spread through the brain (Ewers et al., 2011). AD mainly affects the hippocampus region and destroys cognitive ability including reading, learning, etc. in patients. Hence, early identification of disease is a very important task to protect the patient's life quality from this complex disease (Weller and Budson, 2018). Expert systems come into the picture at this point, as they can participate in the early diagnosis of AD. There are several expert systems available that can diagnose CE (Hinrichs et al., 2009; Ding et al., 2018; Munir et al., 2019; Oehm et al., 2003). Two different case studies for AD are discussed here.

Case study 1. Here, we describe a method developed by Mallika et al., (Mallika et al., 2019) in brief, to understand how one can create an expert system that can participate effectively in AD diagnosis. In this approach, they used fuzzy logic (FL), which is a popular mathematical approach of soft computing and inferences. Set theory and crisp logic are generalized by FL, which is employed in the concept of a fuzzy set. FL is widely used with success in various fields such as image processing, medical diagnosis, knowledge engineering, and pattern recognition, etc. In this study, they developed an expert system, called a fuzzy inference system (FIS), for AD diagnosis using the hippocampus as a biomarker. This system can classify non-AD (normal control), AD, and MCI patients using image data visual features. They have taken brain MRI images from the OASIS database (https://www.oasis-brains.org/) and preprocessed them by segmenting. The segmented images were then used for the extraction of hippocampus volume and then the classification was performed by using the fuzzy inference system. The methodology is shown in Fig. 5. The accuracy, sensitivity, and precision of the three regions are shown in Table 2.

6.2.1 Algorithm of fuzzy inference system

Three steps are involved in the classification of the MRI images by using extracted features in the FIS. The internal structure of the FIS(Siler and Buckley, 2005) is shown in Fig. 6.

1. In the first step, the fuzzification of input variables is done.
2. A decision-making logic is built by using the fuzzy inference engine based on fuzzy rules as described in following text.
3. To crisp the value, defuzzification of the generated output was carried out.

They generated three fuzzy rules based on hippocampus volume, which is described in various research articles for AD and non-CE (Vijayakumar and Vijayakumar, 2013). These fuzzy rules are used in the previously described FIS algorithm.

The three rules that they generated are as follows:

1. If the volume (V) of the hippocampus is in interval V_{low} it represents AD.
2. If the volume (V) of the hippocampus is in interval V_{medium} it represents MCI.
3. If the volume (V) of the hippocampus is in interval V_{high} it represents non-AD.

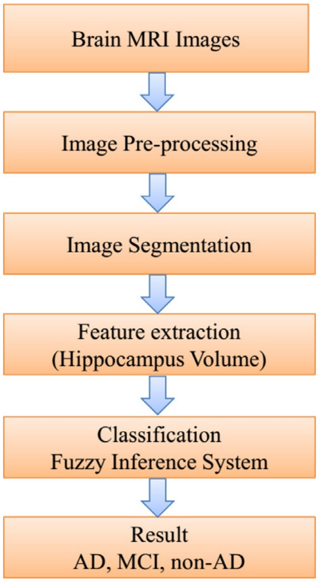

FIG. 5

The flow diagram of fuzzy inference system.

Table 2 The classification evaluations of FIS.

Brain MRI projection	Accuracy (%)	Precision (%)	Sensitivity (%)
Sagittal	82.21	91.95	87.43
Coronal	84.13	91.03	90.59
Axial	86.53	91.71	92.73

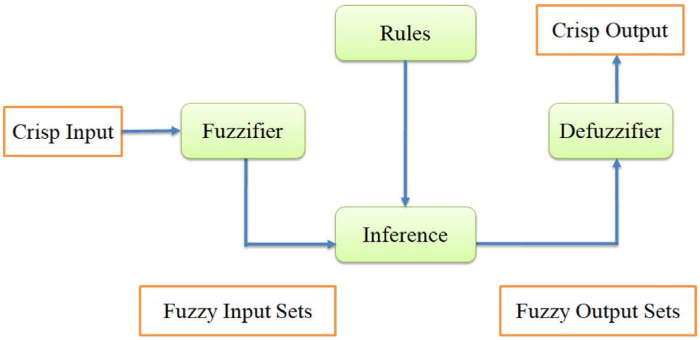

FIG. 6

The internal structure of fuzzy inference system (FIS).

According to these rules, the FIS classified the MRI images into AD, non-AD, and MCI classes.

Case study 2: Lazli et al. (2019) described a computer-aided diagnosis method on the basis of multimodal fusion (fusion of MRI and PET images). A hybrid fuzzy-genetic-possibilistic model was used to quantify the brain tissue volume and discriminate the classes using a classifier of support vector data description (SVDD). The flow diagram of the methodology is shown in Fig. 7.

This method is mainly categorized into two parts. In the first part, the fusion approach is used to quantify the brain tissue volume by using three consecutive steps: modeling, fusion, and decision.

1. The modeling is also divided into three parts. First, it is initialized by tissue cluster centroids by using a clustering algorithm of bias-corrected fuzzy C-means (BCFCM) (Ahmed et al., 2002) (Algorithm 1). Second, the optimization of the initial partition is performed by using the genetic algorithm. Finally, the possibilistic fuzzy C-means clustering algorithm (PFCM) (Pal et al., 2005) (Algorithm 2) is used for the quantification of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) tissues.
2. In the second step, the fusion of the MRI and PET images is performed by using the possibilistic operator, which highlights the redundancies and manages the ambiguities.
3. In the third step, the decision offers the more representative anatomy-functional fusion images.

In the second part, SVDD is used to classify AD after normal aging and it automatically detects abnormal values. After that, a "divide and conquer" strategy is used to speed up the SVDD processing, which decreases the computational cost of the calculation results. The method also has proved its efficacy on synthetic datasets retrieved from Alzheimer's disease neuroimaging (ADNI) (http://adni.loni.usc.edu/), Open Access Series of Imaging Studies (OASIS) (https://www.oasis-brains.org/), and real images.

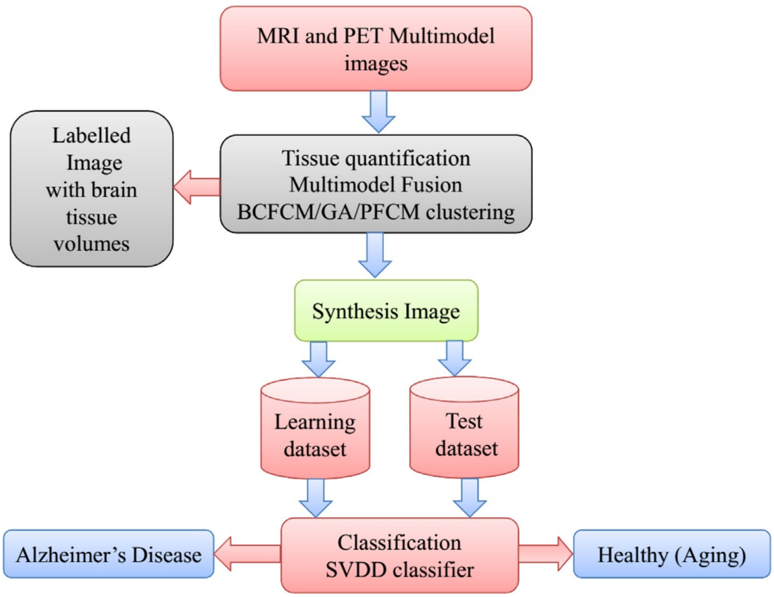

FIG. 7

The complete flow diagram of multimodal CAD system used for AD diagnosis proposed by Lazli et al. (2019).

The classification evaluation including accuracy, sensitivity, specificity, and area under the ROC curve for the ADNI dataset was 93.65%, 90.08%, 92.75% and 97.3%; for the OASIS dataset the values were 91.46%, 92%, 91.78% and 96.7%; and for real images they were 85.09%, 86.41%, 84.92% and 94.6%, respectively.

ALGORITHM 1 DESCRIBES THE PSEUDOCODE FOR BCFCM

Let $X = \{x_j\}$, the voxels set; $U = \{\mu_{ij}\}$, the matrix of membership degrees; and $B = \{b_{ij}\}$, the matrix of cluster center, with $1 \leq I \leq C$, $1 \leq j \leq N$.m the degree of fuzzy, and Ɛ the threshold representing convergence error.

1. Initialize the center vectors $B^{(0)} = [b_j]$ and the degree of belonging matrix $U(0)$ by random values in the interval [0,1] satisfying Eq. (2).
2. At k-step:
   - Compute the belonging degrees matrix $U^{(k)}$ using Eq. (3).
   - Compute the center vectors $B(k) = [bj]$ using Eq. (4).
   - Estimate the bias term $\beta_j^{(k)}$ using Eq. (5).
   - Compute the objective function $J_{BCFCM}^{(k)}$ using Eq. (1).
3. Update: $B^{(k+1)}$, $U^{(k+1)}$, $\beta_j^{(k+1)}$, and $J_{BCFCM}^{(k+1)}$
4. If $\|J_{BCFCM}^{(k+1)} - J_{BCFCM}^{(k)}\| < Ɛ$ then STOP otherwise return to step 2.

Equations used in Algorithm 1:

$$J_{BCFCM}(B,U,X,\beta) = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m}\left\|x_j - \beta_j - b_i\right\|^2 + \frac{\alpha}{N_i}\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m}\left(\sum_{x_k \in N(x_j)} \|x_k - \beta_k - b_i\|^2\right) \tag{1}$$

where:

- B denotes the centroids matrix and center of cluster i $(1 \leq i \leq C)$ with C, the number of cluster.
- X is the voxels vectors matrix and xj $(1 \leq j \leq N)$ is the observed value of log-transformed intensities at the jth voxel.
- U denotes the matrix of degrees of membership μ_{ij}^{m} with m being a parameter controlling the degree of fuzzification.
- β_j is the bias field value at the jth voxel, which helps in removing the effect of inhomogeneity.
- N_i denotes the size of neighborhood that is to be considered.
- $N(x_j)$ represents the set of neighbors that exist in a window around x_j and is the cardinality of N_i.

$$U\left\{u_{ij}\in[0,1] \,\middle|\, \sum_{i=1}^{C} u_{ij} = 1 \forall j \; and \; 0 < \sum_{j=1}^{N} u_{ij} < N \forall i\right\} \tag{2}$$

$$u_{ij}^{*} = \frac{1}{\sum_{k=1}^{C}\left(\left(w_{ij} + (\alpha/N_i)\gamma_i\right)/\left(w_{kj} + (\alpha/N_i)\gamma_k\right)\right)^{1/(m-1)}} \tag{3}$$

where

$$w_{ij} = \left\|x_j - \beta_j - b_j - b_i\right\|^2$$

$$\gamma_i = \sum_{x_k \in N(x_j)} \left\|x_k - \beta_j - b_i\right\|^2$$

$$b_i^{*} = \frac{\sum_{j=1}^{N} u_{ij}^{m}\left(\left(x_j - \beta_j\right) + (\alpha/N_i)\sum_{x_k \in N(x_j)}\left(x_k - \beta_j\right)\right)}{(1+\alpha)\sum_{j=1}^{N} u_{ij}^{m}} \tag{4}$$

$$\beta_j^{*} = x_j - \frac{\sum_{i=1}^{C} u_{ij}^{m} b_i}{\sum_{i=1}^{C} u_{ij}^{m}} \tag{5}$$

ALGORITHM 2 THE PSEUDOCODE OF THE POSSIBILISTIC FUZZY C-MEANS CLUSTERING ALGORITHM (PFCM)

Let $X = \{x_j\}$ be the voxels vectors, $U = \{\mu_{ij}\}$ is the matrix of membership degrees, and $T = \{t_{ij}\}$ is the matrix of typicality degrees, and $B = \{b_{ij}\}$ is the matrix of cluster centers with $1 \leq i \leq C$, $1 \leq j \leq N$. m being the degree of fuzzy and η being the weight possibilistic degree.

1. Initialization of the centers vectors $B^{(0)} = [b_j]$ and the degree of belonging matrix $U(0)$ using the hybrid BCFCM-GA method.
2. At k-step:
   - Compute the matrix of membership degrees $U(k)$ using Eq. (7).
   - Compute the matrix of typicality degrees $T(k)$ using Eq. (8).
   - Compute the prototype matrix $B(k)$ using Eq. (9).
   - Compute the objective function $J^{(k)}_{PFCM}$ using Eq. (6).
3. Update: $U^{(k+1)}$, $T^{(k+1)}$, $B^{(k+1)}$, and $J^{(k+1)}_{PFCM}$
4. Repeat steps [2] and [3] until the stop criterion is met: $\|J^{(k+1)}_{PFCM} - J^{(k)}_{PFCM}\| < \varepsilon$
   Equations used in Algorithm 2:

$$j_{PFCM}(u,B,m,\eta) = \sum_{i=1}^{N}\sum_{j=1}^{C}\left(au_{ij}^{m} + bt_{ij}^{\eta}\right)\left\|x_i - b_j\right\|^2 + \sum_{j=1}^{C}\gamma_i\sum_{i=1}^{N}\left(1-t_{ij}\right)^{\eta} \tag{6}$$

where u_{ij} are constrained by the probabilistic conditions, while $t_{ij} \in [0,1]$ are subject to:

$$0 < \sum_{i=1}^{C} t_{ij} < C, \forall j$$

$$u_{ij} = \left(\sum_{k=1}^{C}\left(\frac{\left\|x_j - b_i\right\|^2}{\left\|x_j - b_k\right\|^2}\right)^{1/m-1}\right)^{-1} \quad 1 \leq j \leq N, 1 \leq i \leq C \tag{7}$$

$$t_{ij} = \frac{1}{\left(1 + \left(\frac{b\left\|x_j - b_i\right\|^2}{y_i}\right)^{1/\eta-1}\right)} \forall i = 1\ldots..C, \forall j = 1\ldots\ldots N \tag{8}$$

$$bi = \sum_{j=1}^{N}\left(\left(au_{ij}^{m} + bt_{ij}^{\eta}\right)x_j\right) / \left(au_{ij}^{m} + bt_{ij}^{\eta}\right) \forall i = 1\ldots\ldots\ldots C \tag{9}$$

The symbols are the same as described in the previous equations.

7 Significance and novelty of expert systems

Expert systems help to enhance decision quality and reduce the cost of seeking advice from experts to solve problems. Due to the rapid enhancement of AI techniques, expert systems have been used in diverse fields of IoT and the healthcare domain such as cancer, AD, and cardiovascular disease detection. These systems are used to provide fast and efficient solutions for a particular problem and offer high reliability. Expert systems can deal with difficult problems that cannot be easily solved by human experts. It collect alters from expertise and used it proficiently to provide consistent responses for repetitive decisions. Expert systems are always available for users, even on holidays. Human experts may forget some information and make some mistakes, but expert systems use all their information consistently. As the main purpose of expert systems is to use AI technology to make better decisions to improve the health of patients, it is thus an advantage to reduce/eliminate errors and inconsistencies. The main advantage of an expert system is that of permitting nonexpert users to reach very acceptable conclusions.

Since expert systems are used as a platform for disease control, treatment, and diagnostic tools, they can be advantageous in many circumstances, as at least they will not cause harm when making decisions. It is certain that human intervention will have a better impact on the performance of expert systems. By combining technology with computing and Big Data analysis, these systems may represent an effective solution to improve healthcare services that will also enable real-time decision-making processes.

8 Limitations of expert systems

Although expert systems offer many advantages, there are still some limitations to consider. In the case of a large population, expert systems may not be very accurate. Expert systems will never be too accurate to replace human predictions, but they can help to alleviate some of the issues of the infrastructure of healthcare. The privacy and security of health data and personal information may be threatened, however. Expert systems can be expensive and time consuming. They are not very flexible, having no "common sense," and are unable to adapt to altering environmental conditions. Expert systems can be difficult to maintain and expensive in the area of development. There is a need for ground verification and unable to process for complex automation. They also need to be updated manually. Different expert systems need to be developed for specific domains.

9 Conclusion

As one of the most important applications of AI, the expert system is the best solution for diagnosing complex diseases that cannot be easily resolved using conventional methods. In fact, information-based expert systems have the advanced skills to effectively solve many problems and have proved their usefulness. The use of expert systems to monitor health is considered a major breakthrough in modern technology. Recently, AI and Big Data analysis have been applied in expert systems to provide a more effective healthcare system. In healthcare, Big Data includes medical images, MRI scans, computed tomography (CT) images, clinical data, prescriptions, doctor notes, laboratory data, pharmacy files, insurance EPR data files, and many other management operations-related data. This chapter provides an overview of different expert systems developed in the area of medical diagnostics. In the past few decades, the expert system has made great contributions to the healthcare sector. Many expert systems have been developed for the diagnosis of human diseases. The running speed of expert systems is faster than that of people, thus they provide a more rapid diagnostic facility. In healthcare research, expert systems are one of the major technological advancements. Applications of AI/machine learning with Big.

Data are considered to be significant achievements of automated diagnostic systems. However, today there is a need to develop more heart- and cancer-related expert systems, because these are the major death-causing diseases globally. We have presented the information on expert systems in a systematic way and anticipate that this chapter will be useful to academic, scientific, and medical field researchers looking for more information on expert systems.

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