A Breast Cancer Diagnosis System using Hybrid Case-based Approach

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ABSTRACT

Nowadays, mammography is recognized as the most effective technique for breast cancer diagnosis.Case-Based Reasoning (CBR) is one of the important techniques used to diagnose the breast cancer disease. The retrieval-only CBR systems do not provide an acceptable accuracy in critical domains such as medical. In this paper, a new breast cancer diagnosis system using hybrid case-based approach is presented to improve the accuracy of the retrieval-only CBR systems. The approach integrates case-based reasoning and rule-based reasoning, and applies the adaptation process automatically by exploiting 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. To evaluate the proposed approach, a prototype was implemented and experimented to diagnose the breast cancerdisease. The final results showed that the proposed approach increases the diagnosing accuracy comparing with the retrieval-only CBR systems, and provides a reliable accuracy comparing to the current breast cancer diagnosis systems.

General Terms
Artificial Intelligence

Keywords
Case-based reasoning (CBR), Rule-based reasoning (RBR), Adaptation rules, Breast cancer diagnosis, Mammography.

1. 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 containing 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 task 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 [10]. 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.

In this paper, a hybrid case-based approach is proposed forbreast cancer diagnosis 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. Both adaptation rules and reasoning rules are generated automatically from the case-base.To achieve the case-based reasoning and rule-based reasoning 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. This paper focuses on the reasoning rules extraction process while the adaptation rules extraction process was introduced in details in our previous work [11]. To evaluate the proposed approach, a prototype was implemented and experimented to diagnose the breast cancer disease. The evaluation results showed that this research increases the accuracy of retrieval-only CBR systems, and achieves great accuracy comparing to the current mammography based breast cancer diagnosis systems.

The rest of this paper is organized as follows. Section 2 reviews the related work while the proposed approach architecture is introduced in section 3. The reasoning rules extraction steps are described in section 4. The prototype implementation and the experimental evaluation results are illustrated in section 5. Finally, section 6 concludes the paper.

2. RELATED WORK

CBR is an appropriate methodology to apply in diagnosis and treatment. Research in CBR is growing especially in the adaptation mechanism [12]. 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, almost all the medical CBR systems become hybrid as they integrate more than one Artificial Intelligence (AI) technique such as rule-based reasoning (RBR), 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 out of forty [15, 16, 17, 18, 19, and 20] adopted and explored different approaches of automatic and semi-automatic adaptation strategies.

Mammography is the most common modality for breast cancer detection and diagnosis and 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 (ANN), Bayesian Network (BN), CBR, and DecisionTree (DT). These models achieved diagnosis performance ranged from 0.83 to 0.965 (area under the Receiver Operating Characteristic curve).

Recently, Huang [22] compared the Particle Swarm Optimizer (PSO) based Artificial Neural Network (ANN), the adaptive neuro-fuzzy inference system (ANFIS), and a case-based reasoning (CBR) classifier with a logistic regression model and decision tree model. The experimental results on the mammography data set showed that the best CBR-based classification accuracy was 83.60%, and the classification accuracies of the PSO-based ANN classifier and ANFIS were 91.10% and 92.80% respectively.

Aiming at improving the medical CBR systems accuracy, this paper proposed a novel hybrid case-based approach for breast cancer diagnosis. 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 achieved high reliable accuracy in breast cancer diagnosis comparing to the above mentioned systems.

3. THE HYBRID CASE-BASED APPROACH ARCHITECTURE

Figure 1 shows the architecture of the proposed hybrid case-based approach for breast cancer diagnosis. The approach integrates case-based reasoning and rule-based reasoning to enhance the diagnosing accuracy obtained from the classical CBR systems.

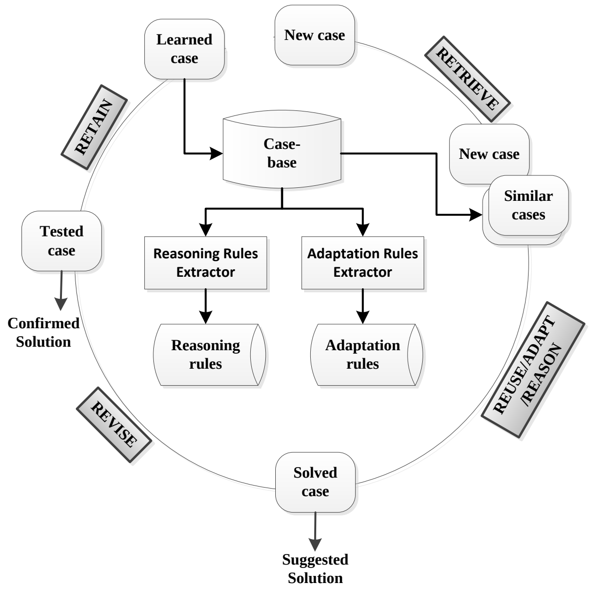

Figure 1. Hybrid case-based approach architecture

To get the case-base in a final form, medical data should be pre-processed to solve the problem of data conflicts .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 applies the same adaptation rules extraction steps proposed in our previous work [11]. The Adaptation Rules Extractor extracts the adaptation rules in three steps: Case-Pair Comparison,Transformational Adaptation Rules Generation, and Range Adaptation Rules Generation. For more details, our previous work [11] presents a great example for extracting and applying range adaptation rules to identify IRIS plant type.

The Reasoning Rules Extractor applies the Rough Set Theory (RST) [23] on the case-base to extract the reasoning rules.

On the other hand, case-based reasoning and rule-based reasoning are integrated to enhance the accuracy of the CBR systems. To achieve the integration, a new process was added to the **REUSE/ADAPT** step of the classical CBR cycle called **REASON** at which the reasoning rules are exploited to infer a solution if both **REUSE** and **ADAPT** processes failed.

Figure 1 depicts the hybrid CBR cycle, where the **REASON** process is added to the **REUSE/ADAPT** step. The cycle starts when a new case needs to be solved. In the **RETRIEVE** step, similar cases to the new case are retrieved from the case-base.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. If both **REUSE** and **ADAPT** processes failed to get a solution to the new case, 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 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 the adaptation rules set and the reasoning rules from scratch, which can quickly generate the complete and non-repetitive rules, and hence a lot of time is saved. Besides, the learning ability during the CBR cycle enriches the CBR system over time.

4. REASONING RULES EXTRACTION

When classical CBR fail to find a solution for a new case, the reasoning rules are used to find a solution. In the Reasoning Rules Extractor module, Rough Set Theory [23, 24] is used to extract the reasoning rules from the case-base. In order to discover the reasoning rules, three steps are needed.

Step1: Attributes Reduction

The reduct process of condition attributes determines the superfluous attributes and yields the reduct attribute sets [25]. A case-reduct is defined as a minimal sufficient subset of a set of attributes, which has the same ability to identify concepts as when the full set of attributes is used [23,26]. Basically, the case-reducts represent necessary condition attributes to make a decision. This process is adopted from Pawlak[23].

Step2: Reasoning Rules Generation

The rules induction 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 (reducts) forms a reduced case-base. These reasoning rules are generated from the reducts extracted in the step1.

Step3: Range Reasoning Rules Generation

The range reasoning rules relate the changing of the problem feature value ranges to the solution feature value. Figure 2 shows a general form of the range reasoning rule in IF-THEN format.

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

Figure2. Range reasoning rule general form

In case of numerical attributes, the Reasoning rules Extractor 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 3 shows the range reasoning rules generation algorithm.

Input: Reasoning rules
Output: Range reasoning rules
Cluster *the rules in the reasoning rules based on the rule conditions (RCCs)*
Foreach *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*

Figure.3. Range reasoning rules generation algorithm

5. EXPRIMENTAL EVALUATION

To evaluate the presented approach, a prototype has been implemented and experimented on the breast cancer disease using mammography data set [27].Mammographic mass data set can be 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 have been identified on full field digital mammograms. The Mammographic mass data set constituted 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).

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 4 shows two screenshots of the developed prototype. The left side screen shows how 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, so they can be loaded at the second time the system is initialized and there is no need to regenerate them again. The right side screen shows how 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. Then the new case with its solution is retained in the case-base.

The experiment was conducted on the data set 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 [28] was used to evaluate the diagnosing accuracy, where k indicates the data division subsets. In our experiment, k was shown 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 are put together to 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.

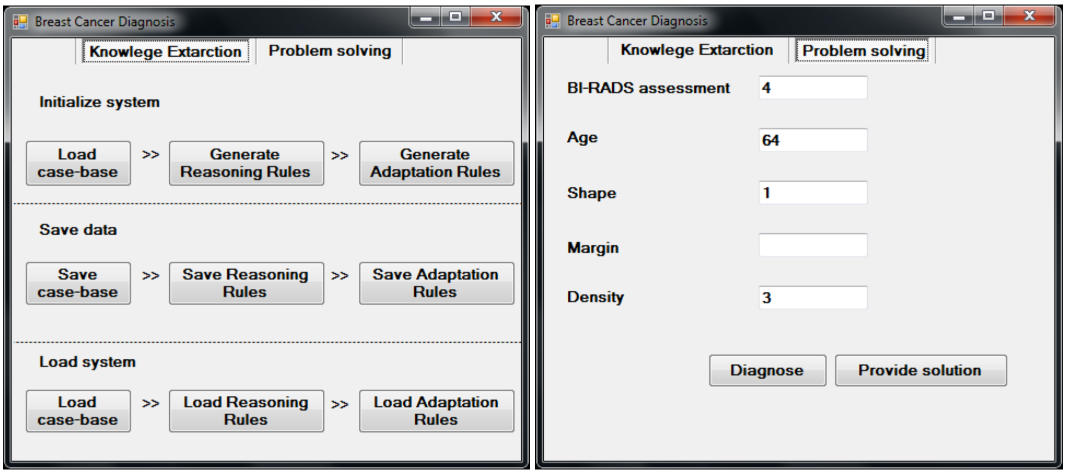

Figure 4.Prototype screenshots

Figure 5 shows the diagnosing accuracies of retrieval only CBR versusthe proposed approach formammography based breast cancer through the 5-fold trails. The developed prototype achieved (99.33%, 100%) for breast cancer diagnosis as average diagnosing accuracy and maximum diagnosing accuracy through the 5-fold trails. The developed prototype increased the diagnosing accuracy comparing with retrieval-only CBR systems as shown in Figure 5. The diagnosing accuracy was calculated using formula (1).

$$Diagnosing\ accuracy = TC/TT \tag{1}$$

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

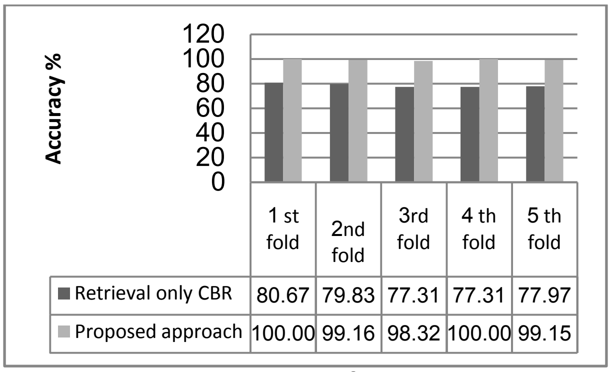

Figure 5. Diagnosis accuracies ofretrieval only CBR vs. proposed approach

For comparison purpose with previous methods, table 1shows that the proposed approach achieved great AUC in breast cancer diagnosis using mammography comparing to other methods.

Table 1. AUC acheived by proposed approach and other methods in mammography based breast cancer diagnosis

Study(year)	*Size of data set*	*Model*	*AUC*
Jiang et al. (1996)[29]	107	ANN	0.92
Markopoulos et al. (2001)[30]	240	ANN	0.937
Huo et al. (2002)[31]	110	ANN	0.96
Floyd et al. (2000)[32]	500	CBR	0.83
Elter et al. (2007)[33]	2100	DT/CBR	0.87/0.89
Chan et al. (1999)[34]	253	LDC	0.91
Gupta et al. (2006)[35]	115	LDA	0.92
Wang et al. (1999)[36]	419	BN	0.886
Chhatwal et al. (2009)[37]	62,219	LR	0.963
Burnside et al. (2009)[38]	62,219	BN	0.960
Ayer et al. (2010)[39]	62,219	ANN	0.965
Bilska-Wolak et al. (2005)[40]	151	LRBC	0.88
proposed approach	595	CBR/RBR	0.996
Area under the curve (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 [41].			

Obviously, from the above comparative empirical study, we can see clearly that the proposed approach is an appropriate approach for mammography based breast cancer diagnosis compared with the other methods. Consequently, it makes us be more convinced that 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.

6. CONCLUSION

In this paper, a new breast cancer diagnosis system using hybrid case-based approach has been proposed to improve the accuracy of a retrieval-only CBR system. This approach has integrated case-based and rule-based reasoning, and exploited adaptation rules. The adaptation rules and the reasoning rules were 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 and there is no need to generate them from the beginning. To evaluate the proposed approach, a prototype was implemented and experimented to diagnose mammography based breast cancer. The experimental results show that the proposed approach increased the diagnosing accuracy comparing with the retrieval-only CBR system. Also, the proposed approach achieved reliable accuracy among the breast cancer diagnosis using mammography systems.Based on the experimental analysis, it can be concluded that, the developed approach can assist the physicians to make very accurate diagnostic decision. The future work will pay much attention to evaluate the proposed approach in other medical diagnosis problems.

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