Computers in Biology and Medicine 39 (2009) 215 – 230

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Knowledge and intelligent computing system in medicine

Babita Pandey*, R.B. Mishra

Department of Computer Engineering, Information Technology, BHU, UP 221005, India

ARTICLE INFO

Article history:
Received 6 February 2008
Accepted 17 December 2008

Keywords:
ANN
CBR
MBR
RBR
KBS
GA
Fuzzy logic
Intelligent computing model

ABSTRACT

Knowledge-based systems (KBS) and intelligent computing systems have been used in the medical planning, diagnosis and treatment. The KBS consists of rule-based reasoning (RBR), case-based reasoning (CBR) and model-based reasoning (MBR) whereas intelligent computing method (ICM) encompasses genetic algorithm (GA), artificial neural network (ANN), fuzzy logic (FL) and others. The combination of methods in KBS such as CBR–RBR, CBR–MBR and RBR–CBR–MBR and the combination of methods in ICM is ANN–GA, fuzzy–ANN, fuzzy–GA and fuzzy–ANN–GA. The combination of methods from KBS to ICM is RBR–ANN, CBR–ANN, RBR–CBR–ANN, fuzzy–RBR, fuzzy–CBR and fuzzy–CBR–ANN. In this paper, we have made a study of different singular and combined methods (185 in number) applicable to medical domain from mid 1970s to 2008. The study is presented in tabular form, showing the methods and its salient features, processes and application areas in medical domain (diagnosis, treatment and planning). It is observed that most of the methods are used in medical diagnosis very few are used for planning and moderate number in treatment. The study and its presentation in this context would be helpful for novice researchers in the area of medical expert system.

1. Introduction

Knowledge-based systems (KBS) are widely used in the areas where knowledge is predominant rather than data and requires heuristic and logic in reasoning to derive new set of knowledge. Ackoff's defined data as a raw which simply exists and has no significance beyond its existence whereas knowledge is the appropriate collection of information which is useful [106]. In medical field, data and knowledge have a proportionate integration of domain knowledge and data for the detection, diagnosis, (interpretation) and treatment of diseases. Depending on problem in hand, the proportionality between data and knowledge varies.

Intelligent computing model such as artificial neural network (ANN), evolutionary computing and fuzzy logic (FL) are data dominant rather than knowledge. The integration of knowledge dominant computing model such as KBS or case-based reasoning (CBR) and data dominant computing models: ANN, genetic algorithm (GA) and FL have been deployed in time to time and problem to problem by many researchers in medical domain.

Basic problem-solving approaches in the field of artificial intelligence are rule-based reasoning (RBR), model-based reasoning (MBR) and CBR [1]. In CBR, the domain knowledge needed to group diagnoses into episodes (events), is implicit knowledge, which lends itself more for reasoning based on analogy than for formulating domain rules or for constructing a model [2].

Due to complementary advantage and disadvantage of RBR, CBR and MBR sometimes, in medical domain, it is difficult to solve problem independently with either. But, if their advantages are exploited and disadvantages are removed then their combination offers significant benefits such as BOLERO [3] and MIKAS [4] which integrate RBR and CBR; PROTOS [5] and CASEY [6] which integrate CBR and MBR and T-IDDM [7] which integrate RBR, CBR and MBR.

The translation of implicit knowledge into explicit rules would lead to loss and distortion of information content [8]. An alternative to this kind of inference is statistical inference such as Baye's theorem, which sets a probabilistic value for each considered output (disease in medical domain) such as ES [9] and MES [10,14]. This type of expert system could be successfully used for mutually exclusive diseases and independent symptoms but fails when some symptoms have the same cause (being connected) and a patient can suffer of more than one disease [11]. Therefore, there are a lot of cases when it is not possible to implement the human intelligence with expert systems for such cases ANN have been developed. ANN have been widely utilized and accepted method for the diagnosis of data intensive. A detailed survey on ANN has been made by Gross et al. [12] which shows that ANN has been used for cardiology [13].

Some of the problems are solved by GA such as in hybrid expert system (HES) [15] which utilize GA to determine (optimize) the number of neurons of the hidden layer.

* Corresponding author.
E-mail address: shukla_babita@yahoo.co.in (B. Pandey).

0010-4825/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compbiomed.2008.12.008

The development of computerized medical systems is difficult due to their uncertainty which arises as a natural occurrence. In such medical system FL is considered as an appropriate tool for modeling and control, since our knowledge and experience are directly contained and presented in control strategies without explicit mathematical models [16].

Multi-agent systems (MAS) are a widely accepted paradigm for distributed and shared work of computation in scientific community. Cooperation and communication are two important functionalities of MAS implemented on FIPA-ACL platform for the diagnosis of acute myeloid leukemia [17], rheumatic fever [18] and interpretation of MRI of brain scan [19].

Data mining (DM) is a technique and tool for the efficient new knowledge discovery from databases. Most of the DM methods in medical domain deploy different techniques for the diagnosis of various diseases such as classification and regression tree for diabetes [20], association rule for heart diseases [21] and prediction rule for obstructive sleep apnea (OSA) [22].

In this paper we have made review of the different methods of detection and diagnosis of different diseases. We mostly cover the methods based upon KBS, intelligent computing system (ICS) and their combination. The KBS comprises RBR, CBR and MBR. The ICS consists of an ANN, GA and FL. The combined methods are RBR–CBR, CBR–MBR, RBR–CBR–MBR, ANN–CBR, ANN–GA, RBR–GA and CBR-RBR–ANN.

In this paper we have also reviewed the fuzzy-based system and their integrated model such as fuzzy–RBR, fuzzy–CBR, fuzzy–ANN, fuzzy–GA, fuzzy–GA–ANN and fuzzy–CBR–ANN in medical domain. DM methods and multi-agent-based models in medical domain have also been described in this work. We have gathered the information regarding this work from the different website resources such as www.google.com, www.ieeexplore.ieee.org, www.sciencedirect.com, www.springer.com and www.inderscience.com.

The rest of the paper has been divided into following sections. Section 2 covers the different ES models in RBR, CBR, ANN, GA and FL. Section 3 deals with various combined methods such as RBR–CBR, CBR–MBR, RBR–CBR–MBR, ANN–CBR, ANN–GA, RBR–GA, CBR–RBR–ANN and fuzzy integrated models such as fuzzy–RBR, fuzzy–CBR, fuzzy–ANN, fuzzy–GA, fuzzy–GA–ANN and fuzzy–CBR–ANN. Section 4 consists of the short and tabular description of MAS. DM methods and means have been described in Section 5. An observation is made on the description, function and features of various methods in Section 6. Section 7 deals with the conclusion.

2. Knowledge and intelligent computing models (individual method)

We have considered RBR, CBR and MBR in a group of KBS and ANN and GA in group of ICMs. KBS group members are knowledge intensive whereas ICM group members are data intensive.

KBS are general purpose problem solver that depends on a rich base of knowledge to perform difficult task. The knowledge is stored in a knowledge base separated from the control and inference programs. Blackboard architecture is KBS which uses a form of opportunistic reasoning [230]. Knowledge in a KBS is represented by frames (F) [34–38], Bayesian network (BN) [52], production rules (PR), etc.

In rule-based system the knowledge is represented by symbolic rules (PR) [23] and inference in the system is performed by a process of chaining through rules recursively, either by backward or forward reasoning [230]. In CBR, the knowledge is stored in form of cases. The new problem in CBR is solved by reusing the past cases. The major tasks of CBR can be divided into five phases such as case representation, indexing, matching, adaptation and storage [24]. When a new problem arrives, the situation of this problem will be identified by case representation phase. After that, the features of new case are assigned to represent it in indexing phase and those indexes are passed to the matching phase. According to the similarity of the indexes, the matching phase retrieves similar cases in the case base. Adaptation phase takes advantage of the solutions of similar cases and some suitable adaptations are applied to solve the new problem. Finally, the new case is stored in the case base after the new problem and its solution are confirmed by the user via the storage phase. In MBR the knowledge base is represented as a set of models (satisfying assignments, examples) of the world rather than a logical formula describing it. When a query is presented, reasoning is performed by evaluating the query on these models [25].

All the above KBS has some advantages and disadvantages such as rules in RBR have some advantages such as an ability to express general knowledge, naturalness of representation, modularity and provision to explanation and disadvantages such as bottleneck of knowledge acquisition, brittleness of rules, inference efficiency problem, difficulty in maintenance of large rule-base, inability of exploiting problem-solving experience and interpretation problem whereas CBR has advantages such as an ability to express specialized knowledge, naturalness of representation, modularity, easy knowledge acquisition, self updatability, handling unexpected or missing inputs and inference efficiency but it also faces some problems such as inability to express general knowledge, knowledge acquisition problem, in some cases efficiency problem, inability of explanation [26,27]. MBR offers enhanced interpretation and explanation power, principled approach that provides the reference for model manipulation and reasoning, provision for the generation or treatment of all cases within a well-defined framework and handling unexpected cases whereas it faces problems such as difficult modeling, lack of model-builders, need for reusable libraries and need for integration with other methods [28]. The comparison of advantages and disadvantages of RBR, CBR and MBR are described in Table 1.

2.1. Knowledge-based and rule-based system

Rule-based model have been developed and utilized by many researchers in the treatment and diagnosis of various diseases. Most of the rule-based model and KBS have utilized RBR for knowledge representation except SBS [34] which used frame whereas some of the system have deployed hybrid model such as PR and frame ESPRE [35], ESTER [36], M-HTP [37] and KBS [38]; rules and BN are deployed in HERME [39] and ES [9]. As a matter of fact most of the RBR and KBS methods use backward chaining (BC) and forward chaining (FC) both but few of them have used FC only. Other reasoning methodologies have also been deployed. The summary of representation and reasoning method of different ES models deploying rule-based or knowledge-based methodology are given in Table 2.

2.2. Case-based reasoning (CBR)

CBR is used in learning and problem-solving system to solve new problems by recalling and reusing specific knowledge obtained from past experience. They are self-updatability and can handle unexpected cases not recorded in the system or missing input values [26]. Finnie and Sun [24] described different CBR models such as Hunt's model [61], Allen's model [62], Kolodner's and Leak model [63], the R^4 model [64] and R^5 model [24]. Table 2 presents the case-based system with their specific features and applications. Most of the systems perform similarity-based retrieval whereas other retrieval method is also deployed. Some of the specific applications implemented by CBR are such as bacterial infection diagnosis, recipe planning, meal design, image analysis, disaster response, stem cell transplantation, menu planning and antibiotics for intensive care. The summary of CBR process used in CBR systems is given in Table 3.

Table 1
Advantages and disadvantages of RBR, CBR and MBR.

Item	RBR	CBR	MBR
Basic unit	*Rule*	*Case*	*Modal*
Advantages	1. Modularity 2. Uniformity 3. Naturalness 4. Compact representation of general knowledge 5. Provision of explanation	1. Easy knowledge acquisition 2. Learning from experiences 3. Applicability 4. Ability to express specialized knowledge 5. Naturalness 6. Modularity 7. Self updatability 8. Handling unexpected or missing value 9. Inference efficiency	1. Provision of explanation and intepretation 2. Principled approach 3. Unexpected cases 4. Completeness
Disadvantages	1. Difficulty in representing informal information 2. Knowledge acquisition bottleneck 3. Inference efficiency problem 4. Difficulty in maintenance of large rule-base 5. No memory 6. Perfectness 7. Brittleness of rule	1. High search cost 2. Case index problem 3. Inability to express general knowledge 4. Inference efficiency problems 5. Provision of explanations 6. Require considerable adaptation knowledge 7. Adaptation knowledge should be domain-specific 8. Knowledge acquisition problems 9. Problem of competence gap	1. Modeling is difficult 2. Lack of model builders 3. Need for reusable libraries 4. Need for integration with other methods

Table 2
Rule-based and knowledge-based system with their applications.

KB/RB system	KR	Reasoning	Application
MYCIN [29]	RBS	BC	Infection in the blood and central nervous system; diagnosis & treatment
EMERGE [30]	PR	Searching in hierarchical manner	Chest pain; diagnosis
RBES [31]	RBES	BC	Fibrillation; diagnosis
ES for diagnosis [32]	Rule	BC	Chronic venous insufficiency; diagnosis
CORONARIA [33]	RBES	BC and FC	Ischemic hear diseases; diagnosis and treatment
SBS [34]	Frame	Matching in a frame	Interpretation of ultra sound images; diagnosis
ESPRE [35]	Frame and PR	Matching in frame	Platelet transfusion decisions; treatment
ESTER [36]	Frame and PR	Matching in frame, BC and FC	Respiratory weaning therapy; treatment
M-HTP [37]	Frame and PR	Matching in frame, BC and FC	Monitors heart transplant patients; treatment
KBS [38]	Frame, PR and probabilistic models	BA with and BC	Anemic patients (hematology); Treatment and Planning
HERMES [39]	IF–THEN rules and BN	BC and FC Bayesian mechanism with belief	Chronic liver diseases; (gastroenterology) diagnosis
KB system [40]	Frame and Rule	BC	EMG abnormalities; diagnosis
ERIC [41]	IF–THEN rule	BC and FC	Chest pain; diagnosis
Probability-based ES [42]	IF–THEN rule	BC	Pacemaker-related complications; diagnosis
Psychiatric treatment [43]	IF–THEN rule	Generating alert	Psychiatric; treatment
ES [9]	IF–THEN rule and BN	BC and Bayes theorem	Pace maker problem; diagnosis
KBS [44]	IF–THEN rule	BC	Ectopic pregnancy and neural tube defects; diagnosis
HEPAXPERT-I [45]	IF–THEN rule	Rule pattern matching algorithm based on indexing	Interprets the results of routine serologic test for infection with hepatitis A or B;diagnosis
DIABETES [46]	PR	BC	Therapy of types I or II diabetic patient; treatment
DIAVAL [47]	BN	Bays rules	Echocardiography; diagnosis
TOXOPERT-I [48]	IF–THEN rule	FC without backtracking	Interpretation of serological test for toxoplasmosis; diagnosis
OPERAS [49]	Heuristic and meta rule	Decision tree	Error detection and elimination in the picture archiving and communication system; diagnosis
PRISM [50]	IF–THEN rule	Backtracking	Menu planning; planning
MES [51]	IF–THEN rule	FC	Cardiac diseases; diagnosis
MUMIN [52]	BN	Bayesian (belief) rules	Neuromuscular diseases; diagnosis
ESEDED [53]	IF–THEN rule	FC	Eye diseases; diagnosis
RBES [54]	IF–THEN rule	Grobner bases	Managing medical appropriateness criteria; treatment
EDSS [55]	PR	Pattern matching BC and FC	Multiple sclerosis; diagnosis
Anorexia ES [56]	Bivalued logic PR	Gröbner bases and normal forms	Anorexia; diagnosis
Bone Browser [57]	Rule-based	Rule-based logic and Bayes' theorem	Bone tumors; diagnosis
ES [58]	Rule-based	Default reasoning	Evaluation of risk in type I diabetes; diagnosis
MES [59]	IF–THEN Rule	FC	Lung problems; diagnosis
ESMIS [60]	IF–THEN rule	BC and FC	Dangerous infection; diagnosis and treatment
MES [10]	IF–THEN rule	Logical and statistical inference (Bayes's theorem)	Hepatitis infection; diagnosis

Notes: P, planning; BN, Bayesian network; F, frame; PR, production rule; BA, blackboard architecture.

Table 3
Case-based medical system and their applications.

CBR system	Specific feature (process and method)	Application/domain
MEDIC [65]	Transformational plan representation, memory consists of schemata and diagnostic memory organization packet, indexing-based retrieval, Substitution adaptation	Bacterial infection, (Pulmonology) diagnosis
CHEF [66]	Transformational plan representation, indexed memory organization, indexing-based retrieval, substitution and transformation adaptation	Recipe planner system, planning
JULIA [67,58]	Hierarchical frame-based representation, constraint guided adaptation	Meal design system, treatment
MACRAD [68]	Representation by relational database, indexing structured about case feature, content related quires, visual memory for storage	Image analysis, (Radiology) diagnosis
CHARADE [69]	Transformational plan representation, similarity-based retrieval, constraint satisfaction adaptation	Diagnosis & treatment
DIAL [70]	Transformational and derivational plan representation, indexed memory organization, similarity-based retrieval, derivational reply and heuristic-based adaptation	Disaster response, diagnosis & treatment
IMAGECREEK [71]	Hierarchal representation, indexed organization, retrieval is combination of failure driven learning and case integration, single case adaptation	Image analysis, diagnosis
SCINA [72]	Case representation by matrix of integers, indexed memory organization, similarity-based retrieval, rule-based adaptation	Coronary heart diseases, diagnosis
CaB-CS [73]	Feature-vector representation, retrieval via similarity measure	Brest cancer, diagnosis
CARE-PARTNER [74]	Case as prototypical cases, template retrieval	Stem cell transplantation, treatment
RBCSHELL [75]	Hierarchal case representation, cases are stored in associative memory, indexed memory organization, similarity-based retrieval, manual adaptation	Illness, diagnosis
CAMP [50]	Case are stored in database, selection by reusability metric, substitution and transformational adaptation	Daily menu planning, planning
HICAP[76]	Hierarchal case representation, indexed memory organization, similarity-based retrieval, case-based, generative adaptation	Diagnosis & treatment
CTS [77]	Case representation by attribute-value pair similarity-based retrieval	Image analysis, diagnosis
EIA [78]	Cases are represented by set, indexed organization, similarity-based retrieval	Endoscope, diagnosis
ICONS [79]	Attribute-value representation, two retrieval strategies: simple indexing for small & medium cases tree-hash retrieval for large case bases, compositional adaptation	Antibiotics for intensive care, treatment
ISOR [80]	Case representation by attribute value pair scheme, cases are indexes by keyword, inductive retrieval	Endocrine, diagnosis & treatment

Table 4
Model-based medical system and their applications.

MBR system	Reasoning	Application
YAQ [81]	Hybrid algebra of qualitative and numerical values, associations and model-based diagnosis	Respiratory distress syndrome (RDS); diagnosis
Pacemaker reprogramming [82]	Model of abnormal behavior, prediction of abnormal findings, predictions are next matched with findings, collection of causes described in the model and associated with predictions that best match the findings observed	Pacemaker reprogramming; treatment

2.3. Modal-based reasoning (MBR)

YAQ [81] ontology is an MBR, applied to the domain of ventilator management in infants with respiratory distress syndrome (RDS). Pacemaker reprogramming [82] is another application that deployed MBR. Pacemaker reprogramming diagnosis may be described in terms of matching abnormal behavior (MAB) [83]. The summary of reasoning used in medical system deployed MBR methodology is given in tabular form in Table 4.

2.4. Artificial neural nets (ANN)

ANN is a data dominant approach and widely used in medical domain deploying supervised ANN, differentiated by the learning law and topology. ANN trained with back propagation (BP) algorithm has been widely used methodology ANN has some advantages over rule-based system: ANN presents a complementary approach to rule-based systems with respect to the numeric knowledge representation by the network weights and the adaptive capability of neural networks adjusting the weights based on training data is widely regarded as learning-like. Although ANN has been successfully used in many areas of medicine as it has been illustrated in an extensive review by Lisboa [117] it has some disadvantages, such as the structure of NN is not transparent, they approximate an arbitrary black-box model of the mapping rule and a priori expert knowledge cannot be considered for better initializing the network parameters in order to improve convergence and to reduce the learning time.

Some of the application includes in our study are: response to HP eradication recurrence, lymph node metastasis, response to interferon in chronic hepatitis C, diagnosis of diabetes occurrence

Table 5
Summary of experiences of ANN with their application.

ANN system	ANN model	Disease/Application
DESKNET [84]	BP	Papulosquamous skin diseases (dermatology); diagnosis
Clinical decision making [85]	BP	Acute coronary occlusion (C); diagnosis
Conventional classifiers [86]	BP	Tissue fluorescence spectra (C); diagnosis
ANN analysis [87]	BP	Acute myocardial infarction (C); diagnosis
Diagnosis of MI [88]	BP	Acute myocardial infarction (C); diagnosis
Noninvasive diagnosis using ANN [89]	BP	Coronary artery disease (C); diagnosis
MES [90]	2 layer perceptron with BP	Canine liver disease; diagnosis
PAPNET [91]	Multi-layer perceptron BP	Cervical cancer; diagnosis
MES [92]	Feedforward BP	Pulmonary diseases; diagnosis
Classification system [93]	BP	Iteracardic arrhythmia (C); diagnosis
Self learning techniques [94]	BP	ventricular tachycardia (C); diagnosis
Hacettepc [95]	BP	Genetical disorders and fetal health problems; diagnosis
Coronary disease prediction [96]	BP	Coronary artery disease (C); diagnosis
ANN for gastric cell [97]	BP vs. LVQ	Gastric cancer (G); diagnosis
ANN aided diagnosis [98]	BP	Focal liver disease (G); diagnosis
Expert system [99]	Feedforward BP	Gastro-esophageal disease (G); diagnosis
Diagnosis of AMI [100]	Feedforward (MLP) BP	Acute myocardial infarction (C); diagnosis
Predict length Stray [101]	BP	Acute pancreatitis, length of stay (G); diagnosis
CDSS [102]	Feedforward BP	ICU patients; treatment
SMART EEG [103]	Multi-layered perceptron BP	Electroencephalograms (EEGs); diagnosis
LCDS [104]	Feedforward FANC	Lungcancer; diagnosis
Andriulli (a) [105]	BP, SN + AO	Dyspeptic syndrome (G); diagnosis
Andriulli (b) [105]	BP, self, TASM Cm + AO	Dyspeptic syndrome, response to HP eradication recurrence (G); diagnosis
Predictive model [107]	Multi-layer perceptron	Acute lower GI haemorrhage (G); diagnosis
CoLD [108]	Multi-layer perceptron	Colorectal cancer; diagnosis
Prediction of lymph node [109]	BP	Esophageal carcinoma, lymph node metastasis (G); diagnosis
Prediction of response [110]	Presumably feedforward BP	Chronic hepatitis C, response to interferon (G); treatment
ANN for diabetes [111]	BP + AO	Chronic pancreatitis diabetes occurrence (G); diagnosis
ANN for prediction [112]	BP, prediction committee	Esophageal carcinoma, survival (G); treatment
MES [113]	RS, BP	Coronary artery disease (C); diagnosis
Diagnosis of GERD [114]	BP, SN, ARCR, TASM + AO	GORD (G); diagnosis
Recognition of atrophic gastritis [115]	BP, SN, ARCR, TASM + AO	Atrophic gastritis (G); diagnosis
Detection of EMG abnormality [116]	BP + RBF	EMG abnormality; diagnosis

Notes: Abbreviations of the different ANN described, which will appear in the results tables—BP, back propagation (standard); LVQ, learning vector quantisation; SN, sine net (Semeion ©); Self, self-recurrent network (Semeion ©); TASM, temporal associative subjective memory (Semeion ©); ARCR, autoRecurrent network; Cm, contractive map; AO, artificial organism; FANC, fast adaptive neural classifier algorithm; RS, rough set; G, gastroenterology; C, Cardiovascular; RBF, radial basis function.

in chronic pancreatitis, prediction of survival, recognition of atrophic gastritis, interpretation of EMG abnormalities as presented in Table 5 with requisite references. Table 5 summaries the main characteristics of problems addressed in each specific selected papers, listed in chronological order.

2.5. Genetic algorithm (GA)

GA is an efficient search method based on the principles of natural selection and population genetics in which random operators on a population of candidate solutions are employed to generate new points in the search space [118]. In medical domain GA is mainly used for optimization of weight of the sing, symptom and specific features (parameters) of the diseases.

Generally GA in medical domain is used for diagnosis and treatment as presented in Table 6. Gross et al. [119] deployed GA to detect rare cancer cells in blood and bone marrow and found good performance. Ezzell [120] deployed GA for three-dimensional radiation therapy treatments planning and found that it produce consistent result compare to simulated annealing. Yu et al. [121] deployed GA in treatment optimization for stereotactic radiosurgery and radiotherapy and found that GA is powerful and versatile as a computationally intelligent counterpart to human-guided strategies. Kupinski and Giger [122] deployed GA for detection of mass lesions in digital mammography and found that GA was able to either outperform or equal the performance of other methods. GENIFER [124] uses GA for diagnosis of breast cancer. Wanschura et al. [125] deployed GA to register time-separated pairs of MRI data sets. Matsopoulos et al. [126] deployed GA optimization technique to register retinal images and found that the proposed automatic scheme in terms of accuracy and consistency. Medical expert system [14] uses GA to perform multi-disorder diagnosis. Table 6 summarizes the operators used in GA-based system. Yu et al. [127] deployed GA optimization in treatment planning for radiation therapy is a multi-objective optimization process and found that the run time for producing an optimal plan is considerably shorter than the typical planning time for human experts.

2.6. Fuzzy system (FS)

FL uses these linguistic variables to define the system's knowledge base as a collection of fuzzy IF–THEN rules. However, one hurdle in the adoption of FL for intelligent system implementation is the difficulty of *knowledge elicitation*. FL-based systems obtain domain knowledge from domain experts to prepare the rules in the system's knowledge base. FL provides advantages such as an intuitive user interface, simplifies the process of knowledge representation and minimizes the system's computational complexity in terms of time and memory usage. On the other hand, FL has problems in knowledge elicitation which render it difficult to adopt for intelligent system implementation [128].

There are several fuzzy techniques deployed in medical application such as fuzzy clustering, fuzzy classification, fuzzy modeling and identification. Different fuzzy clustering algorithm such as Gustafson–Kessel algorithm (GK-FCM) [129], fuzzy c-regression model (FCRM), possibility c-means (PCM) clustering algorithm [130], fuzzy c-means (FCM) clustering algorithm [131] and entropy-based fuzzy clustering (EFC) algorithm [132] are deployed in medicine. Various modeling techniques such as fuzzy k-nearest neighbor algorithm [133], fuzzy clustering-based modeling, and

Table 6
GA-based medical system and their application.

GA-based system	GA operators	Application
Model study [119]	GA optimization, four gate parameter encoding, GA-operator: mutation change a gate parameter, creep randomly increment or decrement one parameter, crossover randomly combines the gate parameter	Breast cancer, diagnosis
Therapy planning [120]	GA optimization, paired list encoding, one-point crossover, mutation by incrementing or decrementing the index	Prostate, pancreas: radiation therapy, treatment
Treatment planning [121]	GA optimization, tournament selection, ordinal ranking, one-point crossover, flip a random bit in individual (mutation)	Radio surgery, treatment
Computerize detection [122]	GA-based feature selection, Wilks' lambda fitness function, crossover & mutation	Memographic, diagnosis
Predicting survival [123]	Individual is Bayesian structure, binary encoding, two point cross-over, mutation by flipping a random bit	Skin melanoma; diagnosis
GENIFER [124]	GA optimization, chromosome contains numeric value gene, Roulette wheel selection, two point cross-over, mutation randomly change the values of some genes	Breast cancer, diagnosis
MR-images [125]	GA optimization, binary encoding, one-point crossover, flip a random bit in individual (mutation)	Arthritic disease, diagnosis
Retinal images [126]	GA optimization, real value encoding, tournament selection, linear and arithmetic crossover	Ophthalmic diseases, diagnosis
MES [14]	GA optimization, chromosome encoded as bit vector, one-point crossover, flip a random bit in individual (mutation), inversion	Multi-disorder, diagnosis
Retinal images [127]	GA optimization, *n*-tournament, crossover by combining randomly paired string, single point mutation	Radio surgery and prostate Brach therapy, treatment

Table 7
Fuzzy system with their application domain.

Fuzzy system	Fuzzy technique	Application
Fuzzy system [136]	SUP-MIN composition	Thyroid diseases, diagnosis
Fuzzy system [137]	Lower–upper inverse	Thyroid diseases, diagnosis
Eye movements [138]	Fuzzy clustering	Nystagmic eye movements, diagnosis
Fuzzy system [139]	Max–min inference	Bacterial infection, diagnosis
Muscle relaxant anaesthesia system [140]	SOFLC	Muscle relaxants, treatment
VAD [141]	FCM	Ventricular arrhythmias, diagnosis
SNP delivery system [142]	Closed-loop control	Postsurgical Patients, treatment
LVA detection [143]	Fuzzy clustering	Cardiology diseases, diagnosis
Therapy system [144]	SFCM	Tumor, treatment
Muscle relaxants system [145]	PD + I and SOFLC	Muscle relaxants, treatment
Fuzzy controller [146]	PD + I	Neuromuscular block, treatment
ECG-based system [147]	Fuzzy modeling	Ischemia, diagnosis
EP estimation [148]	Fuzzy clustering	Brain activity, diagnosis
Brain tumor [149]	SFCM	Brain tumor, diagnosis
FL control system [150]	SOFLC	Neuromuscular block, treatment
Neuromuscular blockade control system [151]	PSOFLC	Neuromuscular block, treatment
FL KB control [152]	PD controller	Muscle relaxation, treatment
Predicted by fuzzy decision [153]	Fuzzy decision	Bone structure, diagnosis
CAD [154]	FCM	Breast cancer, diagnosis
Fuzzy control strategy [155]	FPD	Neuromuscular block, treatment
CAD [156]	FCM	Breast cancer, diagnosis
Medical application [157]	MCDA	Central nervous system tumors, diagnosis
FES system [158]	FLC	Paraplegia, treatment
TBS [159]	FCM	Trabecular bone structure, treatment
BTC [160]	FCM	Neurosurgical, diagnosis
BMS [161]	FCM	Heart valve diseases, diagnosis
Biomedical system [162]	Fuzzy classification	Brain diseases, diagnosis
Medical DM [163]	Fuzzy modeling: fuzzy k-nn, fuzzy clustering-based and adaptive network-based fuzzy inference	Breast cancer, diagnosis
Neuromuscular system [164]	SOFMA	Neuromuscular block, treatment
TBM [165]	FCM and FMLE	Tuberculosis meningitis, diagnosis
FLES [166]	EFC	Adult psychosis, diagnosis
Brain detection system [167]	FCM	Brain activity, diagnosis

the adaptive network-based fuzzy inference system [134], self-organized fuzzy modeling algorithm (SOFMA) [135] are deployed in medicine.

Generally, FL in medical domain is deployed for detection, diagnosis and treatment of diseases as presented in Table 7. Table 7 summaries the main characteristics of problems addressed in each specific selected fuzzy system, listed in chronological order.

3. Integrated model

Single KBS have their own advantages and disadvantages such as knowledge acquisition problem, inference problem, explanation problem, etc., as described in Section 1. The disadvantages of the single KBS are removed by integrating the KBS and ICM approaches.

3.1. Integration of knowledge intensive model and intelligent model

This section shows the advantages obtained from integrated model and their medical applications. The integration of CBR–RBR simplifies knowledge acquisition, improve efficiency and improve accuracy [26], improve performance [168] and decrease competence gap [169]. In medical domain this integrated approach generally used for diagnosis and treatment. The benefit obtained form the integrated approach are: more cost effective system, improved competency, automatic explanation, improved advice as in MIKAS [4], improved problem-solving capability as in CAMPER [50], cope with qualification problem, deal with competence gap problem as in IDDM [171], improves diagnosis accuracy as in CDPD [173]. Some other system that integrates CBR–RBR is BOLERO [3] and INERCA [170].

The integration of CBR–MBR generally makes adaptation process easy [6], improve performance and efficiency [7], integrate generalize and specific knowledge [181]. PROTOS [5] and CASY [6] are the medical system that integrates CBR with MBR.

Integration of CBR with RBR and MBR has advantages to incorporate CBR subtasks into more complex methodologies instead of applying the complete CBR cycle and making use of all available knowledge [180]. The main advantage that the integration of the CBR, RBR and MBR paradigms provides is the capability of exploiting all the available information, from the explicit (i.e., formalized) domain knowledge, to the operative know-how collected in the single organization where the application will be deployed [7]. Very few integrated model of RBR–CBR–MBR are reported in the literature of medical concern. T-IDDM [7] is integrated model used for diabetic treatment that performs a tight integration of CBR, RBR and MBR.

The integration of ANN–GA in medical domain improves performance and accuracy [174], improved prediction rate [176] and optimize the number of neurons in hidden layer [177]. Few models that integrate ANN with GA have been reported in medical literature for diagnosis such as diagnosis of critically ill [171], improved classification performance [175], recognition model [176] for diagnosis of bacterial odour and system for diagnosis of pneumonia [177].

The integration of RBR with GA provide better accuracy then machine learning but lower accuracy then ANN [178]. Few models that integrate ICM with KBS are such as crisp RBS [178], which combines standard genetic programming (GP) and heuristic hierarchical crisp rule-based construction for diagnosis of aphasia. Here GP is used for the production of crisp rule-based systems.

The integration of RBR with ANN in medical domain provides good prediction accuracy [10]. In medical the integrated approach is generally used for diagnosis of disease such as MES [10] for diagnosis of Hepatitis infection. Table 8 presents the specific features of integrated components used in ES with their applications.

3.2. Fuzzy integrated model

RBR, ANN and CBR are two well-known techniques for the implementation of intelligent systems. All these AI techniques face certain problems when implemented alone whereas their integration with FL provides a lot of benefits.

The integration of fuzzy and RBR (FL/RBR) produce reasonable results like in CADIAG-2, handles uncertain data like in PSG-EXPERT, improved target volume definition [188], integrate linguistic and numerical information to provide a flexible and robust description of processes with varying complexity [187] as well as it has some weakness as compositional processing of belief as in CADIAG-2. Successful implementations of the fuzzy–RBR integrated approach in medical have been reported for diagnosis as presented in Table 9.

The hybrid FL/CBR system has several advantages such as possibility of integrating AI algorithm of many fields [193], improved accuracy, easier to use, improved case retrieval, improved system performance, improved linguistic variables, simpler in complexity [128]. This integrated approach is deployed for diagnosis and recognition of facial expression [194,128] as described in Table 9.

The integration of ANN and fuzzy (FL/ANN) approach incorporates the generic advantages of ANN like massive parallelism, robustness and learning in rich environment and the capability of FL such as modeling imprecise data and qualitative knowledge as well as transmission of uncertainty [200]. Other advantages of integrated approaches in medical domain are building of more effective ANN [209], produce quick and accurate decision [205], improved diagnosis accuracy [212,213], improved performance [214]. Successful implementations of the ANN-fuzzy integrated approach in medical have been reported for diagnosis, treatment and prediction as summarized in Table 9.

The integration of fuzzy–ANN–GA (FL/ANN/GA) minimizes some complexity problems pervasive to the artificial intelligence such as the knowledge elicitation process, known as the bottleneck of expert systems, the model choice for knowledge representation to code human reasoning, the number of neurons in the hidden layer and the topology used in the connectionist approach; the difficulty to obtain the explanation on how the network arrived to a conclusion [15]. This integrated approach is used for diagnosis of epilepsy as presented in Table 9.

The integration of fuzzy–GA [186] (FL/GA) has several benefits in medical domain such as they attain high classification performance with the possibility of attributing a confidence measure to the output diagnosis, involve a few simple rules, and are therefore human interpretable [215], optimize the knowledge base and diagnose the diseases effectively [216]. In medical domain this integrated approach is mainly used for diagnosis as presented in Table 9.

The integration of fuzzy–CBR–ANN (FL/CBR/ANN) effectively produces a high-quality diagnosis for a given medical consultation [219].

4. Agent-based system

Agent-based system has been developed with different functionality cooperation, coordination and negotiation as well as mental states: belief, desire and intention (BDI). Lanzola [17] proposed a methodology facilitating the development of interoperable intelligent software agents for medical applications and proposes a generic computational model for implementing them. This model supports all the different information and knowledge related requirements of a hospital information system. This computational model is useful for implementing the agents themselves and enforcing their interactions. This model follows a layered architecture using which many old legacy system can in turn be agents by eliminating or minimizing the changes required to their internal structures, since much of the control for enforcing consistency at the conversation level is shifted at the ACL layer. Lanzola followed KQML specifications which emerged as a part of the knowledge sharing effort (KES).

Mea [220] describes a novel approach to the analysis and development of telemedicine systems, based on the multi-agent paradigm. This system uses agent-based architecture for cooperative negotiation. The system has an agent telemedicine-oriented medical

Table 8
Integrated medical system and their application.

Integrated components	CBS in medicine	Specific feature of CBR, RBC and MBC	Application
CBR–RBR	BOLERO [3]	CBC: case representation via attribute-value, exemplar and dynamic memory modal, retrieval by pattern matching, copy, merging	Pneumonia; diagnosis
	INRECA [170]	CBC: attribute-value pair, retrieval via similarity measure, RBC: assigning weights to attribute for similarity measure	Poison cases; diagnosis
	CAMPER [50]	RBC: heuristic rule, CBC: Case are stored in database, selection by reusability matric, adaptation by substitution rule	Diet prescription; treatment
	IDDM [171]	CBC: Set of features, retrieval via nearest neighbor retrieval, matching via heterogeneous Euclidean-overlap and heterogeneous value difference metric RBC: IF–THEN rules with FC; When CBR fails, RBR alone is used	Diabetes; treatment
	LDD [172]	RBC: IF–THEN rule, CBC: case representation via attribute value, retrieval via similarity measure, RBC & CBC both plays balanced role in reasoning	Lung disease; diagnosis
	MIKAS [4]	RBC: Ripple-down rules (RDR), CBC: Matching by similarity measure, rule-based adaptation, RDR builds CBR	Diet recommendation; treatment
	CDPD [173]	RBC: Production rules, CBC: Prevails in inference process, similarity-based retrieval, exact adaptation, interpolation, using mean values for adaptation and applying adaptation rules	Chronic diseases; diagnosis
CBR–MBR	PROTOS [5]	CBC: Feature-vector representation, exemplar memory model, simantical similarity, R: Direct index and general domain knowledge, MBC: Multi-relational model of knowledge	Audiological disorders; diagnosis
	CASEY [6]	CBC: Feature-vector, indexed memory organization, matching via semantical similarity, transformational adaptation MBC: Model-based adaptation	Heart failure; diagnosis
Integration	**ES in medicine**	**ANN, RBC, GA, CBC**	**Application**
RBR–CBR–MBR	T-IDDM [7]	RBC: IF–THEN Rule with FC, CBC: cases are mapped to periodical control visit, MBC: Probabilistic model of Glucose-Insulin, RBR proposed suitable solution while MBR and CBR (retrieval) are used to specialize the rule behavior	Type 1 diabetes, treatment
ANN–GA	Prediction system [174]	GA to improve NN performance, chromosome is set of neural net represented by string, crossover by natural recombination event, mutation by alteration of randomly chosen bit	Critically ill, diagnosis
	STD [175]	GA-based feature selection, binary encoding, ranking method for selection, two point cross-over, mutation by inverting a random bit, ANN with BP	Skin tumor, diagnosis
	Recognition model [176]	ANN model: BP, GA optimize NN	Bacterial odour detection, diagnosis
	GA for NN [177]	GA to optimize ANN, ANN: FF-BP, chromosome is set of NN represented by binary string, two-point crossover, mutation by flipping a bit at binary locus	Pneumonia, diagnosis
RBR–GA	Crisp RBS [178]	RBC: Crisp RB, GA: Population is represented as tree, crossover, mutation	Aphasia's, diagnosis
RBR–ANN	MES [10]	RBC: IF–THEN Rule with BC, FC and Baye's theorem, ANN model: Feed-forward with BP	Hepatitis infection, diagnosis
RBR–CBR–ANN	MDSS [179] (Loss coupling)	RBC: Production rule with BC & FC, CBC: Feature-vector representation, measure, matching and selection via similarity, ANN model: feed-forward BP and STF	Leukemia, diagnosis and treatment

Notes: CBC, case-based components; RBC, rule-based components; MBC, model-based components; GA, genetic algorithm; STF, sigmoid transfer function; GP, genetic programming.

assistant (TOMAS), which is used by each specialist. As a medical assistant, it has two generic features: an agenda for managing appointments, and methods for access to patient records. Support to telemedicine is given by software features for remote exchange of patient data, cooperative annotation of cases and negotiation of appointments. The community of agents has been developed in Java using an already existing FIPA-compliant platform, i.e., Crepeau's FIPA_SMART 3.0 (FIPA-based Stationary and Mobile Agent Resource Toolkit, version 3.0, 1999). The basic feature of the agent, i.e., the agenda, has been implemented following the FIPA recommendations for the development of personal assistants. AMPLIA [18] is an intelligent probabilistic learning environment, based on BDI architecture designed to support the construction of explanatory models in complex, uncertain domains to support diagnostic reasoning. It also uses BN in the agent's beliefs modeling and mental states to guide the negotiation process. AMPLIA is used for diagnosis of rheumatic fever. AMPLIA agents communicate over a FIPA-OS platform. Godo [221] proposed an MAS approach for monitoring the prescription of restricted use of antibiotics where an agent is attached to each patient which is responsible of checking different medical aspects related to his/her prescribed therapy. It performs cooperation and coordination and is implemented ISLANDER. The system first finds the degree of adequacy of every group of antibiotics to the patient taking into account data about pregnancy, allergic reactions to the antibiotics, renal diseases or genetic alterations. Then considering the diagnosis of the patient it dynamically generates a set of treatments, one for each microorganism. Richard et al. [19] proposed a multi-agent approach for automated segmentation of

Table 9
Integrated fuzzy system.

Integrated component	Fuzzy system	Specific feature	Application
FL/RBR	CADIAG [182]	Fuzzy IF–THEN rule, max–min inference	Internal medicine, diagnosis
	CADIAG-2 [183]	Fuzzy IF–THEN rule, max–min inference	Internal medicine, diagnosis
	Biomedical application [184]	Rules of truth-qualification, fuzzy relation, SUP-MIN composition	Collagen diseases, diagnosis
	Fuzzy system [185]	Fuzzy rules, min–max inference	Cancer, diagnosis
	MedFrame [187] (Sageder et al., 1997)	Frame and rule, max–min inference	Internal medicine, diagnosis
	PSG-EXPERT [188]	Facts represented by fuzzy logic, backward and forward chaining	Sleep disorder, diagnosis
	DoctorMoon [189]	Frame and rule, max–min inference	Lung disease, diagnosis
	FES [190]	Fuzzy IF–THEN rule, max–min inference	Prostate cancer, diagnosis
FL/CBR	ARC system [191]	Memory organized as hierarchy of classes, dynamic memory model, fuzzy patter matching algorithm	Internal medicine, diagnosis
	AIDS [192]	Cases consist of risk behavior, retrieval by fuzzy algorithm, rule-based adaptation	AIDS; diagnosis
	MePoS [193]	Cases are stored as attribute-value pair, retrieval by fuzzy algorithm, adaptation by copy or rule	Anesthesia, diagnosis
	FER [194]	Fuzzy IF–THEN rule, case consist of input-output variable, fuzzy similarity retrieval,	Facial expressions, diagnosis
	FER [128]	Case base populated with fuzzy rule, case consist of input-output variable, similarity-based retrieval	Facial expressions, diagnosis
FL/ANN	Arrhythmias diagnosis [195]	FKCN, FCM	Arrhythmias, diagnosis
	FCNN system [196]	FCNN, FCM, ML-FF with BP	Upper-limb prosthesis, diagnosis
	Fuzzy system [197]	ANFIS	Intensive care, treatment
FL/ANN	NICU [198]	NFIS, NN topology not specified	Heart rate variability, diagnosis
	ANFIS[199]	ANFIS, trained with the BP gradient descent and least squares method, fuzzy IF–THEN-rules	Carotid artery stenosis, diagnosis
	ANFIS [200]	ANFIS, FF–NN + BP fuzzy IF–THEN-rules	Psychosomatic disorders, diagnosis
	ANFIS [201]	ANFIS, fuzzy IF–THEN-rules	Gait event, diagnosis
	NFS [202]	ANFIS, NN to optimize fuzzy rule ANN-BP	Prostate cancer, diagnosis
	ANFIS [203]	ANFIS, trained with the BP Gradient descent and least squares method, fuzzy IF–THEN rules	Ophthalmic artery stenosis, diagnosis
	ECG-arrhythmias [204]	FCNN, FCM + MLP	Arrhythmias, diagnosis
	CDSS [205]	MLP-FF, fuzzy rules represented by fuzzy vector–matrix composition using the composition operator ‘o’	Gynecological disease, diagnosis
	Classification application [206]	EQNFIS, entropy-based fuzzy model, quantum function, SCA; NN-BP	breast cancer, diagnosis
	FECG [207]	ANFIS, least squares method and the gradient descent method	Cardiac diseases, diagnosis
	OAD [208]	ANFIS,	Ophthalmic arterial disorders, diagnosis
	ECG-arrhythmias [209]	T2FCM, MLP + BP	Arrhythmias, diagnosis
	ES [210]	ANFIS, FCM or K-means algorithms least squares method and the gradient descent method	Heart valve diseases, diagnosis
	IDS [211]	ANFIS, PCA, Fuzzy IF–THEN rule	Heart valve diseases, diagnosis
	IDS [212]	ANFIS, PCA, LMBP	Optic nerve disease, diagnosis
	ESTDD [213]	NEFSCLASS, MLP-FF	Thyroid diseases, diagnosis
	NFS [214]	FF-MLP-BP, Fuzzy min-max inference	Autism, diagnosis
FL/GA	WBCD [215]	Fuzzy max–min inference, GA optimization, bit encoding, GA operator: fitness proportionate selection, one-point crossover, mutation by flipping bits at random	Breast cancer, diagnosis
	GA-fuzzy [216]	FLC & EFC, GA optimization, bit encoding, GA operator: Roulette wheel selection, 2-point crossover and mutation	Pneumonia; diagnosis
	MR-Images [217]	FCM & EFC, GA optimization, binaryencoding, GA operator: crossover and mutation	Brain, diagnosis
	FLES [218]	FCM & EFC, GA optimization, Binary encoding, single point crossover, bitwise mutation	Psychosis, diagnosis
FL/GA/ANN	HES [15]	ANN model: BP GA: Population encoded as binary-valued, string, crossover, mutation, recombination GA optimize ANNL, fuzzy min-max inference	Epilepsy; diagnosis
FL/CBR/ANN	HCBR [219]	Cases are instance of medical diagnosis, retrieval by fuzzy NN	Multiple disease, diagnosis

Notes: FCNN, fuzzy clustering NN architecture; ML-FF, multi-layer Feed forward; BP, back propagation; NFIS, neuro-fuzzy inference system; ANFIS, adaptive neuro fuzzy inference system; T2FCNN, type-2 fuzzy clustering neural network, T2FCM: type-2 fuzzy C-means clustering algorithm; FKCN, fuzzy Kohonen clustering network; EQNFIS, entropy-based quantum neuro-fuzzy inference system; SCA, self-clustering algorithm; LDA, linear discriminant analysis; PCA, principle component analysis; SAFCS, simulated annealing-based fuzzy classification system; SA, simulated annealing; LMBP, Levenberg–Marquard back propagation algorithm; NNFCLASS, neuro fuzzy classification algorithm, HCM: hard C-Means clustering algorithm.

Table 10
Multi-agent system and their application.

MAS	Functionality	Implementation	Application
Medical application [17]	Cooperation Coordination Negotiation	ACL and KQML	Acute myeloid leukemia; diagnosis
Telemedicine system [220]	Cooperative negotiation	FIPA-compliant platform, coded in Java	Healthcare
AMPLIA [18]	BDI Architecture Negotiation	FIPA-OS platform	Rheumatic fever; diagnosis
Monitoring system [221]	Cooperative negotiation	ISLANDER (defines a textual language)	Antibiotic; treatment
MR Image [19]	Cooperative agent based approach	No agent communication language	MRI brain scan; interpretation

human brain MR images. The system is based on cooperative agent-based approach and does not required use of sophisticated agent communication language. Table 10 summaries the functionality, implementation and applications of MAS.

5. Data mining

DM is an emerging area of computational intelligence that offers new theories, techniques and tools for analysis of large data sets. DM methodology has been deployed in diagnosis and treatment of various diseases in medical domain such as diabetes, pulmonary, Alzheimer, heart diseases prediction and OSA. Kusiak et al. [223] developed a novel approach for autonomous decision-making based on the rough set theory of DM and tested the approach on a medical data set for patients with lung abnormalities referred to as solitary pulmonary nodules (SPNs). To accomplish high decision-making accuracy he developed two independent algorithms primary decision making algorithm and confirmation algorithm to either generate an accurate diagnosis or make no decision. The primary decision making algorithm is based on prior data and built on the concepts of rough set theory, cluster analysis, and measure theory. The proposed approach is used for diagnosis of patients with SPNs, a lung abnormality that could potentially become cancerous, using information from noninvasive tests. Lillington [228] show that the number of features (results of noninvasive tests, patient's data, etc.) necessary to diagnose an SPN is smaller than the number used in current medical practice. At the same time, the decision-making accuracy is significantly improved. Breault et al. [20] examine a diabetic data warehouse, showing a method of applying DM techniques, and some of the data issues, analysis problems, and results. In this model, the tree models recursively partition the input variable space to maximize purity in the terminal tree nodes. CART's uses Gini splitting criterion for splitting. CART is used to find clusters of deviance from glycemic control.

Walker et al. [225] addresses the problem of dealing with microarray data that come from two known classes (Alzheimer and normal). Walker et al. applied three separate techniques to discover genes associated with Alzheimer disease (AD). Gene expression DM involves studies that combine the use of domain knowledge with data obtained from AD class and normal class to discover genes that are associated with a particular problem. The BioMiner DM software was used for the DM experiments.

Ordonez [21] used association rules to improve heart disease prediction. The data consist of numeric, categorical and image data. The data include risk factor attributes such as age, race, gender and smoking habits and measurements on the patient such as weight, heart rate, blood pressure and information regarding the pre-existence of other diseases like diabetes. Kwiatkowska et al. [22] uses clinical prediction rules (CPR) for the diagnosis of OSA. The CPR can be represented as IF–THEN rules or arithmetic formulas for calculation of OSA probability based on particular predictors such as suspected symptom, sign, correlate or comorbid condition [229]. Table 11 describes the process and implementation details of DM system.

6. Observation

In this paper we have made a study of the medical expert systems which deploy five independent ES methodologies such as knowledge-based/rule-based (KB/RB), case-based (CB), model-based (MB), ANN and GA and seven integrated approaches such as CBR–RBR, CBR–MBR, RBR–CBR–MBR, ANN–GA, RBR–GA, RBR–ANN and RBR–CBR–ANN. Table 12 contains the number of cases used for diagnosing planning and treatment of different diseases based upon single ES methodology or integrated model. Each application either performs only diagnosing planning or treatment or performs combination of any two such as ESMIS [60] performs both planning and treatment; thus ESMIS is counted both in planning and treatment. The row headed by total in Table 12 presents the actual total number of application observed in each ES methodology which may be or maybe not equal to sum of diagnosis, treatment or planning row.

It is observed from Table 12 and Fig. 1 that among 34 cases of KBS and RBR most of them are for diagnosis (26) while least is for planning (2) and medium is for treatment (10) and among 17 cases of CBR mostly is for diagnosis (12), medium for treatment (7) and least for planning (2). In MBR methodology one–one application for each diagnosis and treatment are observed. Most of the applications in ANN methodology are for diagnosis (30) and least for treatment (3). In GA methodology only seven medical diagnosis applications and three applications of treatment are observed. In hybrid model such as CBR–RBR (4) and CBR–MBR (2) and ANN–GA (4) has most of the application are for diagnosis whereas RBR–GA and RBR–ANN has only one medical diagnosis application. CBR–RBR has medium treatment application (3). The integrated model of RBR–CBR–ANN and RBR–CBR–MBR has only one application of medical diagnosis whereas the integrated model RBR–CBR–ANN has one application of treatment.

It is observed that among 114 cases pertaining to application of the above methods in medical domain, most of the application, i.e., 96 in number are deployed by only singular ES methodology while remaining 18 cases are deployed by integrated approach. In this study, we have calculated the relative use of each ES methodology with respect to total cases using singular ES methodology which is represented as (a, c%), where a is number of cases using a particular ES methodology (e.g., RBR/KBS) and c is percentage ratio of a (34) is to total cases using singular ES methodology (34+17+2+33+10=96) as presented in row 4 (total) of Table 12. Therefore the relative use of KB

Table 11
Data mining system and their applications.

DM system	Process & Implementation	Application
Medical diagnosis [222]	Rule induction and instance-based learning	Rheumatic diseases; diagnosis
Autonomous decision-making [223]	Decision making algorithm and confirmation algorithm	Solitary pulmonary nodules (SPNs); diagnosis
Melanoma prediction [224]	Rule induction	Melanoma; diagnosis
Data mining [20]	Classification and regression Trees	Diabetes; diagnosis
DM for gene expression [225]	Pattern recognition and individual dichotomization search technique, *P*-value and ratio threshold, Virtual reality for visualizing databases BioMiner data mining software	Alzheimer; diagnosis
Melanoma diagnosis [226]	C4.5 rules	Melanoma; diagnosis
Heart disease prediction [21]	Association rule	Heart diseases; diagnosis
KB data analysis [229]	Clinical prediction rules	Obstructive sleep apnea (OSA); diagnosis
Rotavirus treatment [227]	Decision tree	Rotavirus diarrhea; treatment

Table 12
Comparative view of numeric assessment for different computing models.

Application (114)	Standalone application (96)					Integrated application (18)						
	KBS/RBR	CBR	MBR	ANN	GA	CBR–RBR	CBR–MBR	RBR–CBR–MBR	ANN–GA	RBR–GA	RBR–ANN	RBR–CBR–ANN
Diagnosis	26	12	1	30	7	4	2	–	4	1	1	1
Planning	2	2	–	–	–	–	–	–	–	–	–	–
Treatment	10	7	1	3	3	3	–	1	–	–	–	1
Total	34	17	2	33	10	7	2	1	4	1	1	2
% use	35	18	2	34	10	39	11	6	22	6	6	11

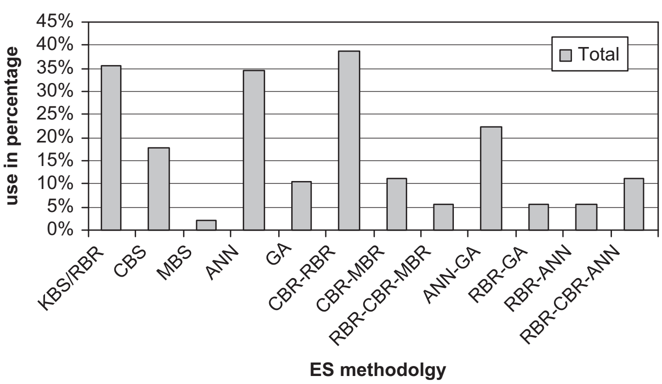

Fig. 1. Comparative view of use (absolute value) of ES methods.

and RB methodology is (34, 35%), CBS is (17, 18%), MBS (2, 2%), ANN (34, 34%) and GA (10, 10%) as presented in Table 12. Similarly, for integrated model same computations are performed and represented as (*e*, *g*%), where *e* is number of cases using a particular integrated model and *g* is percentage ratio of *e* is to total number of integrated model, i.e., 18. Therefore the relative use of CBR–RBR is (7, 39%), CBR–MBR is (2, 11%), RBR–CBR–MBR is (1, 6%), ANN–GA is (4, 22%), RBR–GA is (1, 6%), RBR–ANN is (1, 6%) and RBR–CBR–ANN is (1, 11%) as presented in Table 12. Table 12 presents a comparative view of numeric assessment for different computing models.

In this study, we have also computed relative use of diagnosis, treatment and planning application in each ES methodology and integrated model which is presented in Table 13. The entries in Table 13 is the ratio of the each elements of first column to the last element of column for, e.g., the entries in Table 13, 76% is the ratio of first element of first column in Table 12, i.e., 26 is to the 34. Similarly, second and third entries are 2 is to 34 and 10 is to 34. Similarly, entries in the each column of Table 13 are obtained for corresponding entries in Table 12 as per calculation mentioned above.

From Table 14 it is clear that among 32 fuzzy-based system most of the applications are of diagnosis (20) and medium are of treatment applications (12). It is also observed from Table 14 that among 39 integrated fuzzy-based system such as FL/RBR, FL/CBR, FL/ANN, FL/GA, FL/GA/ANN, FL/CBR/ANN most of the application deployed hybrid FL/ANN approach (20/39 = 51%) whereas least of application deployed integrated approach FL/GA/ANN (3%) and FL/CBR/ANN (3%).

It is observed from Fig. 1 that most of the applications in medical domain deploy either KB/RB or ANN methodology while most of the hybrid models deploy CBR–RBR integration. CB methodology is used by medium number of medical applications. While other singular methodology such as MBR and GA and integrated methodology such as RBR–CBR–MBR, RBR–GA, RBR–ANN and RBR–CBR–ANN are used in very few applications.

It is observed from Fig. 2 that most of the medical applications deploying singular methodology are for diagnosis while least for planning except in CB methodology which is mostly used for diagnosis and planning and least for treatment. It is also observed from Fig. 2 that most of the integrated models are deployed for diagnosis and treatment.

It is observed from Table 6 that most of the agent-based model performs cooperation and coordination for diagnosis and treatment of different diseases. DM methods have deployed decision tree and association rules for classification in the detection and diagnosis of different diseases.

7. Conclusion

The paper aims at presenting a comprehensive view in the development and deployment of various ES methodologies and ICM. We have made a survey of the papers in these fields from mid 70s to 2008, covering 185 papers in the areas of ES and ICM applications in medicine. It is observed that KBS in general, and RBR and CBR in particular are widely used methods in the diagnosis and treatment of various diseases. Most of the method has been developed for the diagnosis of the diseases. ANN models have also been deployed in the most of the problems of medical diagnosis and

Table 13
Comparative view of numeric assessment in percentage for different computing model.

Application	KBS/RBS	CBS	MBS	ANN	GA	CBR–RBR	CBR–MBR	RBR–CBR–MBR	ANN–GA	RBR–GA	RBR–ANN	RBR–CBR–ANN
Diagnosis (%)	76	71	50	91	70	57	100	–	100	100	100	50
Planning (%)	6	12	–	–	–	–	–	–	–	–	–	–
Treatment (%)	29	41	50	9	30	43	–	100	–	–	–	50

Table 14
Fuzzy alone and fuzzy integrated system.

Application (71)	Integrated fuzzy application (39)						
	FL (32)	FL–RBR	FL–CBR	FL–ANN	FL–GA	FL–GA–ANN	FL–CBR–ANN
Diagnosis	20	8	5	19	4	1	1
Treatment	12	–	–	1	–	–	–
Total	32	8	5	20	4	1	1
% use		21	13	51	10	3	3

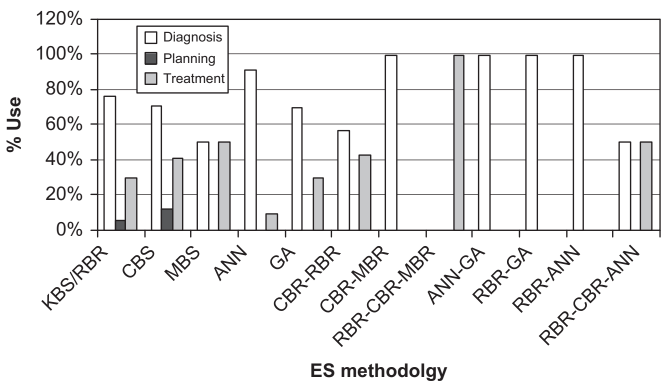

Fig. 2. Comparative view of percentage use of ES methods.

treatment where data dominates the knowledge and reasoning is less required. Hybrid models perform both the computation and reasoning process in the diagnosis. Integrated multi-modals (RBR–CBR–MBR and RBR–CBR–ANN) are although very effective but are used very less in the practice. Hybrid and integrated fuzzy system are widely deployed for diagnosis in medical area. As a further extension to this work we are in the process of enumerating and tabulating web-based expert systems. Our study would be helpful for the novices that may emerge/resume their research in the areas of medical expert and intelligent systems.

8. Summary

KBS are widely used in the areas where knowledge is predominant rather than data and requires heuristic and logic in reasoning to derive new set of knowledge.

Basic problem-solving approaches in the field of artificial intelligence are RBR, MBR and CBR. Due to complementary advantage and disadvantage of RBR, CBR and MBR sometimes, in medical domain, it is difficult to solve problem independently with either. But if their advantage are exploited and disadvantages are removed then their combination offers significant benefits.

An alternative to rule-based inference (which is called logical inference), statistical inference such as Baye's theorem, which sets a probabilistic value for each considered output (disease in medical domain), is deployed. Another type of reasoning implements the human intelligence with expert systems for such cases ANN.

The GA performs well independently of the order of symptoms, and has the potential to perform multi-disorder diagnosis using existing or newly developed knowledge bases. GA and ANN individually both has some complexity problems, some of these problems are solved by integrating ANN and GA.

The FL provides an intuitive user interface, simplifies the process of knowledge representation, and minimizes the system's computational complexity in terms of time and memory usage.

The integration of knowledge dominant computing model such as KBS or CBR and data dominant computing models such as ANN and GA have been deployed in time to time and problem to problem by many researchers in medical domain.

MAS are a widely accepted paradigm for distributed and shared work of computation in scientific community. Cooperation and communication are two important functionalities of MAS implemented on FIPA-ACL platform for the diagnosis.

DM is a technique and tool for the efficient new knowledge discovery from databases. Most of the DM methods in medical domain deploy different techniques for the diagnosis of various diseases such as classification and regression tree, association and prediction rule, etc.

In this paper, we have made review of the different methods of KBS, ICM and their combinations for the detection and diagnosis of different diseases. The KBS comprises RBR, CBR and MBR. The ICS consists of a ANN, GA and FL. The combined methods are RBR–CBR, CBR–MBR, RBR–CBR–MBR, ANN–CBR, ANN–GA, RBR–GA and CBR–RBR–ANN, FL–GA, FL–CBR, FL–RBR, FL–GA–ANN and FL–RBR–ANN.

The observation is made to show the absolute and percentage use of different KBS and ICM computing models and their intra or inter combination models as mentioned above. It is observed that mostly KBS, ANN and their integrated methods are used in medical diagnosis.

Conflict of interest statement

Area of expert systems in medicine.

References

[1] G.F. Luger, W.A. Stubblefield, Knowledge-intensive problem solving, in: Artificial Intelligence: Structures and Strategies for Complex Problem Solving, Addison-Wesley, Reading, MA, 1998, pp. 207–246.
[2] M.C.J. Biermans, D.H. de Bakker, R.A. Verheij, J.V. Gravestein, M.W. van der Linden, P.F. de Vries Robbe, Development of a case-based system for grouping diagnoses in general practice, International Journal of Medical Informatics 77 (7) (2007) 431–439.
[3] B. Lopez, E. Plaza, Case-based learning of plans and medical diagnosis goal states, Artificial Intelligence in Medicine (9) (1997) 29–60.
[4] A.S. Khan, A. Hoffmann, Building a case-based diet recommendation system without a knowledge engineer, Artificial Intelligence in Medicine 27 (2003) 155–179.

[5] B.W. Porter, E.R. Bareiss, PROTOS: an experiment in knowledge acquisition for heuristic classification tasks, in: Proceedings of the First International Meeting on Advances in Learning (IMAL), Les Arcs, France, 1986, 159–174.
[6] P. Koton, Reasoning about evidence in causal explanations, in: Proceedings of the Seventh National Conference on Artificial Intelligence, AAI Press, Menlo Park, CA, 1988, pp. 256–263.
[7] S. Montani, P. Magni, R. Bellazzi, C. Larizza, A.V. Roudsari, E.R. Carson, Integrating model-based decision support in a multi-modal reasoning system for managing type 1 diabetic patients, Artificial Intelligence in Medicine 29 (2003) 131–151.
[8] J.M. Zurada, Introduction to Artificial Neural Systems, West Publishing Company, USA, 1992.
[9] A.D. Bernstein, C.J. Chiang, V. Parsonnet, Diagnosis and management of pacemaker-related problems using and interactive expert system, in: IEEE 17th Annual Conference on Engineering in Medicine and Biology Society, vol. 1, 1995, pp. 701–702.
[10] D. Dragulescu, A. Albu, Expert system for medical predictions, in: 4th International Symposium on Applied Computational Intelligence and Informatics, 2007, pp. 13–18.
[11] A. Albu, L. Ungureanu, Artificial Neural Network in Medicine ⟨www.bmf.hu/conferences/saci2005/Albu.pdf⟩. (accessed 1/2008).
[12] E. Grossi, A. Mancini, M. Buscema, International experience on the use of artificial neural networks in gastroenterology, Digestive and Liver Disease 39 (2007) 278–285.
[13] D. Itchhaporia, P.B. Snow, R.J. Almassy, W.J. Oetgen, Artificial neural networks: current status in cardiovascular medicine, Journal of the American College of Cardiology 28 (2) (1996) 515–521.
[14] S. Vinterbo, L. Ohno-Machado, A genetic algorithm approach to multi-disorder diagnosis, Artificial Intelligence in Medicine 18 (2000) 117–132.
[15] L.M. Brasil, F.M. de Azevedo, J.M. Barreto, Hybrid expert system for decision supporting in the medical area: complexity and cognitive computing International, Journal of Medical Informatics 63 (2001) 19–30.
[16] M.F. Abbod, D.G. von Keyserlingk, D.A. Linkens, M. Mahfouf, Survey of utilisation of fuzzy technology in medicine and healthcare, Fuzzy Sets and Systems 120 (2001) 331–349.
[17] G. Lanzola, L. Gatti, S. Falasconi, M. Stefanelli, A framework for building cooperative software agents in medical applications, Artificial Intelligence in Medicine 16 (1999) 223–249.
[18] R.M. Vicari, C.D. Flores, A.M. Silvestre, L.J. Seixas, M. Ladeira, H. Coelho, A multi-agent intelligent environment for medical knowledge, Artificial Intelligence in Medicine 27 (2003) 335–366.
[19] N. Richard, M. Dojat, C. Garbay, Automated segmentation of human brain MR image using a multi-agent approach, Artificial Intelligence in Medicine 30 (2004) 153–175.
[20] J.L. Breault, C.R. Goodall, P.J. Fos, Data mining a diabetic data warehouse, Artificial Intelligence in Medicine 26 (2002) 37–54.
[21] C. Ordonez, Association rule discovery with the train and test approach for heart disease prediction, IEEE Transactions on Information Technology in Biomedicine 10 (2) (2006) 334–343.
[22] M. Kwiatkowska, M.S. Atkins, N.T. Ayas, C.F. Ryan, Knowledge-based data analysis: first step toward the creation of clinical prediction rules using a new typicality measure, IEEE Transactions on Information Technology in Biomedicine 11 (6) (2007) 651–660.
[23] A. Ligeza, Logical Foundations for Rule-Based Systems Studies in Computational Intelligence, vol. 11, Springer, Berlin, 2006.
[24] G. Finnie, Z. Sun, R^5 model for case-based reasoning, Journal of Knowledge-Based Systems 16 (2003) 59–65.
[25] R. Khardon, D. Roth, Defaults and relevance in model-based reasoning, Artificial Intelligence 97 (1997) 169–193.
[26] J. Prentzas, I. Hatzilygeroudis, Categorizing approaches combining rule-based and case-based reasoning, Expert Systems 24 (2) (2007) 97–122.
[27] M.R. Lee, An exception handling of rule-based reasoning using case-based reasoning, Journal of Intelligent and Robotic Systems 35 (2002) 327–338.
[28] A. Lewis, RIMSAT DSS Project: Integrating Model-Based and Case-Based Reasoning, DSSResources.COM, 04/05/2004.
[29] E.H. Shortliffe, R. Davis, S.G. Axline, B.G. Buchanan, C.C. Green, S.N. Cohen, Computer-based consultations in clinical therapeutics: explanation and rule acquisition capabilities of the MYCIN system, Computers and Biomedical Research 8 (4) (1975) 303–320.
[30] D.L. Hudson, T. Estrin, Derivation of rule-based knowledge from established medical outlines, Computers in Biology and Medicine 14 (1) (1984) 3–13.
[31] K. Krantaz, H. Youssef, R.W. Newcomb, Medical usages of an expert system for recognising chaos, in: 10th Annual International Conference of IEEE Engineering in Medicine and Biology Society, 1988.
[32] A. Conigliaro, A.D. Stefano, O. Mirabella, An expert system for diagnosis, in: Proceedings of the Engineering of Computer-Based Medical System, Minneapolis, MN, USA, 8–10 June, 1988, pp. 75–81.
[33] E. Kekes, I. Laczay, J. Barcsak, P. Koch, Z. Antaloczy, CORONARIA: expert system for diagnosis and therapy of ischemic disease, in: 10th Annual International Conference of IEEE Engineering in Medicine and Biology Society, 1988.
[34] S. Tower, R. Baldock, Application of knowledge-based system to the interpretation of ultra sound images, in: 9th International Conference on Pattern Recognition, vol. 1, 1988, pp. 107–110.
[35] B.H. Sielaff, D.P. Connelly, E.P. Scott, ESPRE: a knowledge-based system to support platelet transfusion decisions, IEEE Transactions on Biomedical Engineering 36 (5) (1989) 541–546.
[36] C. Hernandez-Sande, V.E. Moret-Bonillo, A. Alonso-Betanzos, ESTER: an expert system for management of respiratory weaning therapy, IEEE Transactions on Biomedical Engineering 36 (5) (1989) 559–564.
[37] C. Larizza, A. Moglia, M. Stefanelli, M-HTP: a system for monitoring heart transplant patients, Artificial Intelligence in Medicine 4 (2) (1992) 111–126.
[38] S. Quaglini, R. Bellazzi, C. Berzuini, M. Stefanelli, G. Barosi, Hybrid knowledge-based systems for therapy planning, Artificial Intelligence in Medicine 4 (3) (1992) 207–226.
[39] I. Bonfa, C. Maioli, F. Sarti, G.L. Milandri, P.R. Dal Monte, HERMES: an expert system for the prognosis of hepatic diseases, in: Proceedings of First New Zealand International Two-Stream Conference on Artificial Neural Networks and Expert Systems, 1993, pp. 240–246.
[40] R.B. Mishra, S. Dandapat, A knowledge-based interpretation system for EMG abnormalities, Clinical Monitoring and Computing 10 (1993) 131–142.
[41] D. Assanelli, L. Cazzamalli, M. Stambini, M.L. Poeta, Correct diagnosis of chest pain by an integrated expert system, in: Proceedings of Computers in Cardiology, 1993, pp. 759–762.
[42] C.J. Chiang, A.D. Bernstein, V. Parsonnet, A probability-based expert system for diagnosing pacemaker-related complications, Computers in Cardiology (1994) 89–92.
[43] J.W. Goethe, J.D. Bronzino, An expert system for monitoring psychiatric treatment, IEEE Engineering in Medicine and Biology (1995) 776–780.
[44] A.M. Sundari, S. Raghavan, R. Balasundaram, Computerization in obstetrics and gynaecology—an expert system approach, in: Proceedings of the RC IEEE-EMBS & 14th BMESl, 1995, pp. 1.55–1.56.
[45] K.-P. Adlassnig, W. Horak, Development and retrospective evaluation of HEPAXPERT-I: a routinely-used expert system for interpretive analysis of hepatitis A and B serologic findings, Artificial Intelligence in Medicine 7 (1995) 1–24.
[46] B.V. Ambrosiadoua, D.G. Goulis, C. Pappasa, Clinical evaluation of the DIABITIES expert system for support decision support for multiple regime insulin dose adjustment, Computer Methods and Programs in Biomedicine 49 (1996) 105–115.
[47] F.J. Diez, J. Mira, E. Iturralde, S. Zubillaga, DIAVAL, a Bayesian expert system for echocardiography, Artificial Intelligence in Medicine 10 (1997) 59–73.
[48] S. Nagy, M. Hayde, B. Panzenbiick, K.-P. Adlassnig, A. Pollak, Toxopert-I, knowledge-based automatic interpretation of serological tests for toxoplasmosis, Computer Methods and Programs in Biomedicine 53 (1997) 119–133.
[49] M. Wiltgen, An expert system for troubleshooting in a picture archiving and communication system, Engineering Applications of Artificial Intelligence 11 (1998) 469–475.
[50] C.R. Marling, G.J. Petot, L.S. Sterling, Integrating case-based and rule-based reasoning to meet multiple design constraints, Computational Intelligence 15 (3) (1999) 308–331.
[51] E. Bursuk, M. Scan, B. Ilerigelen, A medical expert system in cardiological diseases, in: Proceedings of the First BMES/EMBS Conference Serving Humanity, Advancing Technology, Atlanta, GA, USA, October 1999, pp. 13–16.
[52] M. Suojanen, S. Andreassen, K.G. Olesen, A method for diagnosing multiple diseases in MUNIN, IEEE Transactions on Biological Engineering 48 (5) (2001) 522–532.
[53] F. Ibrahim, J.B. Ali, F. Jaais, M.N. Taib, Expert system for early diagnosis of eye diseases infecting the Malaysian population, in: Proceedings of IEEE Region 10 International Conference on Electrical and Electronic Technology, vol. 1, 2001, pp. 9–22.
[54] L.M. Laita, E. Roanes-Lozano, V. Maojo, E. Roanes-Macias, L.D. Ledesma, L. Laita, An expert system for managing medical appropriateness criteria based on computer algebra techniques, Computers and Mathematics with Applications 42 (2001) 1505–1522.
[55] M. Gaspari, G. Roveda, C. Scandellari, S. Stecchi, An expert system for the evaluation of EDSS in multiple sclerosis, Artificial Intelligence in Medicine 25 (2002) 187–210.
[56] C. Pérez-Carretero, L.M. Laita, E. Roanes-Lozano, L. Lázaro, J. González-Cajal, L. Laita, A logic and computer algebra-based expert system for diagnosis of anorexia, Mathematics and Computers in Simulation 58 (2002) 183–202.
[57] I. Lejbkowicz, F. Wiener, A. Nachtigal, D. Militiannu, U. Kleinhaus, Y.H. Applbaum, Bone browser a decision-aid for the radiological diagnosis of bone tumors, Computer Methods and Programs in Biomedicine 67 (2002) 137–154.
[58] L. Nallamshettyt, S.A. Eschricht, D. Cuthbertsont, J. Malloyt, D.B. Goldgoft, A.M. Alexander, M. Trucco, J. Ilonenf, H.K. Akerblom, J.P. Krischert, An expert system for evaluating risk in type-1 diabetes, IEEE International Conference on Systems, Man and Cybernetics 2 (2003) 1660–1665.
[59] K.S. Devan, P.A. Venkatachalam, A.F.M. Hani, Expert system with an embedded imaging module for diagnosing lung diseases, in: Proceedings of Seventh International Workshop on Enterprise Networking and Computing in Healthcare Industry, 2005, pp. 229–234.
[60] E. Lamma, P. Mello, A. Nanetti, F. Riguzzi, S. Storari, G. Valastro, Artificial intelligence techniques for monitoring dangerous infections, IEEE Transactions on Information Technology in Biomedicine 10 (1) (2006) 143–155.
[61] J. Hunt, Evolutionary case based design, in: I.D. Waston (Ed.), Progress in Case-based Reasoning, Lecture Notes in Artificial Intelligence, vol. 1020, Springer, Berlin, 1995, pp. 17–31.
[62] B.P. Allen, Case-based reasoning: business applications, Communications of the ACM 37 (3) (1994) 40–42.
[63] J.L. Kolodner, Case-Based Reasoning, Morgan Kaufmann, CA, 1993.

[64] A. Aamodt, E. Plaza, Case-based reasoning: foundational issues, methodological variations, and system approaches, AI Communications 7 (1) (1994) 39–59.
[65] R. Turner, Opportunistic use of schemata for medical diagnosis, in: Proceedings of the Tenth Annual Conference of the Cognitive Science Society, Erlbaum, Northvale, NJ, 1988.
[66] K.J. Hammond, On functionally motivated vocabularies: an apologia, in: Proceedings of the Second Workshop on Case-Based Reasoning, Pensacola Beach, FL, US, 1989.
[67] T. Hinrichs, Problem Solving in Open Worlds: A Case Study in Design, Lawrence Erlbaum Associates, Hillsdale, NJ, 1992.
[68] R.T. Macura, K.J. Macura, V.E. Toro, E.F. Binet, J. H Trueblood, K. Ji, Computerized case-based instructional system for computed tomography and magnetic resonance imaging of brain tumors, Investigative Radiology 29 (4) (1994) 497–506.
[69] F. Ricci, P. Avesani, Learning a local similarity metric for case-based reasoning, in: M. Veloso, A. Aamodt (Eds.), Proceedings of the First International Conference on Case-Based Reasoning Research and Development, Lecture Notes in Artificial Intelligence, vol. 1010, Springer, Berlin, 1995, pp. 23–26.
[70] D. Leake, A. Kinley, D. Wilson, Acquiring case adaptation knowledge: a hybrid approach, in: Proceedings of the Thirteenth National Conference on Artificial Intelligence, AAAI Press, Menlo Park, CA, 1996, pp. 684–689.
[71] M. Grimnes, A. Aamodt, A two layer case-based reasoning architecture for medical image understanding, in: I. Smith, B. Faltings (Eds.), Advances in Case-Based Reasoning, Springer, Berlin, 1996, pp. 164–178.
[72] M. Haddad, K.P. Adlassnig, G. Porenta, Feasibility analysis of a case-based reasoning system for automated detection of coronary heart disease from myocardial scintigrams, Artificial Intelligence in Medicine 9 (1) (1997) 61–78.
[73] F Golobardes, Contribution to the case-based classifier system, Ph.D Thesis, Enginyeria I Ariquitectura I.a. Salle, Universitat Ramon Lliull, July 1998.
[74] I. Bichindaritz, E. Kansu, K.M. Sullivan, Case-based reasoning in CARE-PARTNER: gathering evidence for evidence-based medical practice, in: B. Smyth, P. Cunningham (Eds.), Proceedings of the Fourth European Workshop on CBR, Springer, Berlin, 1998, pp. 334–345.
[75] S. Guardati, RBCShell: a tool for the construction of systems with case-based reasoning, Journal of Expert System with Application 14 (1998) 63–70.
[76] H. Munoz-Avila, D.W. Aha, L.A. Breslow, D. Nau, HICAP: an interactive case-based planning architecture and its application to NEOs, in: Proceedings of the Eleventh Conference on Innovative Applications of Artificial Intelligence, AAAI Press, Menlo Park, CA, 1999, pp. 870–875.
[77] P. Perner, An architecture for a CBR image segmentation system, Journal of Engineering Application in Artificial Intelligence 12 (6) (1999) 749–759.
[78] C.L. Guillou, J.-M. Cauvin, B. Solaiman, M. Robaszkiewicz, C. Roux, Knowledge representation and cases indexing in upper digestive endoscopy, in: Proceedings of the Second Annual EMBS International Conference, Chicago IL, July 2000, pp. 23–28.
[79] R. Schmidt, L. Gierl, Case-based reasoning for antibiotics therapy advice: an investigation of retrieval algorithms and prototypes, Artificial Intelligence in Medicine 23 (2001) 171–186.
[80] R. Schmidt, O. Vorobieva, Case-based reasoning investigation of therapy inefficacy, Knowledge-Based Systems 19 (5) (2006) 333–340.
[81] S. Uckun, B.M. Dawant, D.P. Lindstrom, Model-based diagnosis in intensive care monitoring: the YAQ approach, Artificial Intelligence in Medicine 5 (1) (1993) 31–48.
[82] P.J.F. Lucas, A. Tholen, G. van Oort, An intelligent system for pacemaker reprogramming, Artificial Intelligence in Medicine 17 (1999) 249–269.
[83] P.J.F. Lucas, Symbolic diagnosis and its formalization, Knowledge Engineering Review 12 (2) (1997) 109–146.
[84] Y. Yoon, W. Robert, P.R. Bergstresser, L.L. Peterson, Automatic generation of a knowledge-base for a dermatology expert system, in: Proceedings of the Third Annual IEEE Symposium on Computer-Based Medical System, June 1990, pp. 306–312.
[85] W.G. Baxt, Use of an artificial neural network for data analysis in clinical decision-making: the diagnosis of acute coronary occlusion, Neural Computation 2 (1990) 480–489.
[86] G.R. Gindi, C.J. Darken, K.M. OBrien, M.L. Stetz, L.1. Deckelbaum, Neural network and conventional classifiers for fluorescence-guided laser angioplasty, IEEE Transactions on Biomedical Engineering 38 (1991) 246–252.
[87] J.W. Furlong, M.E. Dupuy, J.A. Heinsimer, Neural network analysis of serial cardiac enzyme data: a clinical application of artificial machine intelligence, American Journal of Clinical Pathology 96 (1991) 134–141.
[88] W.G. Baxt, Use of an artificial neural network for the diagnosis of myocardial infarction, Annals of Internal Medicine 115 (1991) 843–848.
[89] M. Akay, Noninvasive diagnosis of coronary artery disease using a neural network algorithm, Biological Cybernetics (67) (1992) 361–367.
[90] M.B. Gorzalczany, M. McLeish, Combination of neural networks and fuzzy sets as a basis for medical expert system, in: Fifth Annual IEEE Symposium on Computer-Based Medical Systems, 1992, pp. 412–420.
[91] L.J. Mango, Computer assisted cervical cancer screening using network, Cancer Letters 77 (1994) 155–162.
[92] G.-P.K. Economou, C. Spiropoulos, N.M. Economopoulos, N. Charokopos, D. Lymberopoulos, M. Spiliopoulou, E. Haralambopulu, C.E. Goutis, Medical diagnosis and artificial neural networks: a medical expert system applied to pulmonary diseases, in: Proceedings of the 1994 IV IEEE Workshop on Neural Network for Signal Processing, 1994, pp. 482–489.
[93] Y. Ming-Chuan, B. Pariseau, J.M. Jenkins, L.A. DiCarlo, Iteracardic arrhythmia classification using neural network and time frequency analysis, in: Proceedings of Computer in Cardiology, 1994, pp. 449–452.
[94] W.R. Dassen, V.L. Karthaus, J.L. Talmon, R.G. Mulleneers, J.L. Smeets, H.J. Wellens, Evaluation of new self-learning techniques for the generation of criteria for differentiation of wide-QRS tachycardia in supraventricular tachycardia and ventricular tachycardia, Clinical Cardiology 18 (1995) 103–108.
[95] M.S. Beksac, B. Durak, O. Ozkan, A.N. Cakar, S. Balcl, O. Karaka, Y. Laleli, An artificial intelligent diagnostic system with determine genetical disorders and fetal health serum markers neural networks to by using maternal, European Journal of Obstetrics & Gynecology and Reproductive Biology 59 (1995) 131–136.
[96] D. ltchhaporia, R. Almassy, L. Kaufman, P. Snow, W. Oetgen, Artificial neural networks can predict significant coronary disease [abstract], Journal of the American College of Cardiology 25 (1995) 328A.
[97] P. Karakitsos, E.B. Stergiou, A. Pouliakis, M. Tzivras, A. Archimandritis, A. Liossi, et al., Comparative study of artificial neural networks in the discrimination between benign from malignant gastric cells, Analytical and Quantitative Cytology and Histology 19 (1997) 145–152.
[98] K. Rudzki, M. Hartleb, T. Sadowski, J. Rudzka, Focal liver disease: neural network-aided diagnosis based on clinical and laboratory data, Gastroenterologie Clinique et Biologique 21 (1997) 98–102.
[99] H. Song, J. Lin, B. Xu, X. Lin, F. Zhu, R. Chen, S. Tan, Research of gastro-oesophageal disease aided diagnose expert system, in: 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam, 1996, 167–168.
[100] R.L. Kennedy, R.F. Harrison, A.M. Burton, H.S. Fraser, W.G. Hamer, D. MacArthur, R. McAllum, D.J. Steedman, An artificial neural network system for diagnosis of acumyocardial infarction (AMI) in the accident and emergency department: evaluation and comparison with serum myoglobin measurements, Computer Methods and Programs in Biomedicine 52 (1997) 93–103.
[101] W.E. Pofahl, S.M. Walczak, E. Rhone, S.D. Izenberg, Use of an artificial neural network to predict length of stay in acute pancreatitis, American Surgeon 64 (1998) 868–872.
[102] M. Frize, C.M. Ennett, M. Stevenson, H.C.E. Trigg, Clinical decision support systems for intensive care units: using artificial neural networks, Medical Engineering & Physics 23 (2001) 217–225.
[103] C. Castellaro, G. Favaro, A. Castellaro, A. Casagrande, S. Castellaro, D.V. Puthenparampil, C.F. Salimbeni, An artificial intelligence approach to classify and analyse EEG traces, Neurophysiologie Clinique 32 (2002) 193–214.
[104] Z.-H. Zhou, Y. Jiang, Y.-B. Yang, S.-F. Chen, Lung cancer cell identification based on artificial neural network ensemble, Artificial Intelligence in Medicine 24 (2002) 23–36.
[105] A. Andriulli, E. Grossi, M. Buscema, V. Festa, M. Garbagnana, M. Intraligi, et al., Contribution of artificial neural networks to the classification and treatment of patients with uninvestigated dyspepsia, Digestive and Liver Disease 35 (2003) 222–231.
[106] R.L. Ackoff, From data to wisdom, Journal of Applies Systems Analysis 16 (1989) 3–9.
[107] A. Das, T. Ben-Menachem, G.S. Cooper, A. Chak, J.M.V. Sivak, et al., Prediction of outcome in acute lower-gastrointestinal haemorrhage based on an artificial neural network: internal and external validation of a predictive model, The Lancet 18 (2003) 1261–1266.
[108] D.E. Maroulis, D.K. Iakovidis, S.A. Karkanis, D.A. Karras, CoLD: a versatile detection system for colorectal lesions in endoscopy video-frames, Computer Methods and Programs in Biomedicine 70 (2003) 151–166.
[109] T. Kan, Y. Shimada, F. Sato, T. Ito, K. Kondo, G. Watanabe, et al., Prediction of lymph node metastasis with use of artificial neural networks based on gene expression profiles in esophageal squamous cell carcinoma, Annals of Surgical Oncology 11 (2004) 1070–1078.
[110] P.A. Maiellaro, R. Cozzolongo, P. Marino, Artificial neural networks for the prediction of response to interferon plus ribavirin treatment in patients with chronic hepatitis C, Current Pharmaceutical Design 10 (2004) 2101–2109.
[111] N. Pagano, M. Buscema, E. Grossi, M. Intraligi, G. Massini, P. Salacone, et al., Artificial neural networks for the prediction of diabetes mellitus occurrence in patients affected by chronic pancreatitis, Journal of Pancreas 5 (Suppl. 5) (2004) 405–453.
[112] F. Sato, Y. Shimada, F.M. Selaru, D. Shibata, M. Maeda, G. Watanabe, et al., Prediction of survival in patients with esophageal carcinoma using artificial neural networks, Cancer 103 (2005) 1596–1605.
[113] L. An, L. Tong, A rough neural expert system for medical diagnosis, in: Proceedings of ICSSSM '05, vol. 2, 2005, pp. 1130–1135.
[114] F. Pace, M. Buscema, P. Dominici, M. Intraligi, E. Grossi, F. Baldi, et al., Artificial neural networks are able to recognise GERD patients on the basis of clinical data solely, European Journal of Gastroenterology & Hepatology 17 (2005) 605–610.
[115] E. Lahner, E. Grossi, M. Intraligi, M. Buscema, V.D. Corleto, F.G. Delle, et al., Possible contribution of advanced statistical methods (artificial neural networks and linear discriminant analysis) in the recognition of patients with suspected atrophic body gastritis, World Journal of Gastroenterology 11 (2005) 5867–5873.
[116] R.B. Mishra, S.K. Upadhyay, ANN based detection and interpretation of EMG abnormalities, Institution of Engineers (India) 88 (2008) 3–11.
[117] J.P. Lisboa, A review of evidence of health benefit from artificial neural networks in medical intervention, Neural Networks 15 (2002) 11–39.
[118] D.D. Goldberg, Genetic Algorithm Search, Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.

[119] H.J. Gross, B. Verwer, D. Houck, R.A. Hoffman, D. Recktenwald, Model study detecting breast cancer cells in peripheral blood mononuclear cells at frequencies as low as 10(−7), Proceedings of the National Academy of Sciences of USA 92 (1995) 537–541.
[120] G.E. Ezzell, Genetic and geometric optimization of three-dimensional radiation therapy treatment planning, Medical Physics 23 (3) (1996) 293–305.
[121] Y. Yu, M.C. Schell, J.B.Y. Zhang, Decision theoretic steering and genetic algorithm optimization: application to stereotactic radiosurgery treatment planning, Medical Physics 24 (11) (1997) 1742–1750.
[122] M.A. Kupinski, M.L. Giger, Feature selection and classifiers for the computerized detection of mass lesions in digital mammography, International Conference on Neural Networks 4 (1997) 2460–2463.
[123] B. Sierra, P. Larranaga, Predicting survival in malignant skin melanoma using Bayesian networks automatically induced by genetic algorithms. An empirical comparison between different approaches, Artificial Intelligence in Medicine 14 (1998) 215–230.
[124] X. Llora, J. Garrell, in: Proceeding of Genetic and Evolutionary Computation Conference (GECCO99), Morgan Kaufmann, Los Altos, CA, 1999, p. 797.
[125] T. Wanschura, D.A. COLEY, W. Vennart, S. Gandy, Automatic realignment of time-separated MR images by genetic algorithm, Magnetic Resonance Imaging 17 (2) (1999) 313–317.
[126] G.K. Matsopoulos, N.A. Mouravliansky, K.K. Delibasis, K.S. Nikita, Automatic retinal image registration scheme using global optimization techniques, IEEE Transactions on Information Technology in Biomedicine 3 (1) (1999) 47–60.
[127] Y. Yu, J.B. Zhang, G. Cheng, M.C. Schell, P. Okunieff, Multi-objective optimization in radiotherapy: applications to stereotactic radiosurgery and prostate brachytherapy, Artificial Intelligence in Medicine 19 (2000) 39–51.
[128] A. Khanum, et al., Fuzzy case-based reasoning for facial expression recognition, Fuzzy Sets and Systems 160 (2) (2008) 231–250.
[129] D. Gustafson, W. Kessel, Fuzzy clustering with a fuzzy covariance matrix, in: Proceedings of the IEEE CDC, San Diego, CA, USA, 1979, pp. 761–766.
[130] R. Krishnapuram, J.M. Keller, A probabilistic approach to clustering, IEEE Transactions on Fuzzy System 1 (2) (1993) 98–110.
[131] B.H. Greenberg, A. Trotti, M. Silbiger, Comparison of supervised MRI segmentation methods for tumor volume determination during therapy, Magnetic Resonance Imaging 13 (5) (1995) 719–728.
[132] J. Yao, M. Dash, S.T. Tan, H. Liu, Entropy-based fuzzy clustering and fuzzy modeling, Fuzzy Sets and Systems 113 (2000) 381–388.
[133] J.M. Keller, M.R. Gray, J.A. Givens Jr., A fuzzy K-nearest neighbor algorithm, IEEE Transactions on Systems, Man and Cybernetics 15 (4) (1985) 10000.
[134] S.N. Ghazavi, T.W. Liao, Medical data mining by fuzzy modeling with selected features, Artificial Intelligence in Medicine 43 (2008) 195–206.
[135] D.A. Linkens, J.S. Shieh, J.E. Peacock, Hierarchical fuzzy modelling for monitoring depth of anaesthesia, Fuzzy Sets and Systems 79 (1996) 43–57.
[136] E. Sanchez, Inverses of fuzzy relations, in: Proceedings of IEEE Conference on Decision and Control, IEEE, New York, NY, USA, 1977, pp. 1384–1389.
[137] E. Sanchez, Resolution of eigen fuzzy sets equations, Fuzzy Sets and Systems 1 (1) (1978) 69–74.
[138] M. Arzi, M. Magnin, A fuzzy set theoretical approach to automatic analysis of nystagmic eye movements, IEEE Transactions on Biomedical Engineering 36 (9) (1989) 954–963.
[139] T. Gerstenkorn, A. Kurnatowska, E. Rakus, Use of the fuzzy set theory in the diagnosis and treatment of inflammatory conditions of the genital organs and the urinary system in women, Parasitological News 36 (5–6) (1990) 251–267.
[140] D. Linkens, S. Hasnain, Self-organizing fuzzy logic control and application to muscle relaxant anaesthesia, Proceedings of the Institute of Electrical and Electronics Engineers D 138 (1991) 274–284.
[141] D. Cabello, S. Barro, J.M. Salceda, R. Ruiz, J. Mira, Fuzzy K-nearest neighbor classifiers for ventricular arrhythmia detection, International Journal of Bio-Medical Computing 27 (2) (1991) 77–93.
[142] H. Ying, M. McEachern, D.W. Eddleman, L.C. Sheppard, Fuzzy control of mean arterial pressure in postsurgical patients with sodium nitroprusside infusion, IEEE Transactions on Biomedical Engineering 39 (10) (1992) 1060–1070.
[143] A.E.O. Boudraa, J.-J. Mallet, J.-E. Besson, S.-E. Bouyoucef, J. Champier, Left ventricle automated detection method in gated isotopic ventriculography using fuzzy clustering, IEEE Transactions on Medical Imaging 12 (3) (1993) 451–465.
[144] M. Vaidyanathan, L.P. Clarke, R.P. Velthuizen, S. Phuphanich, A.M. Bensaid, L.O. Hall, J.C. Bezdek, H. Greenberg, A. Trotti, M. Silbiger, Comparison of supervised MRI segmentation methods for tumor volume determination during therapy, Magnetic Resonance Imaging 13 (5) (1995) 719–728.
[145] D. Mason, D. Linkens, M. A,od, N. Edward, C. Reilly, Automated delivery of muscle relaxant using fuzzy logic control, IEEE Engineering in Medicine and Biology Magazine 13 (5) (1994) 678–686.
[146] D. Mason, N. Edwards, D. Linkens, C. Reilly, Performance assessment of a fuzzy controller for atracurium-induced neuromuscular block, British Journal of Anesthesia 76 (3) (1996) 396–400.
[147] J. Presedo, J. Vila, S. Barro, F. Palacios, R. Ruiz, A. Taddei, M. Emdin, Fuzzy modelling of the expert's knowledge in ECG-based ischaemia detection, Fuzzy Sets and Systems 77 (1996) 63–75.
[148] G. Zouridakis, B.H. Jansen, N.N. Boutros, A fuzzy clustering approach to EP estimation, IEEE Transactions on Biomedical Engineering 44 (8) (1997) 673–680.
[149] M. Vaidyanathan, L.P. Clarke, L.O. Hall, C. Heidtman, R. Velthuizen, K. Gosche, S. Phuphanich, H. Wagner, H. Greenberg, M.L. Silbiger, Monitoring brain tumor response to therapy using MRI segmentation, Magnetic Resonance Imaging 15 (3) (1997) 323–334.
[150] J. Ross, D. Mason, D. Linkens, N. Edwards, Self-learning fuzzy logic control of neuromuscular block, British Journal of Anesthesia 78 (4) (1997) 412–415.
[151] M. Mahouf, M. Abbod, D. Linkens, Generalised predictive control integrates with fuzzy logic control to regulate neuromuscular blockade, in: IFAC'97, Modelling and Control in Biomedical Systems, Warwick, UK, 1997, pp. 187–192.
[152] D. Linkens, M. Mahfouf, Fuzzy logic knowledge-based control for muscle relaxant anaesthesia, in: Proceedings of IFAC Symposium Modelling and Control of Biomedical Systems, 1998, pp. 123–128.
[153] Z.-P. Luo, L. Zhang, R.T. Turner, K.-N. An, Effects of mechanical stress/strain and estrogen on cancellous bone structure predicted by fuzzy decision, IEEE Transactions on Biomedical Engineering 47 (3) (2000) 334–351.
[154] S. Sentelle, C. Sentelle, M.A. Sutton, Multiresolution-based segmentation of calcifications for the early detection of breast cancer, Real-Time Imaging 8 (3) (2002) 237–252.
[155] P. Fazendeiro, J.V. de Oliveira, A survey of fuzzy control strategies for neuromuscular blockade using continuous infusion of atracurium, in: Proceedings of IEEE FUZZ, Honolulu, HI, 2002, pp. 547–552.
[156] X. Sun, W. Qian, D. Song, Ipsilateral-mammogram computer-aided detection of breast cancer, Computerized Medical Imaging and Graphics 28 (3) (2004) 151–158.
[157] N. Belacel, M.R. Boulassel, Multicriteria fuzzy classification procedure PROCFTN: methodology and medical application, Fuzzy Sets and Systems 141 (2004) 203–217.
[158] R. Davoodi, B.J. Andrews, Fuzzy logic control of FES rowing exercise in paraplegia, IEEE Transactions on Biomedical Engineering 51 (3) (2004) 541–543.
[159] J. Carballido-Gamio, C. Phan, T.M. Link, S. Majumdar, Characterization of trabecular bone structure from high-resolution magnetic resonance images using fuzzy logic, Magnetic Resonance Imaging 24 (8) (2006) 1023–1029.
[160] Z. Hou, W. Qian, S. Huang, Q. Hu, W.L. Nowinski, Regularized fuzzy c-means method for brain tissue clustering, Pattern Recognition Letters 28 (13) (2007) 1788–1794.
[161] H. Uğuz, A. Arslan, I. Türkoğlu, A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases, Pattern Recognition Letters 28 (4) (2007) 395–404.
[162] H. Uguz, A. Ozturk, R.S. Oglu, A. Arslan, A biomedical system based on fuzzy discrete hidden Markov model for the diagnosis of the brain diseases, Expert Systems with Applications 35 (2008) 1104–1114.
[163] S.N. Ghazavi, T.W. Liao, Medical data mining by fuzzy modeling with selected features, Artificial Intelligence in Medicine 43 (2008) 195–206.
[164] C.-T. Chuang, S.-Z. Fan, J.-S. Shieh, Rule extraction by fuzzy modeling algorithm for fuzzy logic control of cisatracurium as a neuromuscular block, Engineering Applications of Artificial Intelligence (2008), doi:10.1016/j.engappai.2008.05.011.
[165] W. Halberstadt, T.S. Douglas, Fuzzy clustering to detect tuberculous meningitis-associated hyperdensity in CT images, Computers in Biology and Medicine 38 (2) (2008) 165–170.
[166] S. Chattopadhyay, D.K. Pratihar, S.C. De Sarkar, Developing fuzzy classifiers to predict the chance of occurrence of adult psychoses, Knowledge-Based Systems 21 (2008) 479–497.
[167] J. Zhou, J.C. Rajapakse, Fuzzy approach to incorporate hemodynamic variability and contextual information for detection of brain activation, Neurocomputing 71 (16–18) (2008) 3184–3192.
[168] P.-C. Chang, C.-Y Lai, K. Robert Lai, A hybrid system by evolving case-based reasoning with genetic algorithm in wholesaler's returning book forecasting, Decision Support Systems 42 (3) (2006) 1715–1729.
[169] R. Bellazi, S. Montani, L. Portinale, A. Riva, Integrating rulebased and case-based decision making in diabetic patient management, in: Proceedings of the Third International Conference on Case-Based Reasoning, Lecture Notes in Computer Science, vol. 1650, Springer, Berlin, 1999, pp. 386–400.
[170] K.-D. Althoff, R. Bergmann, S. Wess, M. Manago, E. Auriol, O.I. Larichev, A. Bolotov, Y.I. Zhuravlev, S.I. Gurov, Case-based reasoning for medical decision support tasks: the INRECA approach, Artificial Intelligence in Medicine 12 (1) (1998) 25–41.
[171] S. Montani, R. Bellazzi, L. Porinale, M. Stefanelli, A multi-modal reasoning methodology for managing IDDM patients, International Journal of Medical Informatics 58–59 (2000) 243–256.
[172] N.H. Phuong, N.R. Prasad, D.H. Hung, J.T. Drake, Approach to combining case based reasoning with rule based reasoning for lung disease diagnosis, in: 9th International Conference on IFSA World and 20th NAFIPS, vol. 2, 2001, pp. 883–888.
[173] M.-J. Huang, M.-Y. Chen, S.-C. Lee, Integrating data mining with case-based reasoning for chronic diseases prognosis and diagnosis, Expert Systems with Applications 32 (3) (2006) 856–867.
[174] R. Dybowski, P. Weller, R. Chang, V. Gant, Prediction of outcome in the critically ill using an artificial neural network synthesized by a genetic algorithm, Oncology 52 (4) (1999) 281–286.
[175] H. Handels, Th. Roß, J. Kreusch, H.H. Wolff, S.J. Poppl, Feature selection for optimized skin tumor recognition using genetic algorithms, Artificial Intelligence in Medicine 16 (1999) 283–297.
[176] A.K. Pavlou a, N. Magan a, D. Sharp b, J. Brown b, H. Barr b, A.P.F. Turner, An intelligent rapid odour recognition model in discrimination of Helicobacter pylori and other gastroesophageal isolates in vitro, Biosensors & Bioelectronics 15 (2000) 333–342.

[177] P.S. Heckerling, B.S. Gerber, T.G. Tape, R.S. Wigton, Use of genetic algorithms for neural networks to predict community-acquired pneumonia, Artificial Intelligence in Medicine 30 (2004) 71–84.
[178] A. Tsakonas, G. Dounias, J. Jantzen, H. Axer, B. Bjerregaard, D.G. von Keyserlingk, Evolving rule-based systems in two medical domains using genetic programming, Artificial Intelligence in Medicine 32 (2004) 195–216.
[179] Y.M. Chae, Q. Park, K.S. Park, M. Young, Development of medical decision support system for leukemia management, Expert Systems with Applications 15 (1998) 309–315.
[180] R. Schmidt, S. Montani, R. Bellazzi, L. Porinale, Case-based reasoning for medical knowledge-based systems, International Journal of Medical Informatics 44 (2001) 355–367.
[181] L. Shuguang, J. Qing, C. George, Combining case-based and model-based reasoning: a formal specification, in: Proceedings of the Seventh Asia–Pacific Software Engineering Conference, 2000, pp. 416–420.
[182] K.P. Adlassnig, G. Kolarz, W. Scheithauser, H. Effenberger, G. Grabner, CADIAG-approaches to computer-assisted medical diagnosis, Computers in Biology and Medicine 15 (1985) 315–333.
[183] K.-P. Adlassnig, Update on CADIAG-2: a fuzzy medical expert system for general internal medicine, in: W.H. Janko, M. Roubens, H.-J. Zimmermann (Eds.), Progress in Fuzzy Sets and Systems, Kluwer Academic, Dordrecht, 1990, pp. 1–6.
[184] E. Sanchez, Inverses of fuzzy relations, Application to possibility distributions and medical diagnosis, in: Proceedings of IEEE Conference on Decision and Control, IEEE, New York, NY, USA, 1977, pp. 1384–1389.
[185] T. Waschek, S. Levegriin, M. van Kampen, M. Glesner, R. Engenhart-Cabillic, W. Schlege, Determination of target volumes for three-dimensional radiotherapy of cancer patients with a fuzzy system, Fuzzy Sets and Systems 89 (1997) 361–370.
[186] O. Cordon, F. Herrera, F. Hoffmann, L. Magdalena, Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases, World Scientific Publishing, Singapore, 2001.
[187] B. Sageder, K. Boegl, K.P. Adlassnig, G. Kolousek, B. Trummer, The knowledge model of MedFrame/CADIAG-IV, Stud Health Technol Inform 43 (1997) 629–633.
[188] A. Fred, J. Filipe, M. Partinen, et al., PSG-EXPERT: an experts system for the diagnosis of sleep disorders, Stud Health Technol Info 78 (2000) 127–147.
[189] H.P. Nguyen, H.H. Dang, N.R. Prasad, Development of a supporting expert system for lung diseases using Fuzzy Logic, J. Biomed. Soft. Comput. Hum. Sci. 2 (2000) 37–44.
[190] M.J. de Paula Castanho, L.C. de Barros, A. Yamakami, L.L. Vendite, Fuzzy expert system: an example in prostate cancer, Applied Mathematics and Computation 202 (2008) 78–85.
[191] E. Plaza, R. Lopez de Mantaras, A case-based apprentices that learns from fuzzy examples, Methodologies for Intelligent Systems 5 (1990) 420–427.
[192] L.D. Xu, Case-based reasoning for AIDS initial assessment, Knowledge-Based Systems 8 (1) (1995) 32–38.
[193] J. Petersen, Similarity of fuzzy data in a case-based fuzzy system in anaesthesia, Fuzzy Sets and Systems 85 (1997) 247–262.
[194] A. Khanam, M. Zubair Shafiq, E. Muhammad, CBR: fuzzified case retreival approach for facial expression recognition, in: 25th IASTED International Conference on Artificial Intelligence and Applications, Innsbruck, Austria, February 2007, pp. 162–167.
[195] Y. Wang, Y.-S. Zhu, N.V. Thakor, Y.-H. Xu, A short-time multifractal approach for arrhythmia detection based on fuzzy neural network, IEEE Transactions on Biomedical Engineering 48 (9) (2001) 989–995.
[196] B. Karlik, M.O. Tokhi, M. Alci, A fuzzy clustering neural network architecture for multifunction upper-limb prosthesis, IEEE Transactions on Biomedical Engineering 50 (11) (2003) 1255–1261.
[197] H.F. Kwok, D.A. Linkens, M. Mahfouf, G.H. Mills, Rule-base derivation for intensive care ventilator control using ANFIS, Artificial Intelligence in Medicine 29 (2003) 185–201.
[198] R.L. McNamee, M. Sun, R.J. Sclabassi, A neuro-fuzzy inference system for modeling and prediction of heart rate variability in the neuro-intensive care unit, Computers in Biology and Medicine 35 (2005) 875–891.
[199] E.D. Ubeyli, I. Guler, Adaptive neuro-fuzzy inference systems for analysis of internal carotid arterial Doppler signals, Computers in Biology and Medicine 35 (2005) 687–702.
[200] P. Aruna, N. Puviarasan, B. Palaniappan, An investigation of neuro-fuzzy systems in psychosomatic disorders, Expert Systems with Applications 28 (2005) 673–679.
[201] R.T. Lauer, B.T. Smith, R.R. Betz, Application of a neuro-fuzzy network for gait event detection using electromyography in the child with cerebral palsy, IEEE Transactions on Biomedical Engineering 52 (9) (2005) 1532–1540.
[202] L. Benecchi, Neuro-fuzzy system for prostate cancer diagnosis, Urology 68 (2) (2006) 357–361.
[203] E.D. Ubeyli, Adaptive Neuro-Fuzzy Inference System For Analysis of Doppler Signals, in: Proceedings of the 28th IEEE EMBS Annual International Conference, New York City, USA, vol. 1 (1), 2006, pp. 2167–2170.
[204] Y. Özbaya, R. Ceylan, B. Karlik, A fuzzy clustering neural network architecture for classification of ECG arrhythmias, Computers in Biology and Medicine 36 (2006) 376–388.
[205] A. Mangalampalli, S.M. Mangalampalli, R. Chakravarthy, A.K. Jain, A neural network based clinical decision-support system for efficient diagnosis and fuzzy-based prescription of gynecological diseases using homoeopathic medicinal system, Expert Systems with Applications 30 (2006) 109–116.
[206] C.-J. Lin, I.-F. Chung, C.-H. Chen, An entropy-based quantum neuro-fuzzy inference system for classification applications, Neurocomputing 70 (2007) 2502–2516.
[207] K. Assaleh, Extraction of fetal electrocardiogram using adaptive neuro-fuzzy inference systems, IEEE Transactions on Biomedical Engineering 54 (1) (2007) 59–68.
[208] E.D. Ubeyli, Adaptive neuro-fuzzy inference system employing wavelet coefficients for detection of ophthalmic arterial disorders, Expert Systems with Applications 34 (2008) 2201–2209.
[209] R. Ceylan, Y. Özbay, B. Karlik, A novel approach for classification of ECG arrhythmias: type-2 fuzzy clustering neural network, Expert Systems with Applications (2008), doi:10.1016/j.eswa.2008.08.028.
[210] A. Sengur, An expert system based on linear discriminant analysis and adaptive neuro-fuzzy inference system to diagnosis heart valve diseases, Expert Systems with Applications 35 (2008) 214–222.
[211] E. Avci, I. Turkoglu, An intelligent diagnosis system based on principle component analysis and ANFIS for the heart valve diseases, Expert Systems with Applications 36 (2) (2009) 2873–2878.
[212] B. Akdemir, S. Kara, K. Polat, A. Guven, S. Gunes, Ensemble adaptive network-based fuzzy inference system with weighted arithmetical mean and application to diagnosis of optic nerve disease from visual-evoked potential signals, Artificial Intelligence in Medicine (43) (2008) 141–149.
[213] A. Keles, A. Keles, ESTDD: expert system for thyroid diseases diagnosis, Expert Systems with Applications 34 (2008) 242–246.
[214] K. Arthi, A. Tamilarasi, Prediction of autistic disorder using neuro fuzzy system by applying ANN technique, International Journal of Developmental Neuroscience (2008), doi:10.1016/j.ijdevneu.2008.07.013.
[215] C.A. Pena-Reyes, M. Sipper, A fuzzy-genetic approach to breast cancer Diagnosis, Artificial Intelligence in Medicine 17 (1999) 131–155.
[216] A. Roychowdhury, D.K. Pratihar, N. Bose, K.P. Sankaranarayanan, N. Sudhahar, Diagnosis of the diseases—using a GA-fuzzy approach, Information Sciences 162 (2004) 105–120.
[217] M. Sasikala, N. Kumaravel, S. Ravikumar, Segmentation of Brain MR images using genetically guided clustering, in: Proceedings of the 28th IEEE EMBS Annual International Conference New York City, USA, August 30–September 3, 2006.
[218] S. Chattopadhyay, D.K. Pratihar, S.C. De Sarkar, Developing fuzzy classifiers to predict the chance of occurrence of adult psychoses, Knowledge-Based Systems 21 (2008) 479–497.
[219] C.-C. Hsu, C.-S. Ho, A new hybrid case-based architecture for medical diagnosis, Information Sciences 166 (2004) 231–247.
[220] V.D. Mea, Agents acting and moving in healthcare scenario—a paradigm for telemedical collaboration, IEEE Transactions on Information Technology in Biomedicine 5 (1) (2001) 10–13.
[221] L. Godo, J. Puyol-Gruart, J. Sabater, V. Torra, P. Barrufet, X. Fabregas, A multi-agent system approach for monitoring the prescription of restricted use antibiotics, Artificial Intelligence in Medicine 27 (2003) 259–282.
[222] S. Dzeroski, N. Lavrac, Rule induction and instance-based learning applied in medical diagnosis, Technology and Health Care 4 (2) (1996) 203–221.
[223] A. Kusiak, J.A. Kern, K.H. Kernstine, B.T.L. Tseng, Autonomous decision-making: a data mining approach, IEEE Transactions on Information technology in Biomedicine 4 (4) (2000) 274–284.
[224] J.W. Grzymala-Busse, Z.S. Hippe, Melanoma prediction using data mining system LERS, in: 25th Annual International Conference on Computer Software and Applications, Chicago, IL, USA, 2001, pp. 615–620.
[225] P.R. Walker, B. Smith, Q.Y. Liu, A.F. Famili, J.J. Valdes, Z. Liu, B. Lach, Data mining of gene expression changes in Alzheimer brain, Artificial Intelligence in Medicine 31 (2004) 137–154.
[226] R. Andrews, S. Bajcar, J.W. Grzyma, A. Busse, Z.S. Hippe, C. Whiteley, Optimization of the ABCD formula for melanoma diagnosis using C4.5, a Data Mining System, in: Lecture Notes in Computer Science, vol. 3066, Springer Berlin/Heidelberg, 2004, ISSN 0302-9743 (Print) 1611-3349 (Online).
[227] H. Melliez, D. Levy, P.Y. Boelle, B. Dervaux, S. Baron, Y. Yazdanpanah, Cost and cost-effectiveness of childhood vaccination against rotavirus in France, Vaccine 26 (2008) 706–715.
[228] G.A. Lillington, Management of the solitary pulmonary nodule, Hospital Practice (1993) 41–48.
[229] T. Young, J. Skatrud, P.E. Peppard, Risk factors for obstructive sleep apnea, The Journal of the American Medical Association (JAMA) 291 (16) (2004) 2013–2016.
[230] D.W. Patterson, Introduction to Artificial Intelligence and Expert System, Prentice-Hall, Inc., Englewood Cliffs, NJ, USA, 1990.

Babita Pandey is a Research Scholar in the Department of Computer Engineering, IT, BHU, India. The area of interest includes expert system, artificial intelligence and its medical applications.

R.B. Mishra is a Reader in the Department of Computer Engineering, IT, BHU, India, He has a teaching experience of 28 years. His area of interest includes expert system, artificial intelligence and its medical applications.