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# A New Hybrid Case-Based Reasoning Approach for Medical Diagnosis Systems

**Dina A. Sharaf-El-Deen · Ibrahim F. Moawad · M. E. Khalifa**

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**Abstract** Case-Based Reasoning (CBR) has been applied in many different medical applications. Due to the complexities and the diversities of this domain, most medical CBR systems become hybrid. Besides, the case adaptation process in CBR is often a challenging issue as it is traditionally carried out manually by domain experts. In this paper, a new hybrid case-based reasoning approach for medical diagnosis systems is proposed to improve the accuracy of the retrieval-only CBR systems. The approach integrates case-based reasoning and rule-based reasoning, and also applies the adaptation process automatically by exploiting adaptation rules. Both adaptation rules and reasoning rules are generated from the case-base. After solving a new case, the case-base is expanded, and both adaptation and reasoning rules are updated. To evaluate the proposed approach, a prototype was implemented and experimented to diagnose breast cancer and thyroid diseases. The final results show that the proposed approach increases the diagnosing accuracy of the retrieval-only CBR systems, and provides a reliable accuracy comparing to the current breast cancer and thyroid diagnosis systems.

**Keywords** Case-based reasoning (CBR) · Rule-based reasoning (RBR) · Hybrid medical diagnosis system · Adaptation rules · Breast cancer diagnosis · Thyroid disease diagnosis

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## Introduction

Nowadays, medical knowledge is expanding rapidly to the extent that even experts have difficulties in following all the new results, changes and new treatments. Decision Support Systems (DSS) that bear more similarities with human reasoning are often easily accepted by physicians in the medical domain [1]. Moreover, recent DSS tend towards the hybrid integration of two or more intelligent techniques [2].

Case-Based Reasoning (CBR) system is a valuable example of decision support systems [3]. It is a reasoning methodology that simulates human reasoning using past experiences to solve new problems [4]. Generally, the problem solving cycle of the classical CBR model consists of four steps [5]:

(1). **RETRIEVE** step that is responsible for retrieving one or more similar cases to the new case.
(2). **REUSE/ADAPT** step that is responsible for reusing the solution of the most similar case to the new case. It may include the adaptation process in which the solution of the retrieved case is adapted to fit the new case.
(3). **REVISE** step that is responsible for revising the suggested solution for confirmation.
(4). **RETAIN** step that is responsible for retaining the learned case for future use.

CBR has been successfully applied in the medical domain [4, 6–9]. However, adaptation is often a challenging issue, because it is traditionally carried out manually by domain experts. Moreover, most CBR systems that do not apply adaptation (retrieval-only CBR systems) fail to solve some of new problems, and hence they do not provide convincing accuracy in critical domains like medical [10].

In this paper, a new hybrid case-based reasoning approach for medical diagnosis systems is proposed to improve the accuracy of the retrieval-only CBR systems. This approach integrates case-based reasoning and rule-based reasoning, and applies the adaptation process automatically. To achieve the integration, a new process is added to the **REUSE/ADAPT** step of the classical CBR cycle called **REASON** at which the reasoning rules are applied to infer a solution if both **REUSE** and **ADAPT** processes failed to find a solution. The proposed approach contains two phases: Knowledge Extraction Phase and Problem Solving Phase. During the Knowledge Extraction Phase, both adaptation and reasoning rules are extracted from the case-base. After that, the adaptation rules and the reasoning rules are exploited and updated dynamically in the Problem Solving Phase. This paper introduces the two phases while our previous work [11] focused on the reasoning rules extraction process, and the adaptation rules extraction process was introduced in [12]. Besides, a prototype was implemented and experimented to diagnose breast cancer and thyroid diseases. The evaluation results shows that this research increases the accuracy of retrieval-only CBR systems, and achieves great accuracy comparing to the current mammography based breast cancer diagnosis and thyroid diagnosis systems.

The rest of this paper is organized as follows. The Related work section reviews the recent related medical systems. The proposed approach architecture is introduced in The hybrid case-based approach architecture section while the approach phases are described in the Hybrid case-based approach phases section. The thyroid disease diagnosis case study is presented in Thyroid disease diagnosis as a case study section. The prototype implementation and the experimental evaluation results are illustrated in the Prototype implementation and experimental evaluation section. Finally, the Conclusion section concludes the paper.

## Related work

In this section, the related work is presented using two viewpoints. The first view point presents the recent medical CBR systems while the second viewpoint presents the medical diagnosis systems that we are going to compare our system with.

CBR is an appropriate methodology to apply in medical diagnosis and treatment systems. CBR systems may use adaptation technique to solve more new problems [13]. However, adaptation is often a challenging issue in the medical domain and is carried out manually by physicians/domain experts. Nowadays, most medical CBR systems became hybrid as they integrate more than one artificial intelligence technique such as rule-based reasoning, data mining, and rough set theory to handle the underlying complexities in the medical domain [2]. According to Shahina Begum et al. [10] and Yusof and Buckingham [14], only six recent medical CBR systems [15–20] out of 40 introduce different approaches of automatic and semi-automatic adaptation strategies.

Huang et al. [15] implemented a system for chronic disease diagnosis and prognosis. The system applied adaptation in chronic disease diagnosis using transformational adaptation rules. Rainer and Olga [16] presented a CBR system for long-term therapy support in the endocrine domain and in psychiatry. Semi-automatic adaptation is applied as it takes place as a dialogue between the doctor, the patient, and the system. Marling et al. [17] described a case-based decision-support system to assist in the daily management of patients with Type 1 diabetes on insulin pump therapy. The system integrated CBR with rule-based reasoning and a probabilistic model of the effects of insulin on blood glucose over time. Rainer and Lothar [18] presented a method for prognosis of temporal courses, which combines temporal abstractions with case-based reasoning. They applied their method on the prognosis of kidney function courses and on the prognosis of the spread of infectious diseases, especially of influenza. Concerning the kidney function, they built a retrieval-only system that visualizes current kidney function courses in comparison to similar former ones while for influenza forecast, automatic adaptation is applied to decide whether early warnings are appropriate or not. Ochoa et al. [19] presented an intelligent tutoring CBR system for providing medical education on Tourette syndrome. O'Sullivan et al. [20] developed a case-based decision-support system by exploiting patients' electronic health records delivered through wireless networks. The system facilitates knowledge sharing in the domain and allows "remote-access health-care". Although most of these systems apply adaptation, the adaptation knowledge remains static during the CBR lifecycle.

There are other medical diagnosis systems for the breast cancer and thyroid disease applying different techniques. Mammography is the most common modality for breast cancer detection and diagnosis, and it is often complemented by ultrasound and Magnetic Resonance Imaging (MRI). However, similarities between early signs of breast cancer and normal structures in these images make detection and diagnosis of breast cancer a difficult task. Ayer Turgay et al. [21] provided a comprehensive survey of the computer-aided breast cancer diagnostic models that have been proposed to aid in mammography, ultrasound, and MRI interpretation. Those computer models utilized many techniques such as artificial neural network, Bayesian network, CBR, and decision tree. These models achieved diagnosis performance ranged from 0.83 to 0.965 (Area under the Receiver Operating Characteristic curve). Recently, Huang et al. [22] compared the particle swarm optimizer based artificial neural network (PSO-based ANN), the Adaptive Neuro-Fuzzy Inference System (ANFIS), and a case-based reasoning classifier with a logistic regression model and decision tree model. Their experimental results on the mammography dataset showed that the best CBR-based classification accuracy, the classification accuracies of the PSO-based ANN classifier and ANFIS were 83.60 %, 91.10 %, and 92.80 % respectively.

On the other hand, the primary role of the thyroid hormone produced by the thyroid gland is to help regulation of the body's metabolism. Producing too little thyroid hormone (hypothyroidism) or too much thyroid hormone (hyperthyroidism) defines the type of thyroid disease. Proper interpretation of the thyroid gland functional data is an important issue in the diagnosis of thyroid disease [23]. Many systems [23–31] applied different methods to diagnose thyroid disease. The accuracy of these systems ranged from 36.74 to 97.7 %.

For example, K. Polat et al. compared between Artificial Immune Recognition System (AIRS) only and Artificial Immune Recognition System integrated with Fuzzy weighted pre-processing [26]. A. Keles et al. presented expert system for thyroid disease diagnosis with neurofuzzy classification [27]. F. Temurtas used multi-layer perception with levenberg-marquardt algorithm [28]. E. Dogantekina et al. used generalized discriminant analysis and wavelet support vector machine [29]. H. L. Chen et al. used fisher score, particle swarm optimization, and support vector machine [30]. Finally, P. K. Srimani and M. S. Koti used Ensemble Classifiers [31].

Aiming at improving the medical CBR systems accuracy, this paper presents a new hybrid case-based reasoning approach for medical diagnosis systems. The approach integrates case-based reasoning and rule-based reasoning, and exploits the adaptation rules. Both adaptation rules and reasoning rules are generated automatically from the case-base. After solving a new case, the case-base is expanded, and both adaptation and reasoning rules are updated automatically. Furthermore, the proposed approach was experimented in diagnosing both breast cancer and thyroid diseases, and the results showed high reliable accuracy.

## The hybrid case-based approach architecture

Figure 1 shows the architecture of the proposed hybrid case-based approach for medical diagnosis systems. The approach integrates case-based reasoning and rule-based reasoning to enhance the diagnosing accuracy obtained from the classical CBR systems. As shown, the architecture consists of two phases: Knowledge Extraction Phase and Problem Solving Phase.

In the *Knowledge Extraction Phase*, the case-base acts as a knowledge source for extracting both adaptation and reasoning rules using the Adaptation Rules Extractor and the Reasoning Rules Extractor modules respectively. The Adaptation Rules Extractor module extracts the adaptation rules in three steps: Case-Pair Comparison, Transformational Adaptation Rules Generation, and Range Adaptation Rules Generation. The Reasoning Rules Extractor applies the Rough Set Theory (RST) [32] on the case-base to extract the reasoning rules.

On the other hand, in the *Problem Solving Phase*, case-based reasoning and rule-based reasoning are integrated by adding a new process to the **REUSE/ADAPT** step of the classical CBR cycle called **REASON.** The **REASON** process exploits the reasoning rules to infer a solution in case of failing of both **REUSE** and **ADAPT** processes failed.

## Hybrid case-based approach phases

### Knowledge extraction phase

In this phase, knowledge extraction techniques are applied on the case-base to extract both adaptation rules and reasoning rules using the Adaptation Rules Extractor and the Reasoning Rules Extractor modules respectively.

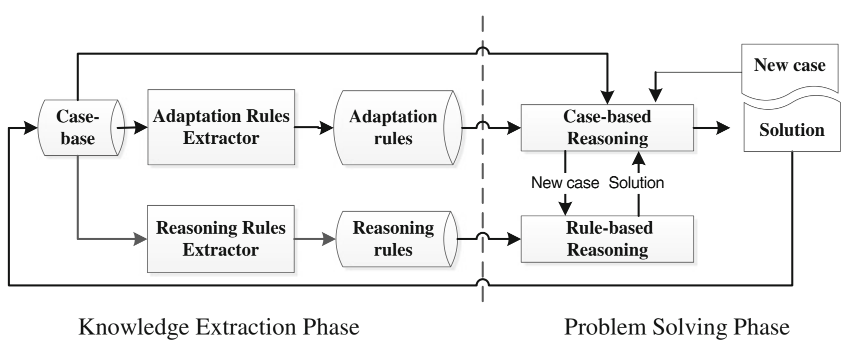



**Fig. 1** Hybrid case-based approach architecture for medical diagnosis systems

| | C1 | C2 | C3 | .. | Cn |
|---|---|---|---|---|---|
| **C1** | 0 | $d_{12}$ | $d_{13}$ | .. | $d_{1n}$ |
| **C2** | $d_{21}$ | 0 | $d_{23}$ | .. | $d_{2n}$ |
| **C3** | $d_{31}$ | $d_{32}$ | 0 | .. | $d_{2n}$ |
| **..** | .. | .. | .. | .. | .. |
| **Cn** | $d_{n1}$ | $d_{n2}$ | $d_{n3}$ | .. | 0 |

**Fig. 2** Case-pair distance matrix

### *Adaptation rules extractor*

The Adaptation Rules Extractor module extracts the adaptation rules in three steps: Case-Pair Comparison, Transformational Adaptation Rules Generation, and Range Adaptation Rules Generation.

Step 1. *Case-Pair Comparison*

This step calculates the dissimilarity between all cases. The case-pair comparison technique [33, 34] is exploited to generate the transformational adaptation rules. Formula (1) [35] is used to compute the distance between two cases ($q$ *and* $c$), where $W_f$ represents the weight of feature $f$ and $dif(q_f,c_f)$ represents the difference between the feature values of $q$ and $c$ cases calculated by formula (2).

$$distance(q,c) = \sqrt{\sum_{f=1}^{N} w_f dif^2\left(q_f, c_f\right) \Big/ \sum_{f=1}^{N} w_f} \tag{1}$$

$$dif\left(q_f, c_f\right) = \begin{cases} \left|q_f - c_f\right| & , \text{ if } f \text{ is a numerical feature} \\ 0 & , \text{ if } f \text{ is a nominal feature, and } q_f = c_f \\ 1 & , \text{ if } f \text{ is a nominal feature, and } q_f \neq c_f \\ 0.5 & , \text{ if } c \text{ or } q \text{ has missing value on } f \end{cases} \tag{2}$$

As a result of distance calculating, a diagonal matrix is generated, which contains the distances between all cases as shown in Fig. 2.

Step 2. *Transformational Adaptation Rules Generation*

The transformational adaptation rules relate the changing of the problem feature values to the changing in the solution feature value. Figure 3 shows a general form of the transformational adaptation rule in IF-THEN format.

**Rule :**Rule1 ***Confidence value****: c1*
**IF** PFeature$_1$ *changes from val$_1$ to val$_2$*
**AND** PFeature$_2$ *changes from val$_3$ to val$_4$*
**AND...**etc.
**THEN** SolFeature$_1$ *changes from X* to *Y*

**Fig. 3** Transformational adaptation rule general form

**Rule :**RangeRule1 ***Confidence value****: c1*
**IF** PFeature$_1$ *changes from* [*min$_1$ , max$_1$*] *to* [*min$_2$ , max$_2$*]
**AND** PFeature$_2$ *changes from* [*min$_3$ , max$_3$*] *to* [*min$_4$ , max$_4$*]
**AND...**etc.
**THEN** SolFeature$_1$ *changes from X* to *Y*

**Fig. 4** Range adaptation rule general form

After the case-pair distance matrix is derived in step 1, it is used to generate the transformational adaptation rules. The differences between the feature values of each pair of the compared cases are used to generate the antecedent part of the transformational adaptation rule and the differences between the solutions in the compared cases become the rule consequent part.

Step 3. *Range Adaptation Rules Generation*

The range adaptation rules relate the changing of the problem feature value ranges to the changing in the solution feature values. Figure 4 shows a general form of the range adaptation rule.

In case of numerical attributes, the Transformational Adaptation Rules Generation step generates a lot of adaptation rules, so they need to be generalized to extract the range adaptation rules to be exploited during the CBR cycle. Figure 5 shows the range adaptation rules generation algorithm.

For more details, our previous research [11] presents a detailed example for extracting and applying range adaptation rules to identify IRIS plant type.

### *Reasoning rules extractor*

In the Reasoning Rules Extractor module, Rough Set Theory [36, 37] is used to extract the reasoning rules from the case-base. In order to discover the reasoning rules, three steps are applied.

**Input**: Transformational adaptation rules (AR)
**Output**: Range adaptation rules
***Begin***
***Cluster*** *the adaptation rules (AR) based on the adaptation rule conditions (ARCCs)*
***For each*** *cluster C in (ARBCs) clusters* ***do***
***Cluster*** *the adaptation rules in cluster C based on adaptation rule action (ARACs)*
***For each*** *cluster A in (ARBAs) clusters* ***do***
***For*** *each condition feature (Fi) in adaptation rule conditions* ***do***
***Get*** *minimum value of the From part (FromMin Fi)*
***Get*** *maximum value of the From part (FromMax Fi)*
***Get*** *minimum value of the To part (ToMin Fi)*
***Get*** *maximum value of the To part (ToMax Fi)*
***Generate*** *the feature Fi changing ranges:*
*From range of (Fi)=[FromMin Fi , FromMax Fi]*
*and To range of (Fi)= [ToMin Fi, ToMax Fi]*
***Generate*** *the range adaptation rule Ri*
***Add*** *Ri to the range adaptation rules*
***End***

**Fig. 5** Range adaptation rules generation algorithm

**Rule :**RangeRule1 ***Confidence value**: c1*
**IF** PFeature$_1$ *IN* [*min* , *max*]
**AND** PFeature$_2$ *IN* [*min*, *max*]
**AND...**etc.
**THEN** SolFeature$_1$ = X

**Fig. 6** Range reasoning rule general form

Step 1. *Attributes Reduction*

The reduction process of condition attributes determines the superfluous attributes and yields the case-reduct attribute sets [38]. A case-reduct is defined as a minimal sufficient subset of a set of attributes. This set of attributes is enough to identify the solutions [39]. Basically, the case-reducts represent the necessary condition attributes to make a decision. This process is adopted from Pawlak [38].

Step 2. *Reasoning Rules Generation*

The reasoning rules generation process extracts the knowledge hidden in the case-base that may be discovered and expressed in the form of reasoning rules. Basically, a set of reasoning rules forms a reduced case-base. These reasoning rules are generated using the reducts extracted in step1.

Step 3. *Range Reasoning Rules Generation*

The range reasoning rules relate the changing of the problem feature value ranges to the solution feature value. Figure 6 shows a general form of the range reasoning rule in IF-THEN format.

In case of numerical attributes, the reasoning rules generation step generates a lot of reasoning rules, so they need to be generalized to extract the range reasoning rules to be exploited during the hybrid CBR cycle. Figure 7 shows the range reasoning rules generation algorithm.

## The problem solving phase

Figure 8 depicts the hybrid CBR cycle where the **REASON** process is added to the **REUSE/ADAPT** step. The cycle starts

**Input**: Reasoning rules
**Output**: Range reasoning rules
***Begin***
***Cluster*** *the rules in the reasoning rules based on the rule conditions (RCCs)*
***For each*** *cluster C in (RCCs) clusters* ***do***
***Cluster*** *the rules in cluster C based on rule action (RACs)*
***For each*** *cluster A in (RACs) clusters* ***do***
***For*** *each condition feature (Fi) in rule conditions* ***do***
***Get*** *minimum value of feature (Fi) (Min Fi)*
***Get*** *maximum value of feature (Fi) (Max Fi)*
***Generate*** *the feature Fi changing range:*
*range of (Fi)=[ Min Fi , Max Fi]*
***Generate*** *the range rule Ri*
***Add*** *Ri to the range reasoning rules*
***End***

**Fig. 7** Range reasoning rules generation algorithm

when a new case needs to be solved. In the **RETRIEVE** step, similar cases to the new case are retrieved from the case-base. Also, Fig. 9 shows a flowchart for the proposed approach diagnosis process.

In the **REUSE/ADAPT/REASON** step, the solution of one of the retrieved similar cases is either reused **(REUSE process)** to the new case or adapted (**ADAPT process**) using the adaptation rules to fit the new case as a suggested solution. To select the appropriate adaptation rule to be used in the **ADAPT process**, the difference attributes set between the retrieved similar case and the new case is derived using formula (3) [40].

$$\mathrm{DiffAtt}(e,t) = \{a_e \in C_e |\ a_t \neq a_e, a_t \in C_t, e \in E, t \in T\}, \tag{3}$$

Where $C_e$ is the attributes set of a retrieved case $e$, $C_t$ is the attributes set of the new case $t$, $a_e$ denotes attribute of the retrieved case $e$, $a_t$ denotes an attribute of the new case $t$, $E$ is the retrieved cases space, and $T$ is the new case space.

If both **REUSE and ADAPT** processes failed to get a solution, the **REASON** process invokes the rule-based reasoning to suggest a solution. If **REUSE/ADAPT/REASON** step failed, the most similar case to the new case is returned.

After that, in the **REVISE** step, the suggested solution is revised to be confirmed. If the suggested solution is suitable, the adaptation rules or the reasoning rules are updated by increasing the confidence value of the used rule. Otherwise, if the suggested solution is not

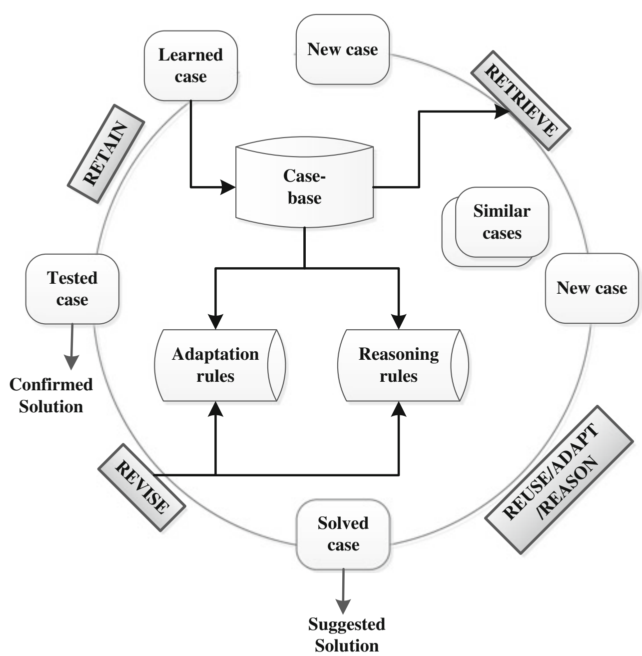



**Fig. 8** The hybrid case-based reasoning cycle

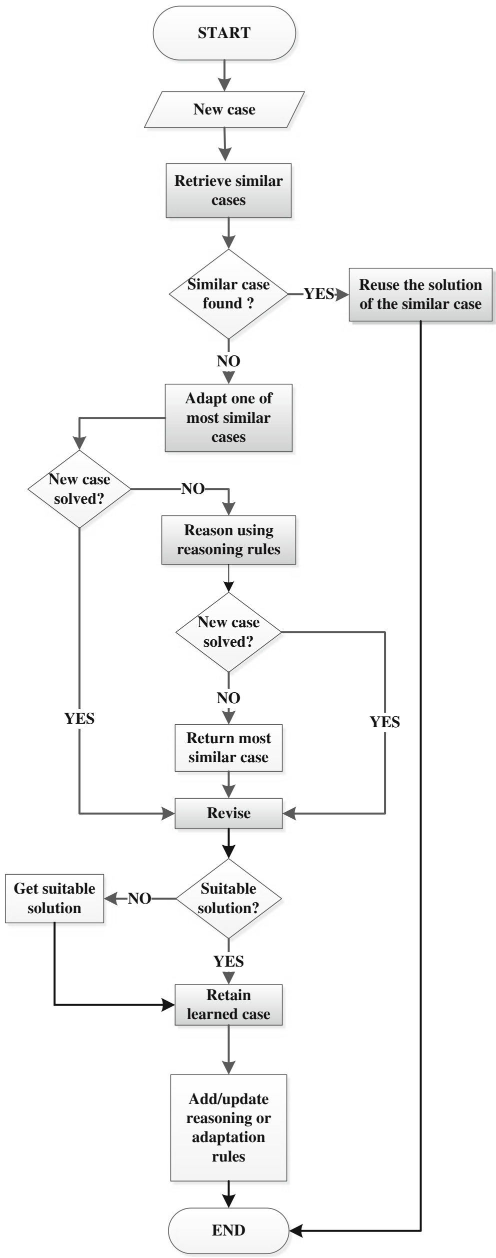



**Fig. 9** The flowchart of hybrid CBR diagnosis process

suitable for the current case, the confidence value of the used rule is decreased and a more suitable solution is provided by a domain expert.

In the **RETAIN** step, the case-base is expanded by adding the new learned case, and hence the Adaptation Rules Extractor may add/update the adaptation rules. Besides, the Reasoning Rules Extractor may add/update the reasoning rules. Therefore, it is unnecessary to regenerate all adaptation rules and reasoning rules again, which can save a lot of time. Besides, the learning ability during the CBR cycle enriches the CBR system over time.

**Table 1** Thyroid disease case-base sample

| Feature Case | F1 | F2 | F3 | F4 | F5 | Class |
|---|---|---|---|---|---|---|
| Case 1 | 98 | 9.1 | 1.4 | 1.9 | −0.3 | 1 |
| Case 2 | 116 | 9.2 | 2.7 | 1 | 4.2 | 1 |
| Case 3 | 118 | 8.1 | 1.9 | 1.5 | 13.7 | 1 |
| Case 4 | 105 | 17.4 | 1.6 | 0.3 | 0.4 | 2 |
| Case 5 | 89 | 20.1 | 7.3 | 1.1 | −0.2 | 2 |
| Case 6 | 123 | 5.6 | 1.1 | 13.7 | 56.3 | 3 |
| Case 7 | 115 | 6.3 | 1.2 | 4.7 | 14.4 | 3 |

F1:T3, F2: Serum thyroxin, F3:Serum triodo, F4:TSH,F5:Max.abs dif
Class values: 1=normal, 2=hyper, 3=hypo

## Thyroid disease diagnosis as a case study

To show how the proposed approach works, a case study is presented to illustrate the proposed approach phases for thyroid disease diagnosis. Table 1 shows a sample of the thyroid disease case-base while Table 2 shows new cases are needed to be diagnosed. To diagnose the new cases, the presented approach should go through two phases: Knowledge Extraction Phase and Problem Solving Phase.

Firstly, during the Knowledge Extraction Phase, the adaptation and the reasoning rules are generated from the case-base to be used in the CBR cycle. By default, the confidence values of the adaptation and the reasoning rules are set to 1. Table 3 shows a sample of the adaptation rules generated from the case-base while Table 4 shows a sample of the generated reasoning rules.

Secondly, during the Problem Solving Phase, the hybrid CBR cycle steps are invoked to diagnose the two new cases as follow.

- **The RETRIEVE Step**

  In the **RETRIEVE** step, the distances between the new cases and every case in the case-base are calculated using formula (1). No case with distance 0 to the new cases is found, so the case with the smallest distance to each new case is returned. Concerning case 8, case 3 is returned as the most similar case while for case 9, case 1 is returned.

**Table 2** Thyroid disease new cases

| Feature Case | F1 | F2 | F3 | F4 | F5 |
|---|---|---|---|---|---|
| Case 8 | 102 | 5.3 | 1.4 | 1.3 | 6.7 |
| Case 9 | 98 | 10.4 | 1.6 | 2.3 | −0.7 |

**Table 3** Adaptation rules sample

| | | |
|---|---|---|
| Rule 1 | | |
| IF | "Serum thyroxin" changes from [5.9,15.3] to [0.5,6.8] | AND |
| | "Serum triodo" changes from [1.1,3.1] to [0.2,2.5] | AND |
| | "TSH" changes from [0.6,3.7] to [1.2,56.4] | AND |
| | "Max.abs dif" changes from [0.1,13.7] to [1.4,56.3] | |
| THEN | class changes from "normal" to "hypo" | |
| Rule 2 | | |
| IF | "T3" changes from [65,97] to [110,121] | AND |
| | "Serum thyroxin" changes from [14.2,18.2] to [9.2,10.1] | AND |
| | "Serum triodo" changes from [3.6,10] to [1.6,1.7] | |
| THEN | class changes from "hyper" to "normal" | |
| Rule 3 | | |
| IF | "T3" changes from [108,120] to [76,98] | AND |
| | "Serum thyroxin" changes from [3,3.5] to [16.7,25.3] | AND |
| | "Serum triodo" changes from [0.6,2.5] to [4.3,4.5] | AND |
| | "Max.abs dif" changes from [1.4,4.5] to [−0.1,0.2] | |
| THEN | class changes from "hypo" to "hyper" | |
| Rule 4 | | |
| IF | "T3" changes from [89,105] to [98,118] | AND |
| | "Serum thyroxin" changes from [17.4,20.1] to [8.1,9.2] | AND |
| | "Serum triodo" changes from [1.6,7.3] to [1.4,2.7] | AND |
| | "TSH" changes from [0.3,1.1] to [1,1.9] | AND |
| | "Max.abs dif" changes from [−0.2,0.4] to [−0.3,13.7] | |
| THEN | class changes from "hyper" to "normal" | |

- **The REUSE/ADAPT/REASON Step**

  In the **REUSE/ADAPT/REASON** step, the retrieved solution of case 3 is needed to be adapted to fit case 8. To select the appropriate adaptation rule to be used in **ADAPT** process, the difference attributes set is derived using formula (3). For example, the difference attributes set between case 3 and case 8 can be derived as *the DiffAtt (Case 3, case 8)={"Serum thyroxin", "Serum triodo", "TSH","Max.abs dif"}*. The adaptation rules that include these difference attributes are chosen from the adaptation rules set, and then they are sorted by their confidence values in a descending order. Based on the transition range of attribute values, the range "adaptation rule 1" is chosen and the solution of Case 3 is updated to fit case 8 by substituting the value of "class" attribute from "1" to "3". Therefore, case 8 is diagnosed as "hypo thyroid".

  For case 9, in **ADAPT** process, no adaptation rules are found to diagnose it, and hence the **REASON** process succeeds to diagnose it using "reasoning rule 3". Subsequently, case 9 is diagnosed as "normal thyroid".
- **The REVISE and RETAIN Steps**

  By comparing the derived solutions of the new cases with their solutions in the testing dataset, they are correct. Therefore, the confidence values of the adaptation rule 1 and the reasoning rule 3 are incremented by one, and two new learned cases are added to the case-base. As a result of adding the two learned cases, the adaptation rules or the reasoning rules are updated if necessary. Table 5 shows a sample of the new generated/updated adaptation rules. As shown, adaptation rule 5 is one of the new generated adaptation rules, so the problem feature values ranges of adaptation rule 4 are updated. Besides, Table 6 shows a

**Table 4** Reasoning rules sample

| | | |
|---|---|---|
| Rule 1 | | |
| IF | "T3" IN [89, 105] | AND |
| | "TSH" IN [0.3,1.1] | |
| THEN | class="hyper" | |
| Rule 2 | | |
| IF | "T3" IN [115,123] | AND |
| | "Serum triodo" IN [1.1,1.2] | AND |
| | "TSH" IN [4.7,13.7] | |
| THEN | class="hypo" | |
| Rule 3 | | |
| IF | "T3" IN [90,133] | AND |
| | "Serum thyroxin" IN [4.2, 16.1] | AND |
| | "Serum triodo" IN[0.9,3.1] | AND |
| | "TSH" IN [0.3,3.7] | AND |
| | "Max.abs" dif IN [−0.5,13.7] | |
| THEN | class="normal" | |

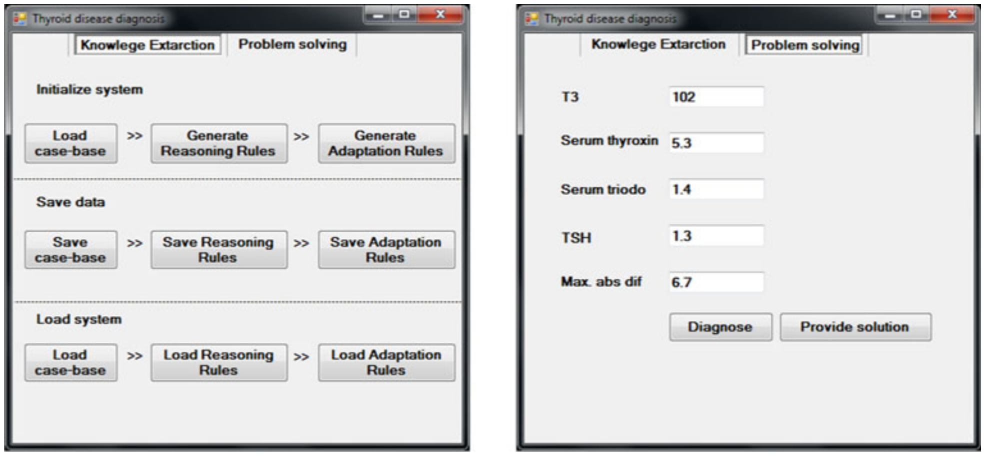
**Table 5** New generated/updated adaptation rules sample

| | | |
|---|---|---|
| Rule 5 | | |
| IF | "T3" changes from 89 to 98 | AND |
| | "Serum thyroxin" changes from 20.1 to 10.4 | AND |
| | "Serum triodo" changes from 7.3 to 1.6 | AND |
| | "TSH" changes from 1.1 to 2.3 | AND |
| | "Max.abs dif" changes from −0.2 to−0.7 | |
| THEN | class changes from "hyper" to "normal" | |
| Rule 4 | | |
| IF | "T3" changes from [89,105] to [98,118] | AND |
| | "Serum thyroxin" changes from [17.4,20.1] to [8.1,10.4] | AND |
| | "Serum triodo" changes from [1.6,7.3] to [1.4,2.7] | AND |
| | "TSH" changes from [0.3,1.1] to [1,2.3] | AND |
| | "Max.abs dif" changes from [−0.2,0.4] to [−0.7,13.7] | |
| THEN | class changes from "hyper" to "normal" | |

**Table 6** New generated/updated reasoning rules sample

| | | |
|---|---|---|
| Rule 4 | | |
| IF | IF "T3"=102 | AND |
| | "Serum triodo"=1.4 | AND |
| | "TSH"=1.3 | |
| THEN | class="hypo" | |
| Rule 2 | | |
| IF | IF "T3" IN[102,123] | AND |
| | "Serum triodo" IN [1.1,1.4] | AND |
| | "TSH" IN [1.3,13.7] | |
| THEN | class="hypo" | |

Fig. 10 Prototype user interface




sample of the new generated/updated reasoning rules. As shown in Table 6, reasoning rule 4 is one of the new generated reasoning rules, so the problem feature value ranges of reasoning rule 2 are updated.

## Prototype implementation and experimental evaluation

To evaluate the introduced approach, a prototype was implemented and experimented using two datasets: thyroid disease and mammography based breast cancer disease [41]. To get the case-base in the final form, the medical datasets should be pre-processed to solve the problem of data conflicts. The thyroid disease dataset is used to predict the state of thyroid gland (hypothyroidism, hyperthyroidism, or normal). The dataset contains six attributes (T3, Serum thyroxin, Serum triodo, TSH, Max. abs dif, and Class). “T3” is a percentage attribute representing the T3-resin uptake test. “Serum thyroxin” represents the total serum thyroxin as measured by the isotopic displacement method. “Serum triodo” represents the total serum triiodothyronine as measured by radioimmuno assay. “TSH” represents the basal Thyroid-Stimulating Hormone (TSH) as measured by radioimmuno assay. “Max. abs dif” represents the maximal absolute difference of TSH value after injection of 200 mg of thyrotropin-releasing hormone as compared to the basal value, and the class attribute may contain 1(normal), 2(hyper), or 3(hypo). Initially, the data was pre-processed to remove the data conflicts. The thyroid disease dataset constitutes 215 instances and 5 equally weighted attributes and the class attribute (1=normal, 2=hyper, 3=hypo with the class distribution 150, 35 and 30 respectively).

On the other hand, mammographic mass dataset is used to predict the breast cancer severity (benign or malignant) based on a mammographic mass lesion from BI-RADS attributes and the patient’s age. It contains a BI-RADS assessment, the patient’s age, and three BI-RADS attributes (shape, margin, and density) together with the severity field that has been identified on full field digital mammograms. The Mammographic mass dataset contains 595 instances (after removing data conflicts) and 5 equally weighted attributes and the class attribute (0=benign and 1=malignant with the class distribution 321 and 247 respectively).

The prototype was implemented using C#.NET language. The empirical experiments were conducted on Intel (R) CPU (2.0 GHz) with 4 GB of RAM. Figure 10 shows

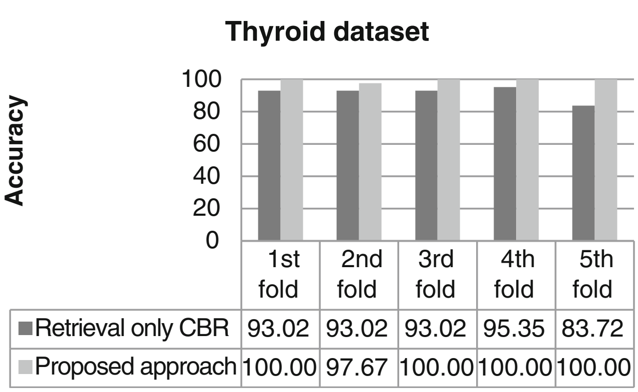



Fig. 11 Diagnosing accuracies for thyroid disease dataset

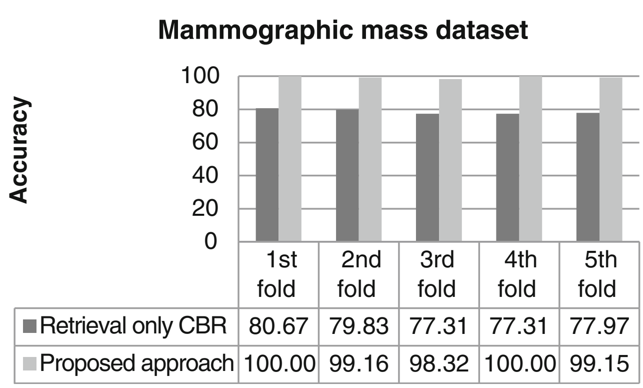



Fig. 12 Diagnosing accuracies for mammographic mass dataset

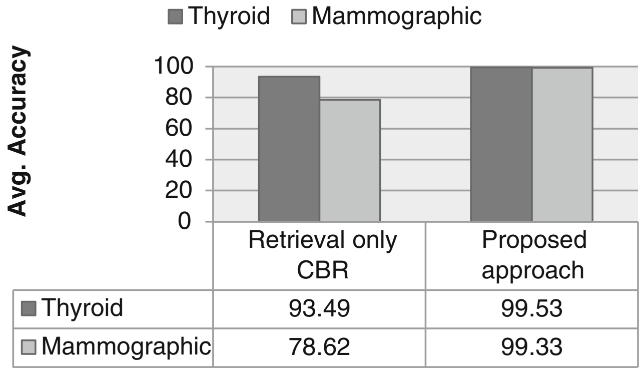



**Fig. 13** Average diagnosing accuracies for thyroid and mammographic mass datasets

two screenshots of the developed prototype. The left side screen shows the knowledge extraction phase where case-base can be loaded, and then both reasoning rules and adaptation rules are generated. Besides, the case-base, the reasoning rules, and the adaptation rules can be saved, and then they can be loaded at the second time the system is initialized. The right side screen shows the problem solving phase at which a new case can be entered to be diagnosed. If the system failed to diagnose the new case, the domain expert can provide a suitable solution, and then the new case is retained in the case-base.

The experiment was conducted on the two datasets in two steps: diagnosing using retrieval-only CBR system and diagnosing using the proposed approach. Also, in order to guarantee the valid results, the k-fold Cross Validation (CV) presented by [42] was used to evaluate the diagnosing accuracy where k indicates the data division subsets. In this experiment, k was chosen to be 5, i.e. the data was divided into five subsets. Each time, one of the five subsets is used as the test set and the other four subsets form a training set. Then the average accuracy across all five trials was computed. The advantage of this method is that all of the test sets are independent and different.

Figures 11 and 12 show the diagnosing accuracies of thyroid disease and mammography based breast cancer diagnosis through the 5-fold trails respectively where Fig. 13 shows the average diagnosing accuracies. The developed prototype achieved 99.53 % and 100 % for thyroid disease diagnosis as average diagnosing accuracy and maximum diagnosing accuracy respectively. It also achieved 99.33 % and 100 % for breast cancer diagnosis as average diagnosing accuracy and maximum diagnosing accuracy respectively. As shown, the developed prototype increased the diagnosing accuracy comparing with retrieval-only CBR systems. The diagnosing accuracy was calculated using formula (4).

$$Diagnosing\,accuracy = TC/TT*100 \quad (4)$$

Where $TC$ is the total number of test cases diagnosed correctly and $TT$ is the total number of the test cases.

In compare to previous systems, Fig. 14 shows the diagnosing accuracies of the proposed approach and the maximum accuracies obtained from the previous systems for thyroid disease diagnosis. As shown, the developed proposed approach can obtain better diagnosing accuracy than the other previous studies. On the other hand, Fig. 15 shows that the proposed approach achieved great Area Under the Curve (AUC) in mammography based breast cancer diagnosis comparing to other previous systems. AUC is interpreted as the average value of sensitivity for all possible values of specificity, and hence it is a measure of the overall performance of a diagnostic test [43].

Obviously, based on the above comparative empirical study, it is clear that the proposed approach gives higher

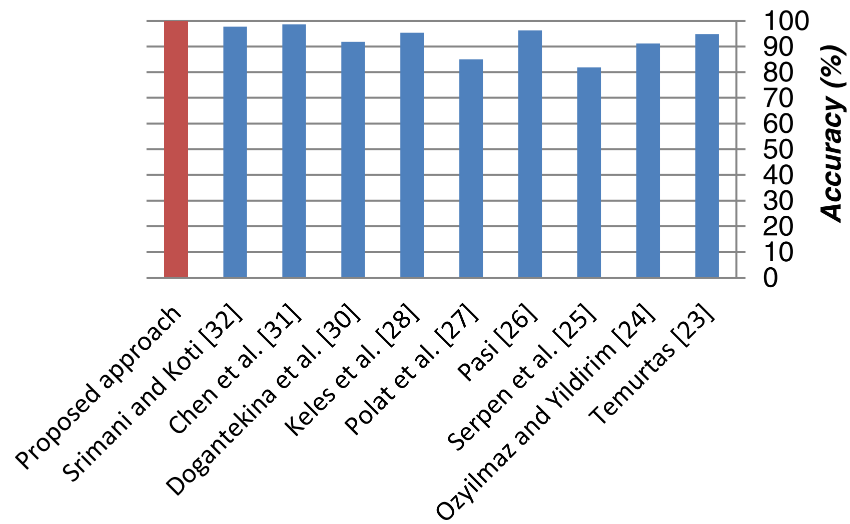



**Fig. 14** Thyroid diagnosis accuracies achieved by the proposed approach and other systems

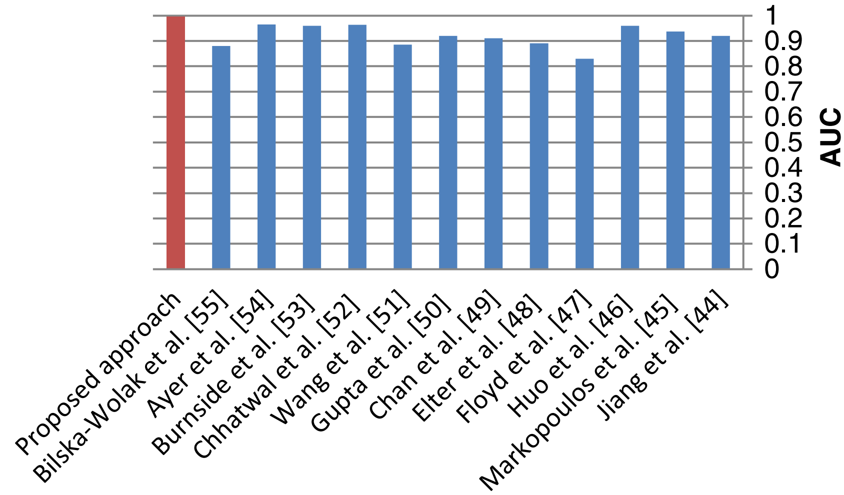



**Fig. 15** AUC achieved by the proposed approach and other systems

accuracy in diagnosing both thyroid and mammography based breast cancer diseases than the other methods. Consequently, the proposed approach can be very helpful in assisting the physicians to make the accurate diagnosis and will show great potential in the area of clinical diagnosis.

## Conclusion

In this paper, a new hybrid case-based reasoning approach for medical diagnosis systems was proposed to improve the accuracy of the retrieval-only CBR system. This approach integrates case-based and rule-based reasoning, and exploits adaptation rules. The adaptation rules and the reasoning rules are automatically generated from the case-base. In this approach, after solving each new case, the case-base is expanded. Therefore, the adaptation rules and the reasoning rules are updated automatically. To evaluate the proposed approach, a prototype was implemented and experimented to diagnose both breast cancer using mammography and thyroid diseases. The experimental results showed that the proposed approach increased the diagnosing accuracy of the retrieval-only CBR system. Also, the proposed approach achieved reliable accuracy among the breast cancer diagnosis using mammography and thyroid disease diagnosis systems. Based on the experimental analysis, it can be concluded that, the developed approach can assist the physicians to make very accurate diagnostic decision.

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