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ORIGINAL PAPER

# Designing and Implementation of Fuzzy Case-based Reasoning System on Android Platform Using Electronic Discharge Summary of Patients with Chronic Kidney Diseases

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**ABSTRACT**

**Introduction:** Case-based reasoning (CBR) systems are one of the effective methods to find the nearest solution to the current problems. These systems are used in various spheres as well as industry, business, and economy. The medical field is not an exception in this regard, and these systems are nowadays used in the various aspects of diagnosis and treatment. **Methodology:** In this study, the effective parameters were first extracted from the structured discharge summary prepared for patients with chronic kidney diseases based on data mining method. Then, through holding a meeting with experts in nephrology and using data mining methods, the weights of the parameters were extracted. Finally, fuzzy system has been employed in order to compare the similarities of current case and previous cases, and the system was implemented on the Android platform. **Discussion:** The data on electronic discharge records of patients with chronic kidney diseases were entered into the system. The measure of similarity was assessed using the algorithm provided in the system, and then compared with other known methods in CBR systems. **Conclusion:** Developing Clinical fuzzy CBR system used in Knowledge management framework for registering specific therapeutic methods , Knowledge sharing environment for experts in a specific domain and Powerful tools at the point of care .

**Key words: Structured record summary, Case-based inference system, Android, Fuzzy systems, Data mining.**

## 1. INTRODUCTION

Today, there is no integrated electronic system available for registration of experts' knowledge in the field of medicine in terms of patient's treatment in Iran. Also, there is no database for rare cases and patients whose treatment has been associated with innovative and noble methods (1). In addition, there is few systematic method to extract important data from patient's medical records to be used to investigate the similarities with other patients (2).

In case of using a system to record the knowledge of professionals for people treatment when experts in a particular field are not accessible, employing this method would be a useful approach (3). Nowadays, large volume of patients' information is recorded and archived in hospital information systems that usually after the completion of patients' treatment process will not be used (4).

Specific therapeutic techniques are employed for treatment of some patients, which are usually reported in the articles, but the source of using such techniques will not be recorded (5).

Study on calculation criteria for similarities of patients is a type of data summarization development (6). In this study, we tried to use the information items documented in patients' medical records summary to measure their similarity rate. It should be noted that in a system working based on Case Based Reasoning (CBR), there are several aspects that two of them have been further investigated: retrieving similar cases and displaying cases in a proper format to interpret and use them. One solution to implement such systems is to use the important information extracted from medical records of patients admitted for building knowledge database and determining of similarity measure of patients with each other in CBR(2).

If CBR systems are not used in a geographic area where access to specialists in various fields of medicine is not possible, the patients' treatment process would not be conducted completely and accurately (7). Also, when the experts in various areas of medical knowledge quit the system for whatever reason, in case of absence of CBR systems in the organization, there would be no method for recording and transmission of their knowledge for future use (8).

CBR is a problem-solving approach in which new problems are solved with looking at the solutions for previous similar problems and relevant knowledge and information (9). The database of these systems will be built through knowledge engineering process or collecting previous similar cases.

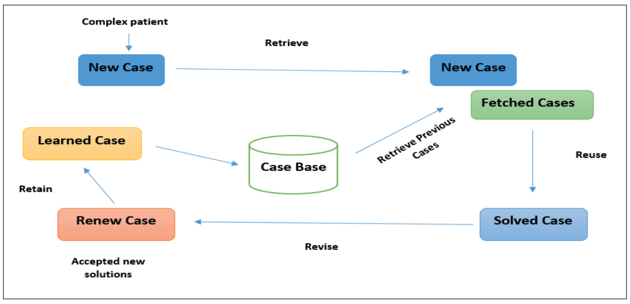


Figure 1. The cycle of a CBR system

The CBR process can be done through the following steps (Figure 1):

- Retrieving the similar cases: During this stage, the search algorithm looks for similar cases within the database.
- Reusing: At this stage, the information retrieved from the previous cases is used to adapt to the new conditions. At the end of this stage, a new method may be suggested to resolve the issue.
- Revising: At this stage, the old methods retrieved will be reviewed and revised, since the old methods may have drawbacks and need to be reformed.
- Retaining: At this stage, new method found to solve the problem will be inserted in the system database.

An important point to be considered in the process of retrieving information from a database is that searching the knowledge database is beyond a simple query of a database. In this process, the similar items must be extracted based on a certain method (10).

**CBR advantages**

Many studies have shown that the inference technique based on similar cases has several advantages compared to other problem solving methods, some of which are mentioned in the following:

- CBR requires no additional analysis in a specific area. CBR may provide a solution for the problem without requiring additional information of the expertise area or even in existence of incomplete information. The only important point about this relationship is the comparing method of two cases.
- CBR will provide a shortcut in a short time to resolve the issue as long as a similar example to solve the problem exists in the knowledge database.
- CBR provides a detailed and comprehensive description functionality; thus, if there were various methods and numerous examples for a problem, we would be able to choose a combined solution or the best course of action to solve the problem.
- CBR reduce the probability of occurring errors. It also makes it possible to analyze the past errors and to determine a solution free of error for the current problems. However, a record of past approaches will be recorded and kept in the database.

**Application of CBR in the health area**

It seems that CBR has been a favorite method since the eighties so far for developing medical applications built by methods of artificial intelligence.

Several studies conducted in this regard have proposed many benefits in using this method in the health care. Some of the key benefits of this approach are as follows:

- CBR provides the possibility of deducing for physicians to perform the treatment process.
- CBR provides regulation feature in a specific area of health and strengthens the knowledge base in the domain.
- CBR is founded based on both objective knowledge and subjective knowledge. Therefore, it will significantly increase the physicians' deduction power.
- CBR provides the possibility of automatic gaining of objective knowledge in the health care field. This knowledge will be increased over time in the knowledge base and strengthened qualitatively.
- CBR can integrate the knowledge base with the hospital information system (11).

In a number of other studies, the defects and problems to implement CBR are mentioned (9, 12).

- Conformity: Due to the large number of features available on a treatment case, the process of determining the appropriate information may appear to be difficult.
- Uncertainty: Adding new items to the existing knowledge base will not always increase the system reliability.
- CBR systems are more source-oriented rather than the diagnostic methods.

**Chronic kidney disease**

Chronic Kidney Disease (CKD) is one of the most common diseases in Iran and around the world. CKD includes a variety of pathophysiological processes, which are associated with abnormal kidney functioning and progressive decline in glomerular filtration rate (GFR). According to definition, GFR decline should have lasted more than three months. Classification of CKD stages based on kidney dialysis outcome quality initiative (KDOQI) manual is as follows (13):

| Stage | GFR |
|---|---|
| 0 | >90 (a) |
| 1 | >=90(b) |
| 2 | 60-89 |
| 3 | 30-59 |
| 4 | 15-29 |
| 5 | <15 |

Table 1. CKD stages

- With CKD risk factors
- Kidney damage indication (Protein in the urine, abnormal urinary sediment, abnormal radiological studies, and disorders in chemical status of urine and blood)

Chronic renal failure (CRF) is used for processes developing irreversible reduction in the number of nephrons, which are matched to CKD stages of 3 to 5. To classify the stages of CKD, the GFR needs to be estimated. Two most common formulas are mostly used to estimate GFR (Table 1).

Normal GFR values occur in the range of 120 ml/min/1.73 m2, which mean value is lower in women than men. The stages 1 and 2 of CKD are not associated with clinical symptoms caused by reduced GFR. The symptoms of the underlying disease just may be seen. If the GFR decline progress to steps 3 and 4, clinical and laboratory complications of CKD will become prominent, and finally, affect all the organs. However, the most obvious complications include anemia, loss of appetite, malnutrition, abnormalities in serum levels of calcium, phosphorus and homeostasis regulating hormones such as PTH, 1, 25 –dihydroxyvitamin D and disruption of homeostasis of sodium, potassium, water and acid-base status (13).

It is estimated that at least 6% of the adult population in America are in stages 1 and 2 of CKD, and an unknown number of these people will progress to the next levels. It is estimated that 5.4% of the U.S. population are in steps 3 and 4 (13).

Risk factors for CKD include blood pressure, diabetes, autoimmune diseases, older age, African race, a family history of kidney diseases, previous attacks of acute kidney injuries, protein in the urine and urinary tract anatomical abnormalities (13).

## 2. METHODOLOGY

1. Preparation of structured medical record summary

To prepare the basic information used in the CBR system, the structured medical record summary was used.

2. Data set

Two data sets with the following characteristics were used for this study:

- Chronic kidney disease patients' dataset, including 33,000 records.

3. Patient's medical records summary with chronic renal failure, including 120 discharge summaries.
4. Data mining

Data mining process was performed on patients' dataset. The significance coefficient of parameters and relationships between the parameters were extracted (table 2).

| | |
|---|---|
| BMI | 0.0416 |
| Protein | 0.0431 |
| Cholesterol | 0.0431 |
| LDL | 0.0456 |
| WBC | 0.0475 |
| Diastolic BP | 0.0479 |
| Height | 0.048 |
| RBC | 0.0492 |
| GFR | 0.1418 |
| Creatinine | 0.1634 |

Table 2. Parameter importance

### System analysis and design

CBR system is composed of two parts:

1. Decision support system (DSS) that is provided in form of a mobile application.
2. Patient information database and Web service provider

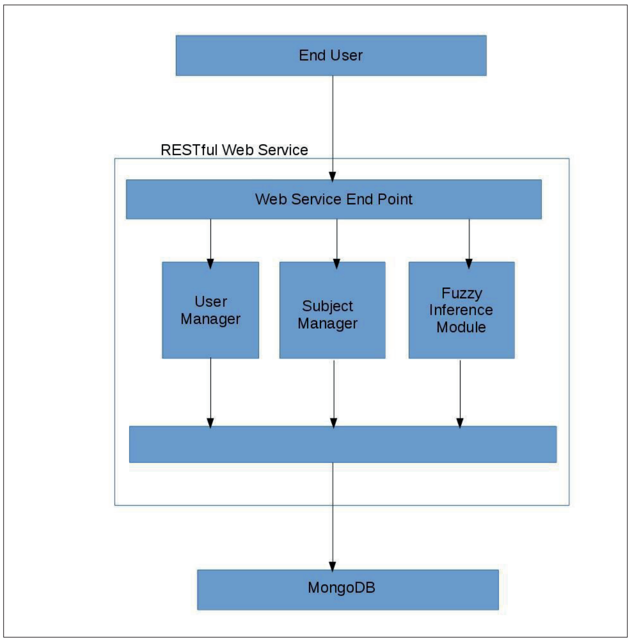


Figure 2. CBR System Architecture

### System components

The most important component of the system is the decision-making unit. With the help of the set of rules designed to detect patients' similarities, this decision-making unit calculates an index for each patient and records it with patient information in the database.

If necessary, according to the patient, the physician inserts input values into the DSS. The system calculates relevant index for the patient and sends a request to the Web Server as JSON object.

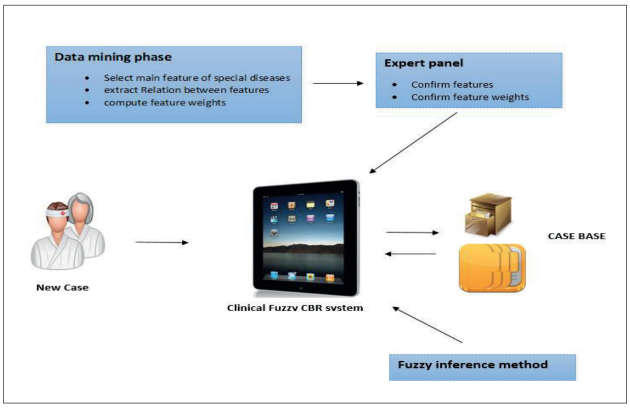


Figure 3. Clinical Fuzzy CBR components

The Web Server is a system consisting of user management unit, subject management unit, fuzzy inference module and database management unit.

MongoDB is used as database management system. This database management system is a production of Document Store systems group. Due to non-schematic informational structure of the system, it allows to store a wide range of patient records in the system with no need to change the information structure (Figures 2 and 3).

The user requests to create a new file using a web-based client application. After user authentication, the server provides forms of creating a file to the user. After data entry, the system calculates similarity index with respect to the patient

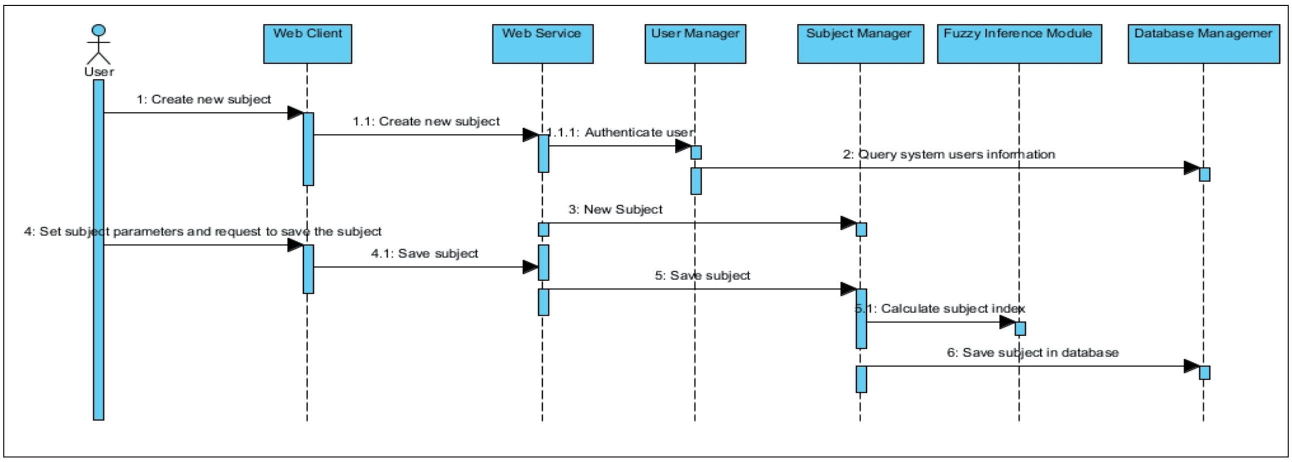


Figure 4. The process of registration of new patient information

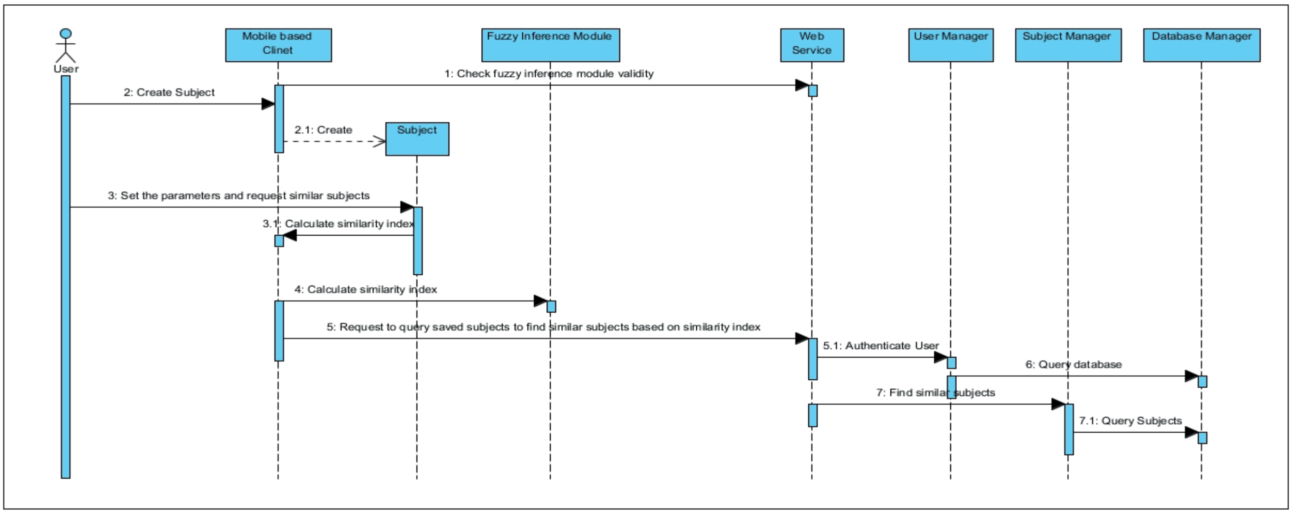


Figure 5. The process of finding similar patients

information and by using the fuzzy decision-making unit and stores the information in the database (Figure 4).

To find similar patients, the user enters parameter values available in the decision support system. Due to values of parameters and fuzzy decision-making, the system calculates the similarity index and sends a request for finding similar cases to the Web service. Then, the web service finds similar cases and send them back to user (Figure 5).

The fuzzy decision-making unit exits in both the Web Service and client. Thus, to coordinate these units, client compares its version of decision-making unit with the web service, and in case of difference, update procedure would be run.

**System implementation**

The system is designed based on two separate data structure management:

- Fuzzy decision-making unit
- Case decision-making unit

Fuzzy decision making unit (Module) is composed of a number of rules. Each rule is formed of two parts of "Antecedent" and "Consequence" that each of which narrates the membership of a variable in the fuzzy set. In fuzzy logic, contrary to what observed in classical logic, the membership value of a variable in a set is a number between 0 and 1. Thus, to define a fuzzy decision-making unit, we had first to define the variables, then the series, and finally, the rules. This system allows to create and manage two types of fuzzy rules: Mamdani and Sugeno.

## 3. RESULTS

To assess implemented system, data obtained from 100 discharge summary of patients with chronic renal failure were used. Similarity coefficient was measured for 30 patients using the above system. For the remaining 70 patients, similarity coefficient was calculated using Euclidean method and reviewed by experts. The results are shown in Table 3.

| No | Datasets | Expert1 | | | Expert2 | | | Expert3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | M1 | M2 | M3 | M1 | M2 | M3 | M1 | M2 | M3 |
| 1 | Dataset 1 | 67% | 60% | 65% | 66% | 65% | 65% | 72% | 71% | 73% |
| 2 | Dataset 2 | 73% | 72% | 70% | 58% | 58% | 53% | 68% | 70% | 71% |
| 3 | Dataset 3 | 58% | 40% | 38% | 60% | 63% | 63% | 61% | 61% | 59% |
| 4 | Dataset 4 | 66% | 65% | 66% | 67% | 67% | 65% | 66% | 67% | 67% |

Table 3. Similarity methods comparisons. Note: M1: Fuzzy similarity method M2: Euclidian method M3: Normal distance metho

## 4. DISCUSSION

Most of CBR systems collect data and run in specific domain only (8, 14-16), but suggested Fuzzy CBR runs on the Android platform for mobile devices. Previous CBR systems used limited number of cases in their case base (2, 3, 5, 17, 18) while present Fuzzy CBR uses real online cases. In addition, algorithms and methods used in traditional CBR systems are not flexible (6, 15, 19-21). Using fuzzy method to measure similarity, can lead to higher flexibility compared to other methods.

## 5. CONCLUSION

Developing fuzzy CBR system and related architecture have this benefits:

- Knowledge management framework for registering specific therapeutic methods;
- Knowledge sharing environment for special in a specific domain;
- Powerful tools at the point of care.

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