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A Case-Based Reasoning system for complex medical diagnosis

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Abstract: *A Case-Based Reasoning (CBR) system for medical diagnosis mimics the way doctors make a diagnosis. Given a new case, its accuracy in practice depends on successful retrieval of similar cases. CBR systems have had some success in dealing with simple diseases because of the robustness of their case base. However, their diagnostic accuracy suffers when dealing with complex diseases particularly those that involve multiple domains in medicine. An example of such a condition is Premenstrual syndrome (PMS) as it falls under both gynaecology and psychiatry. To address this issue, the paper proposes a CBR-based expert system that uses the K-nearest neighbour (KNN) algorithm to search k similar cases based on the Euclidean distance measure. The novelty of the system is in the design of a flexible auto-set tolerance (T), which serves as a threshold to extract cases for which similarities are greater than the assigned value of T. A prototype software tool with a menu-driven Graphical User Interface (GUI) has been developed for case input, analysis of results, and case adaptation within the system. Finally, the performance of the tool has been checked on a set of real-world PMS cases.*

Keywords: CBR system, PMS, Master Case base (MCB), menu-driven approach (MDA), auto-set tolerance (T), KNN

1. Introduction

The use of intelligent systems in health sciences is popularly termed as Artificial Intelligence in Medicine (AIM), and a Case-Based Reasoning (CBR) system is one way of applying AIM in medical decision-making. CBR systems, which represent the traditional way of designing Knowledge-Based (KB) systems, work with the principle of analogy and derivational analogy among cases (Kolodner, 1993; Veloso & Carbonell, 1993). A CBR system is able to recapitulate previous learning and therefore able to infer for a new case with a degree of confidence or maturity, which is measured by its accuracy and speed (Aamodt & Plaza, 1994). Such systems have had some success in dealing with simple diseases because of the robustness of their cases base. However, their diagnostic accuracy suffers when dealing with complex diseases particularly those that involve multiple domains in medicine. An example of such a condition is Premenstrual syndrome (PMS) that falls under gynaecology as well as psychiatry.

The organization of the remaining portion of this paper is as follows. The next section introduces some background information on CBR and presents the aims and objectives of the study that is concerned with the development of a CBR system specifically aimed at targeting the requirements of a complex case study. Section 3 describes the methodology used and Section 4 discusses the results. Finally, the paper is concluded in Section 5.

2. Aims and objectives of the study

2.1. CBR systems: an overview

Thecentral feature of a CBR system is four intertwined processes that are retrieving similar cases from case sets, reusing the retrieval processes for future similar cases, revising the extraction process based on the errors generated, and retaining the experience gained by appending new cases with time (Liu *et al*., 2009). Figure 1 shows a schematic diagram of a CBR cycle.

To support this cycle, a CBR system provides the following essential functions:

- Searching and retrieving similar cases in the Master Case base (MCB).
- Updating the MCB.

Available studies show that *search* can be made using the following algorithms:

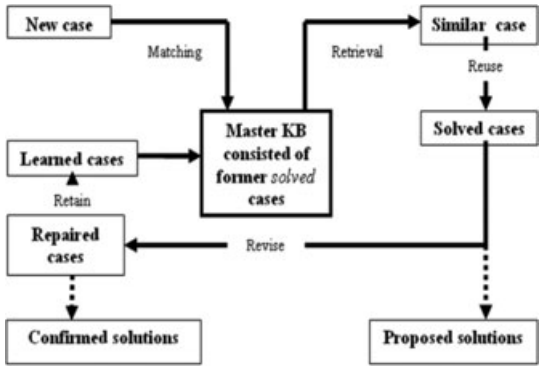

Figure 1: *A schematic diagram of Case-Based Reasoning system.*

- Sequential or non-sequential indexing (Stottler *et al.*, 1989; Broder, 1990).
- K-nearest neighbourhood (KNN) matching (Gierl, 1992).
- Classification (Puppe *et al.*, 1995).
- Heuristic search (Aamodt, 1994).

Updating the database is one key function, which matures any given CBR system by appending new cases in its MCB. Such updating of the database is performed using generalized adaptation algorithms and this task is highly domain-specific (Aamodt, 1994).

CBR systems have been tried in medical science for decades (Turner, 1988; Bradburn & Zeleznikow, 1993). The principle aim of designing, developing, and implementing a CBR system is to provide faster, reliable and low cost prediction through software. Another merit of a CBR system is its adaptability even in cases where the domain knowledge is not very strong (Schmidt & Gierl, 2001). A CBR system can accommodate multidimensional data in its MCB for years together, while human memory and ability for complex decisions-making may suffer age-induced decay.

2.2. Current state of art: CBR systems in health CBR systems have been used for diverse purposes such as diagnostic, classification, tutoring, and planning in the medical field (Nilsson & Sollenborn, 2004). A well-known example of a CBR system used for diagnostic is MYCIN, which is an AIM-based system, developed using Lisp (Shortliffe, 1976). It contains production cases representing knowledge about infectious diseases (Kulikowski, 1980; Koton, 1988). The principles of MYCIN have been used in two CBR systems – CASEY (Buchanan & Shortliffe, 1984) and PSYXPERT (Overby, 1987), which are discussed next.

CASEY (Buchanan & Shortliffe, 1984) is one of the early CBR systems developed for the diagnosis of heart failure. The working principle of the tool is (1) matching a new case with the most similar stored cases, (2) determining the difference levels, and then (3) adapting the system based on the differences between the calculated and expected outcomes. If the difference is too large, it either retains the most approximate diagnostic decision with some explanation or ignore the given input and prompts for new inputs. Such adaptability is precisely the novelty of CASEY. It uses case-based domain logic and is able to handle the process of adaptation using some general operators. However, its major drawback is that it cannot tackle all case types (e.g. complex cases with multiple attributes/features).

PSYXPERT (Overby, 1987) is a diagnostic tool for psychiatric disorders. Its domain knowledge is represented by production cases with a backward chaining control structure for deriving suitable explanations related to each diagnosis. PSYXPERT has been implemented using Prolog. However, PSYXPERT is still unable to define a line between two very similar illnesses, which is a problem often encountered in psychiatric practice.

FLORENCE (Bradbum, 1993) is another system to diagnose, prescribe, and determine the prognosis of the patients. It is made for the nurses to be used in the lying-in ward. A patient's state of health is described in terms of some weighted values that are matched among the old and the new cases to find out the differences and an adaptation is only made based on some acceptable difference. Such acceptability is dependent on the general knowledge of the nurses regarding the possibility of a case's health status in the ward. FLORENCE also lacks adaptability, which remains the main problem of this system, especially when the inputs are newer or the number of cases is large.

Among other diagnostic CBR systems, FM-ULTRANET (Balaa *et al.*, 2003; Balaa & Traphoner, 2003) has been implemented with multiple CBR modules to screen and diagnose malfunctions of foetuses using ultrasounds. Using attributes derived from the scans of gravid uterus, users are able to screen abnormalities in the foetal organs and extremities with much more precision. The cases are arranged as hierarchies of concepts according to an object-oriented model. A total of 39 concepts have been identified and each concept has one or more attributes, which indicate anatomical features of the foetus, pregnancy history, and obstetrical domain knowledge. Attribute-wise similarities have been calculated using a look-up table, depending on the type of the attribute.

CARE-PARTNER (Bichindaritz *et al.*, 1998; Bichindaritz & Sullivan, 2002) is another CBR-based system for long-term follow-up of stem cell transplanted patients. The objective of this system is to provide necessary feedback to the caregivers of the patients though an Internet connection between the transplant centre and the patients' homes. The heart of such a system is the Multimodal Reasoning (MMR) framework, which again depends on the CBR–RBR (Case-Based Reasoning–Rule-Based Reasoning) combination model. Another key feature of CARE-PARTNER is its rich knowledge base of prototypal cases and medical practice guidelines (i.e. the RBR part of the system) for interpreting medical cases and in turn guiding the CBR.

CBR has also been used in 'classification', as mentioned before. One useful system is TeCoMED (Schimidt & Gierl, 2002), which is aimed at forecasting influenza epidemics based on past experience. It is a combination of CBR with temporal abstractions to handle the problem of the cyclic but irregular behaviour of epidemics. A CBR system has been used in the classification of diabetic treatment described in Montani *et al.*, 2001. In this system, the concept of a simple CBR system, which has been expanded to MMR, is a combination of RBR, CBR, and Model-Based Reasoning (MBR). The authors argue that such a combination gives more precision in classifying the best possible treatment for diabetic patients when compared with a single system. In another study (Montani *et al.*, 2003), authors have focused on the CBR system applied assessing only the benefits of haemodialysis in 'End-stage renal disease' (ESRD). Each

new case of haemodialysis is considered to be a new case for the system. Patients' past history, failure patterns, comparison of treatment response across patients are the attributes chosen to get a solution, that is, best effect of haemodialysis for the given case. Moreover, the features are grouped into static (e.g. patients' age, immediate past history) and dynamic (e.g. treatment response and other online measurements of vital parameters of the patient). The authors have observed that CBR is useful to analyse the benefits in a given patient with much more accuracy.

CBR has also been tried as a 'tutoring' system [e.g. WHAT (Evans-Romanie & Marling, 2003)] and as a 'planning' system [e.g. Auguste project (Marling & Whitehouse, 2001), SMARTHOUSE (Davis *et al.*, 2003)].

In addition to all these past tools, researchers are still exploring various CBR systems to assess the diagnostic and prognostic issues in various healthcare domains. It clearly indicates that the strength of such a system is well recognized in the cross-domain research fields. In view of this, few current studies have been discussed below.

Data-mining techniques, such as rule mining combined with medical cases, have been used to develop a CBR system to evaluate the prognostic issues of chronic diseases (Huang *et al.*, 2007). In another study, historical cases have been used to make clinical recommendation (Doyle *et al.*, 2006). The study observed that such a recommendation system could be much useful to the medical doctors.

Missing values in a CBR system is a serious issue. It has been effectively handled by filter imputation and the performance of the tool has been tested on the treatment of prostate cancer (Jagannathan & Petrovic, 2009).

A CBR system has been developed to effectively screen hyperactive attention deficit disorder in both children and adults (Brien *et al.*, 2010). Hierarchical tree-based fuzzy model has also been tried with success to classify 'borderline' PMS (Chattopadhyay & Acharya, 2011). In another study, the shortfall of CBR system, that is, its inability in assigning optimum weights to the attributes, has been tackled by combining it with the genetic algorithm (Ahn & Kim, 2009). The hybrid is then tested in classifying breast diseases based on its cytology and has been found more effective than the CBR system alone. The motivation of this study is to design a CBR system for diagnosing an illness involving multiple medical domains, as seen in PMS, which falls under both gynaecology and psychiatry. This study, therefore, is novel in nature, compared to the available works.

2.3. PMS: a complex medical illness

Anxiety, lethargy, household confinement, blood loss, irregularity, weakness, and deep-rooted cultural taboos make menstruation a known physiological stressor (Chattopadhyay, 2004). Often a series of physical and emotional turmoil is observed in some particular group of females just for few days prior to menstruation. This clinical entity is referred to as PMS (Premenstrual syndrome, 20002003). The etiopathology, diagnostic criteria, prognosis, etc. of PMS have been outlined by the American College of Obstetrics and Gynecology (ACOG) (Premenstrual syndrome, 20002003) for clinicians to screen PMS. Table 1 shows the list of criteria under two classes – *affective* and *somatic*.

Table 1: *American College of Obstetrics and Gynecology criteria for Premenstrual syndrome (Premenstrual syndrome, 2000)*

Affective	*Somatic*
Depression	(1) Mastalgia (breast tenderness)
Anxiety	(2) Abdominal bloating
Irritability	(3) Headache
Angry outbursts	(4) Swelling of extremities
Social withdrawals	
Confusions	

Table 2: *Diagnostic and Statistical Manual version IV criteria for Premenstrual Dysphoric Disorder (American Psychiatric Association, 1994)*

(1) Depression
(2) Anxiety
(3) Affective lability (quickly changing emotions)
(4) Decreased interest in usual activities
(5) Lack of concentration
(6) Marked lack of energy
(7) Marked change in appetite (over/under eating)
(8) Hypersomnia/insomnia (increased/decreased sleep)
(9) Feeling overwhelmed
(10) Mastalgia and abdominal bloating

PMS is also called Premenstrual Dysphoric Disorder (PMDD) in the Diagnostic and Statistical Manual version IV (DSM-IV) developed by the American Psychiatric Association (APA) (American Psychiatric Association, 1994). Table 2 describes the list of criteria, of which five should be present and among these five criteria, one of it must be (1), (2), (3), or (4). Therefore, for a set of clinical signs-symptoms in PMS/PMDD, it is a research challenge to engineer which load of morbidity, that is, gynaecological or psychiatric, is more important. This could be explored by extracting the attributes that are clinically present using automatic tools/processes.

2.4. Aims and objectives of the paper

The aim of this paper is to effectively diagnose PMS, measure its severity, and explore the load type – gynaecology and/or psychiatry with minimum number of symptoms. To this end, we propose a CBR-based software tool that offers (1) more *flexibility* in searching and retrieving cases by introducing an auto-set tolerance (AST) level that is able to set itself or allows users to set the tolerance level, depending on the scenarios that tend to vary from case-to-case, and (2) *adaptation* by introducing a menu-driven approach to the users prompting whether they need to modify the retrieved cases or just add a new case to the proposed CBR system. In the following section, we describe how the proposed CBR system has been developed.

3. Methodology

The proposed CBR tool's architecture is illustrated in Figure 2. All previously diagnosed cases are stored in the MCB. The business logic is supported by two components. The Search Module implements the search algorithm and the MCB Manager allows entities in the MCB to be retrieved,

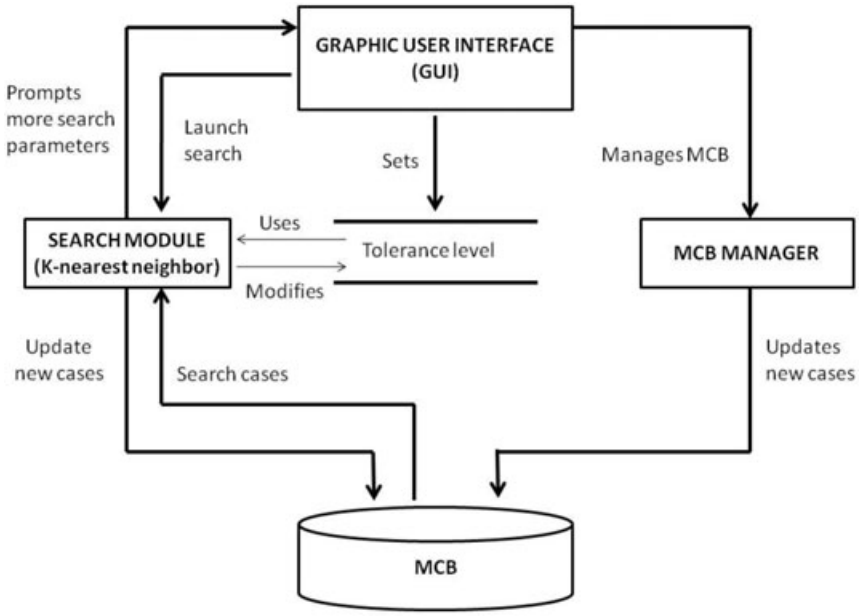

Figure 2: *Schematic representation of the proposed Case-Based Reasoning system.*

updated, or deleted. The system has a Graphical User Interface (GUI) through which users interact.

The proposed CBR system has been developed in three stages:

Stage 1: Training data collection and development of the MCB.

Stage 2: Development of (a) search algorithm [based on KNN algorithm (Cover & Hart, 1967)] and (b) adaptation process.

Stage 3: Testing the performance of the developed tool based on a given set of test cases.

Each stage is now described in more detail.

3.1. Stage 1: data collection and development of the MCB

Established cases of PMS are rare occurrences. Hence, this study was conducted with a set of 53 anonymous PMS cases with their corresponding grades from a group of practicing gynaecologists and psychiatrists. Each patient is represented initially by 21 attributes in which the first 20 indicate the symptoms (independent variables) according to ACOG and DSM-IV criteria and the remaining attribute is the grade/severity of the illness scored by the doctors. It serves as the dependent variable. We also have added four independent new factors based on the available literature, which are age of the patients (Matusevich & Pieczanski, 2008); joint pain (Olson *et al.*, 1988); acne (Grabmeier *et al.*, 2005); and bowel habits (Houghton *et al.*, 2002) to make the MCB-based search more robust. Hence, the total number of independent variables becomes 24. The data, thus collected, have been structured in a matrix (refer to equation (1)).

$$N_i \times M_{jw} \tag{1}$$

Here, 'N_i' indicates patients ('i' = 1–53); 'M_{jw}' denotes the attributes ('j' = 1–24 attributes; and 'w' = weights [−100100]) assigned by the doctors in the MCB. It is important to mention here that in this study, a total of 10 doctors – five gynaecologists and five psychiatrists – have been consulted to collect the data and creating the MCB.

As the sample size is small (i.e. 53 cases), we randomly divided these 53 patients into two subsets – 33 as training data and the remaining 20 as the test data for $k = 10$ different times (Devijver & Kittler, 1982). Of these subsamples, a single subsample of 20 randomly chosen cases is retained as the validation data for testing the model, and the remaining 33 subsamples are used as the training data iteratively and the average error/dissimilarity has been measured attribute-wise. This is also important to state that experts have been consulted after each iteration to assess the reliability of the datasets for noting any redundancy and/or interpretation errors. The advantage of doing so is that we could independently choose the size of the test and training data as well as the number of trials. Leave-one-out (LOO) cross-validation is computationally extensive due to large number of attributes, as viewed in this clinical data type. Hence, LOO cross-validation has not been considered in this work.

In this work, the patient information (i.e. the weights assigned by the doctors) has been normalized between −100 and 100 to render more search space taking '0' as the measure of normalcy. In a prior experiment, we have checked the internal consistency (i.e. the reliability of the experimental data) by measuring the Crohnbach's Alpha (α) (Cronbach, 1951), which is calculated using equation 2 as follows.

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum_{i=1}^{N} \sigma_{y_i}^2}{\sigma_{x_i}^2}\right) \tag{2}$$

Here, 'N' is the number of item sets (i.e. patients), $\sigma_{x_i}^2$ is the variance of the observed total score, $\sigma_{Y_i}^2$ is the variance of the component 'i'.

3.2.1. Stage 2: (a) development of the search algorithm Assuming a new case input by the user, the Search Module finds out the similar cases stored in the MCB within the given tolerance (T). Here, tolerance (T) is nothing but the threshold or limit for accepting the amount of dissimilarities between the input case and the stored cases. Dissimilarities are measured between any two cases by computing the corresponding Euclidean distance (ED), expressed by equation (3). Here, it may be noted that ED refers to the difference/deviation between the 'target' and the 'given' case and the deviation could be at the 'positive' or 'negative' side of the distribution. The objective in setting a 'T' is to retrieve minimum number of important predictors (symptoms) to diagnose a PMS case. It is important to mention here that we have used KNN algorithm (Matusevich & Pieczanski, 2008) in building the said search tool. The search is specifically made attribute-by-attribute based on the corresponding weights by measuring their respective EDs. On the other hand, the auto-adaptive 'T' level decides whether the resultant EDs between the given test case and the stored case in MCB are acceptable or not. It is important to remember that the weights have been assigned by a group of doctors both in building the MCB and during user-defined query. Weights could be positive or negative.

$$ED = d\left(M_{j_w}, U_{j_{w/}}\right) \tag{3}$$

Here, '*d*' is the square root of the sum of the squared differences/deviations between the weighted '*j*th' attributes of a case stored in MCB (denoted by M_{j_w}) and the given attributes of the case under study (denoted by $U_{j_{w/}}$). The tool is designed in such a way that, while searching through noisy data, for example, missing weight values, it attempts to retrieve at least few relevant cases automatically rather than yielding an error report to the users. In such cases, the tool is able to reset its level automatically at 50% of its preceding value such that at least some records could be retrieved. The following algorithm explains how the 'T' level is set and the searches are made:

- Step 1: Initialize T = 0 and search the MCB, if the *number of Records retrieved* (nRec) is >0, go to step 2, else go to step 3.
- Step 2: Display the results and terminate the search.
- Step 3: Reinitialize T = 100 and search the MCB. If nRec = 0, convey a warning message and terminate the search. Else, if nRec < = 5 go to step 2, else go to step 4.
- Step 4: Reduce the value of T by 50% and then search the MCB. If nRec = 0, go to step 5, else if nRec < = 5, go to step 2, else go to step 4 again.
- Step 5: Increase the value of T by taking the average of the current T value and the last T value for which it was able to retrieve some records. If nRec = 0, go to step 5, else if nRec < = 5, go to step 2, else go to step 4.

3.2.2. Stage 2: (b) designing the adaptation process The adaptation of the tool is enabled by the following functions: (1) adding a new case (patient information and diagnosis) in the MCB and (2) modification of existing records when new diagnosis and/or new features/attributes are added. The data flow diagram shown in Figure 3 has explained the working principle of the proposed CBR system. In this figure, it may be noted that the patients' weighted attributes are introduced as inputs to stimulate a search process. Simultaneously, the 'T' level is defined (either manual or automatic) to increase the search space (e.g. 0 to ±100, where '0' serves the normalcy). During the search process, attribute-wise pattern matching is performed using equation (3) inside the existing MCB. Successful pattern matching helps extracting the relevant cases that are in turn stored in a sorted order based on the individual probability indices (i.e. the case with the highest probability index tops the list). High-ranked cases are then selected as the output of the search made. Once the diagnosis is made by the tool, it is verified by the human experts (i.e. the doctors), if found satisfactory, the search process is terminated and the newly obtained correct diagnosis is appended into the MCB. If the search result is unsatisfactory, the search is refined with new T level till the correct and acceptable diagnosis is made. Once the correct diagnosis is obtained, the input parameters that are clinically present are recorded and the remaining parameters are ignored. The advantage of this technique is that for the next similar inputs, a diagnosis could be made only with the significant parameters that are stored during earlier experiments. It eventually reduces the computational complexities and makes diagnosis faster. This is called as 'input filtering', which helps adaptation of the tool to new cases.

3.3. Stage 3: performance testing

Performance of the tool has been tested using the 20 test cases and the error is expressed in terms of average absolute percentage error (AAPE) (refer to equation (4), below)

$$\text{AAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(TO_i - CO_i)}{TO_i}\right| \times 100 \tag{4}$$

Here, TO_i is the *i*th target/theoretical output (given by the doctors), CO_i is the *i*th calculated/experimental output obtained by the CBR tool for $N = 20$ test cases. Absolute values are taken to avoid nullification of positive differences by negative differences. As already mentioned above, the numeric difference values are important and not the + or − direction of the deviation. The results are discussed in the next section.

4. Results and discussions

4.1. Data internal consistency check

In this experiment, Cronbach's alpha (α) (Cronbach, 1951) for the collected data is checked to measure the reliability of the data and assessing the internal consistency. This is needed because (1) the data collected are secondary in nature and subjective and (ii) if the experimental data are unreliable then the results are erratic. The measured α is found to be 0.77, indicating a good internal consistency within the data considering that the common cutoff value is 70% according to Nunnaly (1978).

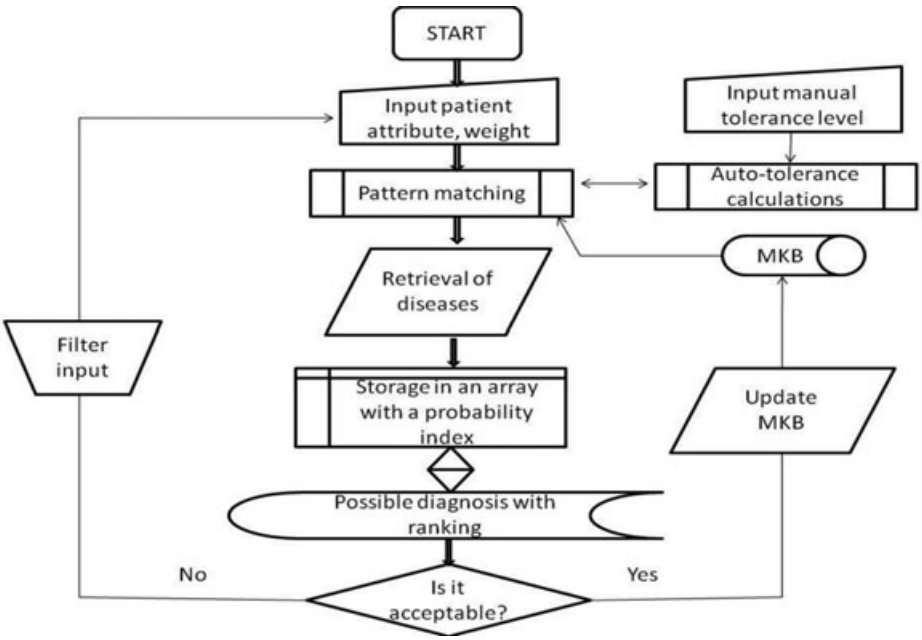

Figure 3: *The flow chart of the proposed Case-Based Reasoning system.*

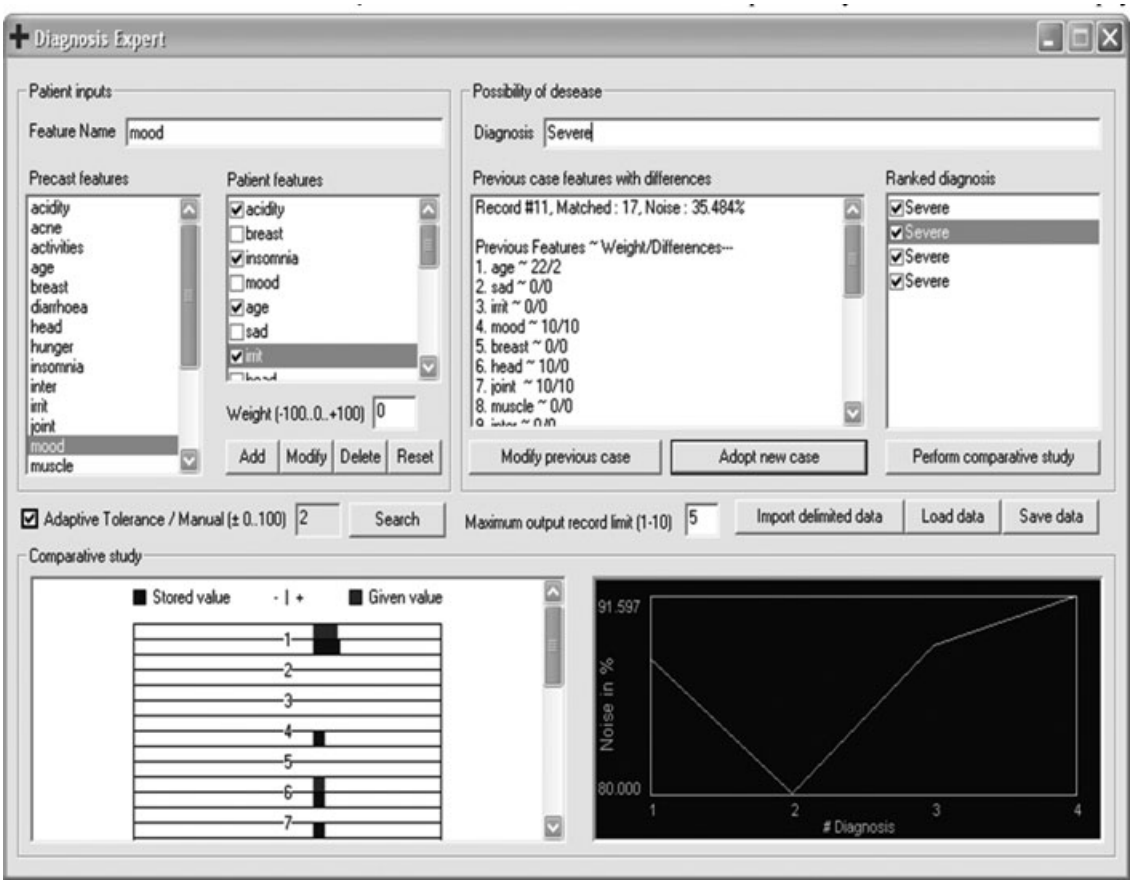

Figure 4: *Running of the tool.*

4.2. Running the tool

As mentioned above, we could only collect 53 cases, of which 20 have been used as test cases. Based on the auto-set T level, for each case, the retrieved record(s) alongside the grade of illness (rank-wise) are displayed on the screen (refer to the example in Figure 4).

In this study, the precast features indicate the 24 independent attributes, which are the patients' features (i.e. signs and symptoms). For screening PMS in these patients, an adaptive T has been set to '2' by the tool itself so that with minimum features, the grade of the illness can be predicted (here, the maximum number of preset features is 5) and any patient showing the absolute difference more than '2' (where '0' serves the normalcy) is ruled out to be a PMS case.

In the present experiment, of 24 precast features, *four* (*acidity*, *insomnia*, *age*, and *irritability*) have been found to be

clinically present for screening and grading the PMS in 70% of the given test patients. Hence, we might argue that this tool is able to assist doctors in screening and diagnosing with minimum feature sets. In addition, it is able to represent the disease load distinctly, for example, in these cases, the gynaecological load is much higher compared to psychiatric load. Similarly, the rest (i.e. 30% cases) could be screened with the additional precast features, such as *headache*, *mastalgia*, and *mood changes* with T as '7' to explore any involvement of the psychiatry domain. In the menu called 'Previous case features' with differences, these attributes could be ranked considering the respective difference (ED) values between each record within the MCB and the given test case. The least value of ED for any attribute indicates best match and hence it is given the highest rank. The list box, namely, 'Ranked diagnosis' indicates the numerical value or the grade or severity of PMS scaled within the 0.0–10.0 interval.

Under the menu 'comparative study' in the GUI, there are two graphs – the bar graph at the left-hand side shows the ED-based matches between the retrieved cases given test cases, while the graph at the right-hand side displays the tools' ability to handle noisy data. The *X*-coordinate indicates the number of cases that could be diagnosed with four attributes – *acidity*, *insomnia*, *age*, and *irritability* with the plausibly high noise level (between 80% and 91%), created manually at a random in the data. The principle has already been mentioned while describing the development of the search algorithm under Section 3, stage 2(a). It is noteworthy that even with high noise level, the tool could fetch at least some similar or closely related cases than nothing.

4.3. Testing the performance of the tool

After running the test cases, the performance of the proposed CBR tool can be summarized as follows:

(1) It is able to screen and predict the severity of PMS cases with minimum numbers of features that could be obtained by virtue of auto-set T.
(2) The search based on the auto-set T is flexible enough to retrieve similar cases from MCB.
(3) The tool can effectively handle noisy data.
(4) The AAPE in predictions has been calculated for 20 test cases using equation (4). The AAPE is just above 12.6%. Table 3 shows the absolute percentage error (APE) among the test cases. It is calculated by subtracting (CO)s from the corresponding target values (TO)s and the absolute difference is then divided by the respective TO. It gives a more holistic view of error/dissimilarity with respect to the corresponding TOs, rather than computing the simple difference between 'TO' and 'CO'. It may be seen that patients 7, 9, 13, and 20 have higher calculated dissimilarities (i.e. 0.232%, 0.253%, 0.333%, and 0.254%, respectively) when compared to the target cases. All these APE values are above the auto-set T (which is set '2' by the tool). It may be recalled that the positive and negative signs denote the direction of deviation from the normalcy (here, '0') hence the directions have no values, except for the AAPE calculation, to avoid nullifications among positive and negetive deviations, described before. So, the tool actually discards these patients to be considered as PMS cases and hence these cases contribute to the higher value of AAPE. But, it is good to see that the rest of the cases are well below the T level and hence are screened as PMS cases.

Table 3: *Absolute error (AE) and absolute percentage error for 20 test cases*

Patient no.	*TO*	*CO*	$AE = \lvert(TO - CO)\rvert/TO$	*APE*
1.	9.39	7.89	0.160	16.00
2.	11.75	11.20	0.047	4.70
3.	9.57	9.14	0.045	4.50
4.	10.38	10.38	0.000	0.00
5.	9.57	8.68	0.093	9.30
6.	8.37	9.04	0.080	8.00
7.	9.51	11.72	0.232	23.24
8.	10.20	9.44	0.075	7.50
9.	10.20	7.62	0.253	25.30
10.	10.69	10.37	0.030	3.00
11.	9.57	8.58	0.103	10.34
12.	8.99	9.31	0.036	3.60
13.	9.08	12.10	0.333	33.30
14.	9.08	10.37	0.142	14.20
15.	9.39	9.08	0.033	3.30
16.	11.75	9.97	0.151	15.15
17.	10.69	11.54	0.080	8.00
18.	7.32	8.66	0.183	18.31
19.	9.95	11.83	0.189	18.90
20.	7.43	9.32	0.254	25.44

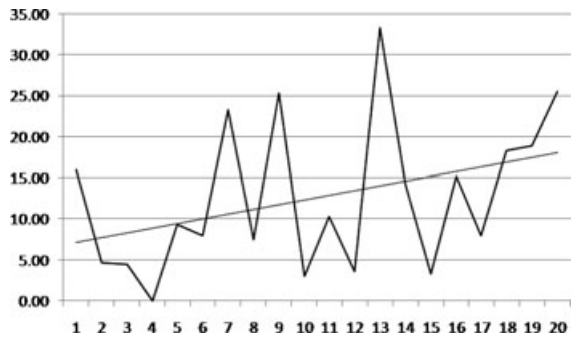

Figure 5: *Absolute error in predictions in 20 test cases.*

Figure 5 shows the absolute error in predictions for 20 test cases.

5. Conclusions and future work

From the above experiments, the following conclusions can be made:

- The AST (T) is found to be the key feature for retrieving similar records from the MCB keeping the number of records as minimum as possible and more importantly, such records are selected based on its high level of influence. Four precast features, that is acidity, insomnia, age, and irritability (obtained using auto-set T) as the important symptoms to screen a given PMS case, have been cross-checked with the gynaecologists and found valid. It corroborates that the designed auto-set T is a useful feature of the designed reasoning tool. Thus, diagnostic inference can be made with minimum records and the complexity (involved with the large number of symptoms) can be reduced. Hence, auto-set T is useful to improve the tool's performance. This is the key objective of the paper.

- As part of the process of adaptation, the diagnosis (i.e. inference on the grade of the illness) with the corresponding patient-information can be stored in the MCB as the new case with corresponding cases.
- The tool is also able to adapt itself to the constant changes in the definitions of the illnesses commonly occurring in medical science by amending new features into its KB systems.
- The structure of the tool makes it adaptable to other complex medical disorders and thus helping the clinicians at large.
- The tool is able to screen and grade PMS with a small number of features that are found to be present behind a case. However, these could not be strictly categorized under gynaecology or psychiatry.

The experiments demonstrated that the developed tool works well and its diagnostic accuracy level is acceptable to the medical doctors.

The application of such a tool is broad. It is best suited to rural health centres where specialist services are unavailable. In such situations, it may be used by general practitioners (GPs) for screening the illness and setting timely patient referrals to the higher health centres; thus, reducing the amount of sufferings and saving valuable time and money for the patients. Moreover, it will be interesting to note which domain (psyche or physical factors) is dominant at the backdrop of PMS and the age groups commonly involved. Such findings could be very useful to set up an appropriate management plan.

This study is the prototype of a full-fledged system and requires a large multi-centric trial for standardization. Immediate application in the clinical set up might be too ambitious at this stage. The tool is currently under a trial.

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