

Case Based Fuzzy Cognitive Maps (CBFCM) : New method for medical reasoning

Comparison study between CBFCM/FCM

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Abstract— Doctor usually uses his experience from the clinical practice to confirm a diagnosis and to prescribe an appropriate treatment for a specific patient. The computerized medical reasoning should not only focus on existing medical knowledge but also on physician's previous experiences and new knowledge. Such knowledge and experience are vague and define uncertain relationships between facts and diagnosis. Case Based Fuzzy Cognitive Maps (CBFCM) are proposed as an evolution of Fuzzy Cognitive Maps (FCM) that allow more complete representation of knowledge since case-based fuzzy rules are introduced to improve FCM decision support systems. Semantic web is used to implement both FCM approaches. A database of 71 patients with urinary tract infections was used to perform the proposed approach. A comparative study between FCM (92%) and CBFCM (99%) was conducted and the results derived by CBFCM approach showed CBFCM to be superior to FCM.

Keywords : *Fuzzy Cognitive Maps, Rules, Decision Support Systems, Knowledge Representation, Clinical Guidelines, Semantic Web, case based reasoning.*

I. INTRODUCTION

In medical practice, the doctor evokes several diagnoses but the differential diagnosis remains the major problem in medical decision making. It requires a several complementary examinations and experts review. Clinical Decision Support Systems (CDSS) are tools to improve patient safety and care processes [1,2]. Several studies and reviews have shown their effectiveness, i.e. [3,4,5,6] in the areas of diagnosis and therapy.

In a recent review, Peleg and others [7] claim that CDSS allow “right knowledge to the right people in the right form at the right time” [8]. The development of CDSS has two knowledge-management tasks: the possibility of integration into the care system workflow, and knowledge management for proper decision making.

CDSS models have to take into consideration issues related to patient data quality that is: incompleteness, poorly structured and sometimes unreliable data, problems associated with inaccuracies and uncertainties in Clinical Practice Guidelines (CPG). Many clinical diagnosis tasks involve reasoning under uncertainty [9]. Modeling a dynamic system can be hard in a computational sense.

The use of CDSS in urinary tract infections will reduce false diagnoses and establish a proper antibiotic regimen. FCMs have proved their efficiency in medical decision support and medical reasoning through the literature [10-14]. This paper describes and evaluates a new method to create a diagnosis model framework based on semantic web approach and Case Based Fuzzy Cognitive Maps (CBFCM). The produced results of the examined framework are compared with those obtained from FCM reasoning approach for 71 patients.

II. BACKGROUND

A. Clinical decision support system

CDSS form a significant part of the field of medical knowledge management technologies through their capacity to support the clinical process and use of knowledge, from diagnosis and investigation through treatment and long-term care. Their role and acceptance in daily clinical practice is increasing [15]. Recent studies [16] showed that CDSS can improve physician performance and accuracy, while the quality of each system may depend on the technical approach they use to model medical information.

CPG are structured documents that list a set of specific cases for which some diagnosis and therapeutic action plans are recommended with a given degree reflecting the strength of the recommendation corresponding to the level of scientific evidence. CPG include the description of the various

alternatives and the factors that would allow establishing decisions amongst them. However, because of the sheer volume of one such CPG and the rigid structure of such guidelines, it is very difficult for the physician to apply and strictly follow the workflow presented by guidelines. Our work is directed towards the creation of a computerised system that dynamically guides the physician through the workflow and assist physicians in diagnosis of clinical forms of UTI (Urinary Tract Infection).

An empirical antimicrobial therapy well suited to the patient requires consideration of the patient treatment parameters (treatment ongoing, drug allergies...) but above all a good first diagnosis is primarily based on a clinical approach. The diagnosis is based on a notion of causality between infectious disease and clinical signs that it generates light in the field of physiological and pathological patient. In order to solve the problem of modeling medical knowledge from guidelines and to assign UTI diagnosis by handling imprecision and uncertainty, the FCMs and their extension, namely CBFCMs, are investigated. The semantic web approach was used to implement the proposed approaches.

B. Cognitive Maps

Cognitive Maps were introduced by R. Axelrod in 1976 to represent political and social knowledge [17]. They are directed graphs with signed edges. The nodes represent variable concepts and the arrows interconnecting concepts represent the relations between concepts. The sign attached to the head of arrows indicates the polarity of the causal relations. A positive arrow from node (concept) C1 to node C2, means C1 causally increases C2. Cognitive maps have been used to model a number of areas (political, social, business, ...).

C. Fuzzy Cognitive Maps (FCM)

FCMs, as an extension of cognitive maps, were developed by R. Kosko [18] to represent the causal relationship between concepts and analyze inference patterns. FCM represents knowledge in a symbolic manner, encoding the relations between the elements of a mental landscape so that the impact of these elements can be assessed. FCMs have gained considerable research interest and have been applied to many areas [Papageorgiou & Arthi, 2010].

FCM inherits the fuzzy logic properties on cognitive maps that allow predicting the change of the concepts represented in Cognitive Maps. The graphical illustration of FCM is signed directed graph with feedback, consisting of nodes and weighted interconnections. Nodes stand for concepts, variables, states that are used to describe the behavior of the system and they are connected by weighted arcs representing the causal relationships among nodes. Each concept is characterized by a fuzzy value usually ranging from $[0...1]$ or $[-1...1]$.

The most important element in describing the system is the determination of which a concept influences which others and with which degrees. There are three possible types of causal relationships among concepts that express the type of influence from one concept to the others. The weight of the interconnection between concept C_i and concept C_j , denoted by W_{ij} , could be positive $W_{ij} > 0$ for positive causality or

could be negative causality $W_{ij} < 0$ or could be null when there is no relationship between concept C_i and concept C_j , thus $W_{ij} = 0$.

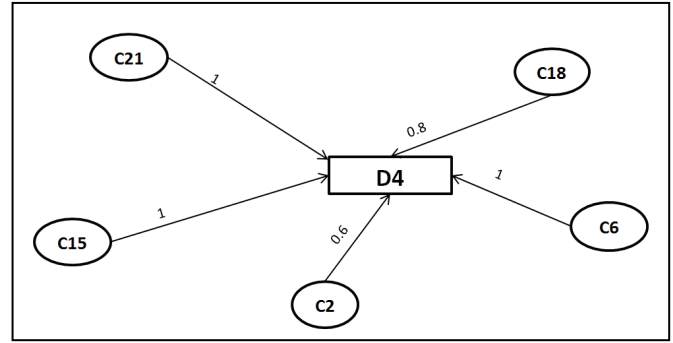


Figure 1. Representation of FCM model of acute prostatitis (C2: Fever, C15: Vesical Uretral Reflux, C8: Vomitting, C18: Flank Pain, C19: Urine Dipstick Test, D8: Acute Prostatitis)

To get the value of a concept C_j , the value of each of its concepts inputs C_i is multiplied by the respective weight W_{ij} which takes values in $[-1..1]$; then the results are added and passed by a non-linear function used to limit the range of possible output values.

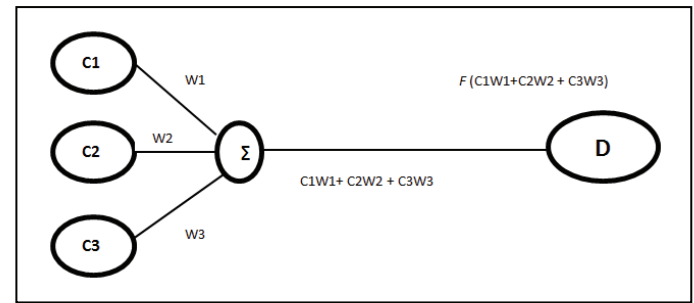


Figure 2. Graphical representation of calculating the value of the concepts of decision

So the value A_i for each concept C_i is calculated by the following rule:

$$A_i(k+1) = f(A_i(k) + \sum_{j=1, j \neq i}^N (A_j(k) \cdot E_{ji})) \quad (1)$$

where $A_i^{(k+1)}$ is the value of concept C_i at simulation step $k+1$, $A_j^{(k)}$ is the value of concept C_j at step k , E_{ji} is the weight of the interconnection between concept C_j and concept C_i and f is a threshold (activation) function that squashes the result of the multiplication in the interval $[0, 1]$.

This equation indicates that a FCM is free to interact; at every step of interaction every concept has a new value. Several formulas can be used as threshold function [19], and as the interval of concept is bivalent (i.e., the concepts belong to the interval $[0, 1]$), we propose the function $f(x)$:

$$f(x) = 1/(1 + \exp(-cx)) \quad (2)$$

where c is a real positive number and x is the value $A_i^{(k)}$ on the equilibrium point. In this work we use $c=1$, because this value showed best results in previous works [20].

Reasoning mechanism

The FCM inference algorithm is consisting of the following steps is used to simulate the process and give the necessary decisions about it.

(Step 1) Definition of the initial vector $\mathbf{A}$ that corresponds to the elements-concepts identified by experts' suggestions and available knowledge.

(Step 2) Multiply the initial vector $\mathbf{A}$ and the matrix $\mathbf{W}$ defined by experts by the eq. (1).

(Step 3) The resultant vector $\mathbf{A}$ at time step k is updating using Eqs. (1)–(2).

(Step 4) This new vector $\mathbf{A}^k$ is considered as an initial vector in the next iteration.

(Step 5) Steps 2–4 are repeated until $\mathbf{A}^k - \mathbf{A}^{k-1} \leq e = 0.001$ (where e is a residual, describing the minimum error difference among the subsequent concepts) or $\mathbf{A}^k = \mathbf{A}^{k-1}$. Thus $\mathbf{A}_f = \mathbf{A}^k$.

In each of the case studies, an initial vector $\mathbf{A}$ is assigned (consisting of A_i values corresponding to each one concept C_i), representing the presented events at a given time of the process, and a final vector $\mathbf{A}_f$ is calculated at the steady state of the system, representing the last state that can be arrived at.

The iteration stops when a limit vector is reached, i.e., when $\mathbf{A}^k = \mathbf{A}^{k-1}$ or when $\mathbf{A}^k - \mathbf{A}^{k-1} \leq e$; where e is a residual, whose value depends on the application type (and in most applications is equal to 0.001).

1) Fuzzy Cognitive Maps extensions

FCMs are limited to the representation of simple monotonic causal relations between concepts and they do not handle the AND/OR relationships among the antecedent nodes, although they represent the causal relations between the antecedent and consequent nodes. Numerous works have been proposed to improve FCMs performances. Many extensions to the FCMs were developed, such as Extended Fuzzy Cognitive Maps (EFCMs), Rule Based Fuzzy Cognitive Maps (RBFCMs), Random Fuzzy Cognitive Maps (RFCMs), Intuitionistic FCMs, Fuzzy Grey Cognitive Maps and so on.

2) Case based reasoning:

Case-based reasoning (CBR) systems reason from experience: they solve new problems by retrieving relevant prior cases and adapting them to fit new situations. In 1988 the first case-based reasoning workshop identified theoretical foundations and fundamental issues for case-based reasoning research [20]. Case-based reasoning systems process new situations by retrieving a relevant prior case from memory, comparing that case to the new situation to determine important similarities and differences, and applying pertinent information from the old case to the new situation. Case-based reasoning has been applied to many tasks and domains, such as message

classification, dispute mediation, explanation, language understanding, legal reasoning and planning.

Motivations for using case-based reasoning include: increasing efficiency in solving new problems, because relevant reasoning can be re-used rather than having to be re-derived; improving the quality of solutions; and simplifying knowledge acquisition. CBR facilitates the knowledge acquisition process because cases can be stored and used without having a perfect domain theory; case acquisition can be achieved without analyzing the interactions between individual factors in a case. Also, extensive pre-existing case libraries are available for many tasks, and those libraries can provide a starting point when building CBR systems [20].

D. Semantic web tools :

1) RDF / RDFS (Resource Description Framework / Schema)

RDF is a standard model for data interchange on the Web. RDF has features that facilitate data merging even if the underlying schemas differ, and it specifically supports the evolution of schemas over time without requiring all the data consumers to be changed. RDF extends the linking structure of the Web to use URIs (Url Resources Identifier) to name the relationship between things as well as the two ends of the link (this is usually referred to as a “triple”). The data are shown in triples:

Subject Verb/Predicate Object

These expressions are known as triples in RDF terminology. The subject denotes the resource, and the predicate denotes traits or aspects of the resource and expresses a relationship between the subject and the object. The subject is a resource identified by a URI (Uniform Resource Identifier), which is described by another resource (object) with a property (Word / Predicate). In the case problem of UTI, an example is given for the “pyelonephritis” diagnosis, where the subject “fever” has the property “symptom” for the object “pyelonephritis”.

Example :

```
<rdf:Description about=
"http://www.spm.jussieu.fr/Pyelonephritis">
<prefix:Symptom>Fever</prefix:Symptom>
</rdf:Description>
```

Using this simple model, it allows structured and semi-structured data to be mixed, exposed, and shared across different applications.

2) Web Ontology Language (OWL):

The Web Ontology Language OWL is a semantic markup language for publishing and sharing ontologies on the World Wide Web. OWL is developed as an extension of RDF vocabulary. It is derived from the DAML + OIL Web Ontology Language. OWL is flexible, extendable, and decentralized because it's designed for use in the dynamic, global environment of the Web. OWL supports hierarchical relationships at their core, allowing for easy incorporation of subclasses and subproperty relationships that are essential for

managing and integrating complex data. We used in our project an ontology written in OWL, which will be described in the material.

3) Notation 3/ N3 logic:

The notation N3 is the format being developed by Tim Berners-Lee and others from the Semantic Web community. RDF / N3 is a rating given by Tim Berners Lee as an alternative to RDF / XML [30]. Notation3, or N3 is more compact and human readable than RDF / XML.

For example, the notion "The Fever is a symptom of Pyelonephritis" in RDF is represented as the triple: a subject denoting "Fever", a predicate denoting "Symptom", and an object denoting "Pyelonephritis". In N3, this is written as an RDF triple just like that:

```
:Fever :Symptom :Pyelonephritis
```

N3 language has been selected on purpose to represent medical knowledge due to its human readability and close relationship to the semantic web. Formalized medical information is represented with ontological concepts using Notation3 format. An example is given:

```
@prefix dco:
<http://www.debugit.eu/ontology/1.0/dco.owl#>.
dco:Fever dco:Symptom dco:Pyelonephritis.
```

N3 Logic is a logical platform that uses semantic web N3 as RDF syntax and expands the vocabulary of predicates. The goal of logic N3 is to give the possibility to integrate an RDF data model, logical rules and provide integrated functions that allow access and reason about data.

This allows expressing knowledge in N3 logic for a specific purpose [21]. In a rule, the premise is the subject and the conclusion is the complement (object). The sign "=>" is a common predicate expression log-rule namely implies.

An example of N3 rule is given:

If the patient is pregnant Then the diagnosis of "PregnancyUrinaryTractInfection" is inadequate for this patient. The main aspects of programming CBFCM approach in N3 are depicted :

```
{ (?P dco:Pregnant) fl:mu 1 } => { (?P
dco:PregnancyUrinaryTractInfection) fl:sigma 0 }.
```

III. MATERIALS AND METHODS

A. Materials

In our project, we used 71 clinical cases to create a database of patient testing. We worked with domain ontology of Infectious Diseases DCO (DebugIT Core Ontology) [22]. DCO serve as the core component of the interoperability platform for the DebugIT project.

Inference engine:

As part of our project, we formalized the rules and we executed by an inference engine. EulerSharp [23] is an inference engine with backward-forward-backward chaining that allows the "loop-checking to ensure the processing of all data, to reason with data, queries and rules in N3". We choose Euler for

historical performance¹, frequent updates², plugins & the ability to integrate new features³ (built in).

B. Methods

1) Case Based Fuzzy Cognitive Maps (CBFCM)

One advantage of the FCM-based decision making is that it resembles human decision making, with its ability to perform approximate reasoning and handle incomplete information. But FCM seems to be limited to the representation of simple monotonic causal relations between concepts and could not handle the AND/OR relationships among the antecedent nodes.

In medical reasoning, many observables/factors such as painful, febrile, old, take the form of fuzzy concepts and used in FCM. These fuzzy concepts can be represented by fuzzy sets. Doctors use their academic knowledge and clinical cases already dealt with that imply a case-based reasoning and a heuristic approximate reasoning. A new method to improve results from the FCM approach is proposed by adding a system of rules based on cases. This method is developed using the tools of the semantic web. Fig3 is a graphical representation of CBFCM method:

A patient 01 represents a set of clinical parameters (C1, C2, and C3). These clinical parameters could be clinical signs, age, gender or biological results. They are used as input concepts in our CBFCM. These concepts are then processed by a set of fuzzy rules that are outcome of our case base. If the patient case is similarly of one of the cases already known then the diagnosis is confirmed by consensus; else we use our FCM algorithm to have a concept D1 for diagnosis decision.

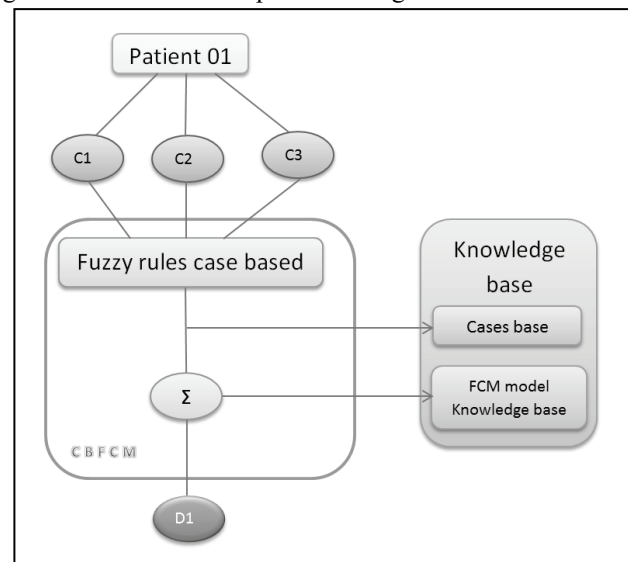


Figure 3. Diagram represents the CBFCM method

2) CBFCM Euler Plugin

To allow management of CBFCM fuzzy rules, FCM plugin for Eye[23] updated several times to change the value of a

¹ <http://eulersharp.sourceforge.net/2003/03swap/dtb-2010.txt>

² <http://eulersharp.sourceforge.net/DONE>

³ <http://eulersharp.sourceforge.net/2003/03swap/euler-builtins.html>

fuzzy set membership (μ_i) and two decisions-conclusions can be arranged at the same rule.

We present in detail the steps followed for the design of our diagnosis model based CBFCM:

Extraction of clinical concepts and diagnostic:

From several CPG, we extracted clinical concepts and diagnostic concepts (all diagnoses).

Standardization of clinical concepts and diagnostic:

We have standardized, manually, concepts with the DebugIT ontology of Infectious Diseases (DCO).

Writing diagnostic rules:

The messages of CPG are as rules “*If Premise Then Conclusion*”. The premise takes into account several patient parameters and it consists of several basic premises. Extracting Knowledge from CPG in fuzzy rules “If-Then”. The rules are formalized as follows:

If the value of the concept C_i is X then the value of D_j is Y with a degree of influence (weight) W_{ij} . Every relationship between a concept and a clinical diagnostic concept is defined by a membership function that determines the degree of causality between two concepts. Example, “If the urine dipstick test is negative then the diagnosis of UTI is wrong with a degree of 0.9”.

In our approach, we use the knowledge from CPGs to build our cognitive maps that these rules represent the relationship between concepts and the weight of this relationship has a fuzzy value.

3) Construction of CBFCM diagnosis model

A number of medical guidelines for the diagnosis problem of UTI were formalized into CBFCM knowledge models using the approach presented in Fig.3. In order to construct our FCM model for medical decision support, the main concepts with their strengths of connections (causal influences) have to be assigned. Also a number of IF-THEN CBFCM rules were extracted to be used to improve the differential diagnosis and manage conflicts. The concepts and their relationships were extracted from CPG and each concept and clinical diagnosis contributes to a node represented in FCM.

All the concepts were defined. The relationships between these concepts and the clinical diagnosis concepts described in the CPG natural language were translated into formal language by defining the fuzzy weight of each concept. The fuzzy weights were determined using the methodology proposed in [24, 25]. These linguistic weights are initially used to describe the influence that exists between a clinical sign (concept) and a clinical diagnosis. Then, these weights are transferred to numerical weights in the range $[-1,1]$ using the centroid defuzzification method of fuzzy logic[26].

a) CBFCM implementation in N3

To implement our algorithm for reasoning in N3, we use plugins of the inference engine EulerSharp developed in

Prolog4. In Appendix B, the main aspects of programming CBFCM approach in N3 are depicted.

Our implementation method is to write rules in N3 logic for reasoning with standardized patients data using the FCM algorithm.

The CBFCM concepts are included in an ontology repository established for the project needs, namely DCO. DCO is updated continuously in order to contain all relevant clinical concepts. We worked with the DebugIT project ontologists to enrich the DCO ontology and can be used with our rules.

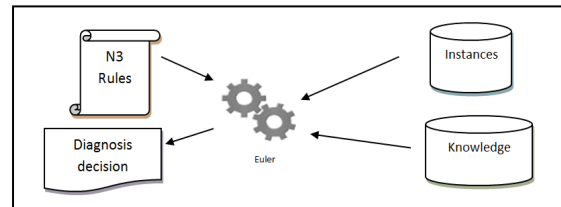


Fig4 - Mechanism representation of diagnosis decision making

Thus, based on this implementation technique, all the concepts, relationships and fuzzy rules for differential diagnosis are written in N3. Then, using the Euler plugin, the reasoning of the constructed model is accomplished, suggesting a differential diagnosis.

IV. RESULTS

The results presented here follow the steps of the methodology previously and the inference mechanism of CBFCMs (Eulersharp/plugin) [23]. The proposed methodology was validated with 71 patient cases derived from several European hospitals.

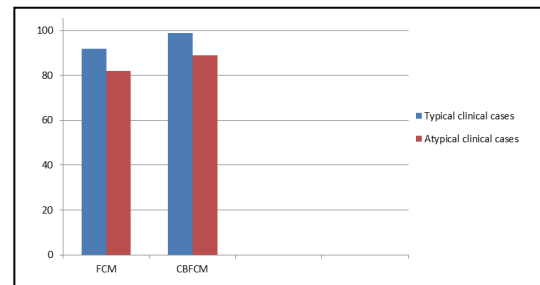


Figure 5 - Graphical representation of results of our study

Since this work is concerned by the modeling of diagnosis guidelines, the results are compared to the recommendations provided by the relevant clinical suggestions. Therefore, according to this approach, the rate of “correct” decisions, i.e. the decisions complying with the clinical diagnosis suggestions, is considered as the success rate of the compared models. The success rate of FCM approach was 92% and 99% of CBFCM approach for 71 examined patient cases. In 92%, and 99% of cases with FCM and CBFCM respectively, the answer given by our system was equivalent to the correct answers in cases involving clinical UTIs and 87%, 89% (FCM, CBFCM) in clinical cases involving other diseases (gynecological diseases, surgery ...) with urinary tract infection.

⁴ <http://eulersharp.sourceforge.net/2006/02swap/fcm-plugin.yap>

Fig5 represent the results of corrects diagnosis given by our system.

V. DISCUSSION

The CBFCM approach allowed us to model medical knowledge of CPGs and to identify causal relationships in close as possible to the human reasoning. The use of CBFCM has enabled us to incorporate a second source of knowledge what we find beneficial to incorporate other types of knowledge. It allows us to model a simple knowledge of a medical field that is broad, complex and closely related to other areas.

The goal of our research study was threefold. First reasoning algorithms of Case Based fuzzy cognitive maps were established. Then, as a result the N3 notation and logic was used for the implementation of our cognitive maps for knowledge formalization of CPG and integration of others knowledge resources (others CPG). Finally, a patient database on which we applied the reasoning of our cognitive maps was created and tested for the model's validation.

We have implemented the knowledge bases, rules and databases in the same environment (RDF, N3, Euler..) without compatibility constraints, this is one of the advantages of using Semantic Web tools. The success rate of the proposed model giving UTI diagnosis was assigned to 99%, which shows the functionality of the model and its future usefulness in clinical practice.

CPG don't cover the whole field of community-acquired infections of the urinary tract in adults and we found a lot of information missing: the relationship between domain concepts. The rules, we have implemented, concern only the community urinary tract infections in adults. Integrating other GBPC, experts review, data mining results covering other areas of infectious diseases will allow us to improve our system.

Future work will be directed towards the construction of more dynamic systems based on the CBFCM methodology that could be integrating more sources of knowledge and data covering other areas of infectious diseases. Another part of the system is not yet developed that involves learning from the new case to enrich our knowledge base and enable close collaboration with practitioners on a daily basis.. The rules will be tested on a larger number of data and will be updated by integrating knowledge from more guidelines/experts and data mining techniques.

VI. CONCLUSION

This under investigation study presents the results of comparison between the two reasoning methods: FCM and CBFCM. We explored the problem of modeling medical knowledge/guidelines and capturing the system's behavior for decision support of UTI diagnosis by using a new soft computing technology of CBFCMs implemented in semantic web. More specific, this work establishes a decision support tool based on CBFCM formalism for UTI diagnosis by proposing the appropriate diagnosis for each individual case.

The developed software tool calculates the diagnosis recommendations for UTIs. It receives the relevant patient state on input from the data store or a clinical information system (CIS). The simulations for test patients that are performed using the implementation of the proposed CBFCMs provide the differential diagnosis for these test patients.

The conducted study allowed us to test cognitive approaches for implementing CPG with Semantic Web tools. The advantage of this approach is to enable the sharing and reuse of knowledge from databases GBPC, experts and simplify maintenance.

This work represents a preliminary step in developing a methodology for the implementation of dynamic heterogeneous knowledge in the medical field and their use in decision support systems.

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