A Fuzzy Cognitive Map based tool for prediction of infectious diseases

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Abstract— **The prediction of pulmonary infections in intensive care unit is a complex medical task where a large number of parameters, tests, clinical symptoms and laboratory results are present. The knowledge of physicians according to the physical examination and clinical measurements are the main point to succeed a diagnosis and monitoring patient status. This paper presents the results of our investigation of the problem of representing knowledge for medical diagnosis systems concentrated on the pulmonary infections. The main topic of the presented effort is the representation of the cause-effect relationships within medical data by the application of the soft computing technique of fuzzy cognitive maps. The fuzzy cognitive map is a knowledge based technique for modeling and representing experts' knowledge. It can handle efficiently with complex modeling problems to assess medical decision making tasks. Due to its easy graphical representation the proposed FCM can be used to make the medical knowledge widely available through computer consultation systems.**

I. Introduction

A Large number of techniques in the field of artificial intelligence used to represent knowledge: production rules, semantic nets, frameworks, scripts, statements, logic, causal cognitive maps, among others. Some of the main topics of artificial intelligence are fuzzy logic and possibility theory based on representation of knowledge and approximation of reasoning with uncertainty. The choice of a particular technique is based on two main factors: the nature of the application and the user's skills. The fuzzy logic theory, based on representation of knowledge and approximation of reasoning with uncertainty, is very close to the expert's reasoning, and it is well known as artificial intelligence-based method. An outcome of this theory is fuzzy cognitive maps [1]. Fuzzy cognitive maps are diagrams used as causal representations between knowledge/data to represent events relations. The fuzzy part allows us to have degrees of causality, represented as links between the nodes of these diagrams, also known as concepts. This structure establishes the forward and backward propagation of causality, admitting the knowledge base to increase when concepts and links between them are increased. Causality is represented as a fuzzy relation between nodes. In the last decade, the use of FCMs for many applications in different scientific fields was proposed [i.e. 2-9].

In this work, our attention primarily has focused on the process of making medical diagnoses. In medical science, patients have symptoms that prompt them to see a doctor. In other words, symptoms are comprised of the observations reported by patients and the observations of doctors while examining patients. The identification of the underlying cause of symptoms is crucial and improves the chance of proper diagnosis of the disease and prescribing the correct treatment. Here, we use FCMs as a first step, to model a physician-expert's behavior in the decision making [9]. The behavior to be modeled is centered in the decision making process, whose reasoning implies to reach a predefined goal, coming from one or more initial states. Therefore, the reasoning system will be more efficient when a least number of transitions to reach the final goal are achieved. Thus, increasing the efficiency implies to minimize intermediate states, and that is represented in the organization of the knowledge base.

FCM for decision support was chosen because of the nature of the application due to the reason that prediction of severity in pneumonia is a complex process with sufficient interacting parameters and FCMs are suitable for this kind of problem, through the available experience and accumulated knowledge from experts, the easy for use and the low time requirement.

The main goal of this work is to present a method based on FCM that can be applied for the development of an expert system for predicting infectious diseases as well as the type and the severity of infection especially in the problem of infectious pneumonia. No any previous work has been done on implementation of FCM technique to handle with the specific problem for defining infectious diseases and/or adverse events in Intensive Care Unit. The FCM approach will be enhanced in our future work by using knowledge from clinical data through data mining techniques.

II. Procedure for Medical Decision Support

A. *Review on Medical Decision Support Systems*

From the first generation of medical decision support systems (MDSS) such as MYCIN, to the second generation, such as Protégé, significant research progress, both theoretically and practically, has been made since today [10]. The generic goal of MDSS is to efficiently manage

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knowledge about a clinical situation, to produce inferences as outputs, that can assist practitioners in their decision making, and to be judged as "intelligent" by the program's users.

From the literature, there is a vast number of knowledge-representation methods that can be considered, as logic (rule-based), procedural, graph/network, structured, conceptual approach. The choice of an appropriate knowledge representation scheme depends on the domain knowledge it represents and the inference process it uses. Inference mechanisms used in MDSS [11] include rule based, Bayesian, belief networks, heuristic, semantic network, neural networks, genetic algorithms and case-based.

In rule-based DSSs, sets of boolean "if-then" rules are processed. The forward and backward chaining of rules may be used to conclude a diagnosis and provide diagnostic explanations for clinical users. In our opinion, one of the main disadvantages for the application of the classic rule-based knowledge representation in MDSS is its limitation of representing some of the more complex associations that may be experienced within the medical data.

Maybe the best-known knowledge representation formalism (conceptual modeling) is represented by ontologies and semantic networks that are able to express concepts and relationships among them. Ontologies can be complemented by other knowledge representation formalisms, such as rules, which have been used to create medical knowledge bases. Maybe less known in computer science are fuzzy cognitive maps (FCMs). Some works on FCMs have been investigated to handle with the task of medical decision making [2,3,9].

B. Fuzzy Cognitive Map for Decision Making

Fuzzy cognitive maps offer an alternative knowledge fusion scheme [1,12]. Knowledge is represented in a symbolic manner using states, processes and events. Kosko introduced the FCMs by suggesting the use of fuzzy causal functions taking numbers in [-1, 1] in concept maps. The nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted interconnections representing the causal relationships that exist between the concepts.

Fig. 1 shows a fuzzy cognitive map designed to model some factors, selectors-measurements, and decisions in medical informatics, as well as their interactions. The main objective of building a cognitive map around a problem is to be able to predict the outcome by letting the relevant issues interact with one another. These predictions can be used in a medical DSS for finding out whether a conclusion arrived at is consistent with the whole collection of stated causal assertions.

The most important element in describing the system is the determination of which concept influences which other and with which degree. There are three possible types of causal relationships among concepts: positive, negative and zero causality.

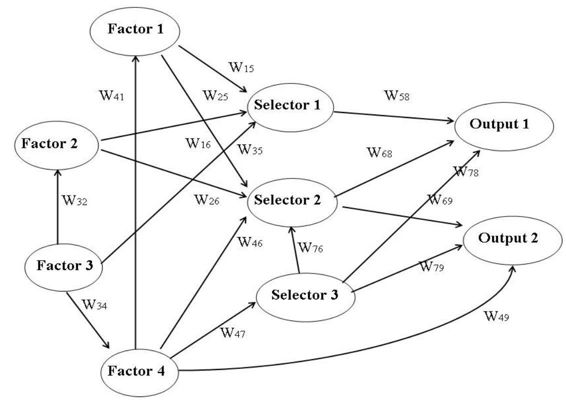


Fig. 1. A generic FCM model for medical decision making

The value of each concept is influenced by the values of the connected concepts with the corresponding causal weights and by its previous value. So the value *Aj* for each concept *Cj* is calculated by the following rule:

$$\mathbf{A} = f(\mathbf{A} + \mathbf{A} \times \mathbf{E}) \qquad (1)$$

or

$$A_i(t+1) = f(A_i(t) + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j(t) \cdot E_{ji}) \qquad (2)$$

where $A_i(t)$ is the value of concept *Ci* at step *t* , $A_j(t)$ is the value of concept *Cj* at step *t*, *Eji* is the weight of the interconnection from concept *Cj* to concept *Ci* and *f* is the threshold 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 [12].

The development and construction method of FCM is of great importance for its potential to sufficiently model a system. More specifically, experts from their experience know the main factors that describe the behaviour of the system; each of these factors is represented by one concept of the FCM. Following the developing methodology, experts are forced to think about and then describe the existing relationship between the concepts using fuzzy if then rules and assume the following form, where **B** and **C** are linguistic variables:

*IF value of concept C_i is **B** THEN value of concept C_j is **C** and thus the linguistic weight e_{ij} is **E***

Where ***B, C, E*** are linguistic variables (determined from the previous membership functions) taking values in the range [0, 1].

Thus, each interconnection is described by an expert with a fuzzy linguistic variable from a determined set, which associates the relationship between the two concepts and determines the grade of causality between the two concepts.

Then, the linguistic variables ***E*** proposed by the experts for each interconnection are aggregated using the SUM method and so an overall linguistic weight is produced which is defuzzified with the Centre of Gravity (CoG) method and finally a numerical weight for E_{ij} is calculated. Using this method, all the weights of the FCM model are inferred. A detailed description of the development of the FCM model is given in [9].

II. Methodology of Fuzzy Cognitive Map for Prediction of Pulmonary Infection

The problem of pulmonary infection is a complex process with enough parameters, factors and different conditions [13,14]. Typical symptoms associated with pneumonia include fever (80%) often accompanied by chills or hypothermia in a small group of patients, altered general well-being and respiratory symptoms such as cough (90%), expectoration (66%), dyspnea-shortness of breath (66%), pleuritic pain-a sharp or stabbing pain, experienced during deep breaths or coughs (50%), and hemoptysis-expectoration of blood (15%). The initial presentation is frequently acute, with an intense and unique chill.

Productive cough is present and the expectoration is purulent or bloody. Pleuritic pain may be present. Physical examination reveals typical findings of pulmonary consolidation- bronchial breath sounds, bronchophony, crackles, increased fremitus, dullness during percussion, tachypnea-increased respiratory rate, tachycardia-high heart rate (pulse should increase by 10 beats per minute per degree Celsius of temperature elevation) or a low oxygen saturation, which is the amount of oxygen in the blood as indicated by either pulse oximetry or blood gas analysis. In elderly and immunocompromised patients, the signs and symptoms of pulmonary infection may be muted and overshadowed by nonspecific complaints. If pneumonia is suspected on the basis of a patient's symptoms and findings from physical examination, further investigations are needed to confirm the diagnosis. Laboratory studies should be performed that include blood cell counts, serum glucose, transaminases, urea, creatinine and electrolyte measurements. These data provide a logical basis for evaluation the severity of pneumonia and the need for intensive care.

Three physicians-experts, two physicians from the General Hospital of Lamia, and one from the Medical University Hospital of Patras, Greece, were pooled to define the number and type of parameters-factors affecting the problem of pulmonary infection. These parameters (concepts) are listed in Table 1 and are well documented in bibliography and represent the main variables that play an important role in the final diagnostic decision about pulmonary infectious disease. For this application, concept values take either two, three, four or five possible discrete or fuzzy values, as shown in Table 1.

Thus, experts designed a FCM model, which consists of 34 concepts (Table 1). The 34 concepts are the factor and selector concepts representing the main variables that physicians in ICU usually take into consideration in assigning the existent and the grade of the infection. The Decision Concept (D1) represents the severity of pulmonary infection and takes four fuzzy values *(low, moderate, moderate severe, severe).*

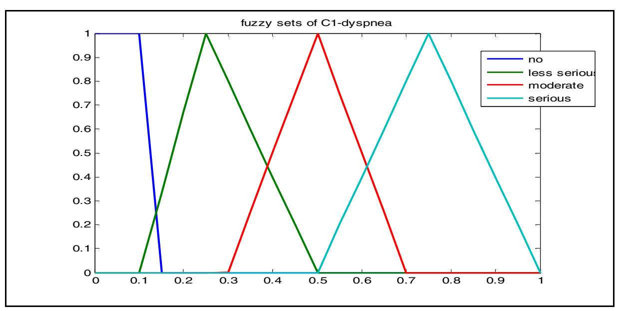
Table 1: Concepts of the FCM-2 model

Concepts	**Description of concepts**	**Type of values**
C1: Dyspnea	**Dyspnea** is a subjective experience of breathing discomfort that is comprised of qualitatively distinct sensations that vary in intesity.	Four fuzzy values (no dyspnea, little serious, moderate serious, serious)
C2: Cough	**Cough** is a deep inspiration folowed by a strong expiration against a closed glottis.	Three fuzzy values (no cough, non-productive and productive)
C3: Rigor/chills	**Rigor** is the involuntary shaking occurring during a high fever.	Three fuzzy values (no chills/rigor, chills, rigor)
C4: Fever	**Fever** is a frequent medical sign that describes an increase in internal body temperature to levels above normal.	Six Fuzzy values (hypothermia, no fever (36-38,4^{0}), low grade (38.5-38.9^{0}), moderate, high grade, hyperpyrexia (>41^{0}))
C5: Loss of appetite	**Loss of appetite** is the decreased sensation of appetite, leading to loss of weight if the symptom prolong	Two discrete values (0,1)
C6: Debility	**Debility** is a non specific symptom of pneumonia refereed to the altered general well-being.	Four discrete values
C7: Pleuritic pain	**Pleuritic pain** is the result of acute inflammation of the pleural surfaces that covers lungs.	Two discrete values (0, 1)
C8: Heamoptysis	**Hemoptysis** or haemoptysis is the expectoration (coughing up) of blood or of blood-stained sputum from the respiratory tract.	Two discrete values (0, 1)
C9: Oxygen requirement	There are four different states describing four progressively more serious states of **oxygen requirement**: no need of oxygen, the need of applying nasal kanula (~ 2-4lt oxygen) or Ventury mask (~ 4-15lt oxygen), NIMV and MV (mechanical ventilation)	Five fuzzy values (no need of oxygen , low, medium and severe)
C10: Tachypnea	**Tachypnea** (or "tachypnoea") is defined as the increase of respiratory rate of > 16 for men and 19 breaths for women breaths per minute.	Two discrete values (0 or 1)
C11: Acoustic characteristics	**Bronchial beath sounds** produced when the lung parenhyma is consolidated and the airway leading to this region is parent.	Three fuzzy values (no rales, localized and generalized)
C12:GCS	**Glasgow Coma Scale(GCS)** is a neurological scale which aims to give a reliable, objective way of recording the conscious state of a person, for initial as well as continuing assessment.	Three fuzzy values: Severe, with GCS ≤ 8, Moderate with GCS 9 – 12, Minor, GCS ≥ 13.
C13:Systolic Blood Pressure	**Blood pressure** is a measurement of the force applied to the walls of the arteries during cardiac cycle The pressure is determined by the force and amount of blood pumped, and the size and flexibility of the arteries. *(British hypertention*	Six fuzzy values (Optimal <120 Normal <130 High-normal 130-139 Grade 1 hypertension 140 – 159 Grade 2

	society)	hypertension 160-179 Grade 3 hypertension >/=180)
C14: Diastolic blood pressure	The bottom number is the **diastolic blood pressure** reading. It represents the pressure in the arteries when the heart is at rest *(British hypertention society)*	Six fuzzy values (i.e. Optimal (<80), Normal(<85), Grade 1 hypertension (90-99))
C15: Tachycardia	**Tachycardia** is the increased heart rate greater than 100 beats per minute.	Four fuzzy values (low, normal, high, very high)
C16: Radiologic evidence of pneumonia	Alveolar infiltrate: localized in segment, lobe, nodular or difuse Interstitial infiltrate; Nodular, reticular, septal, linear pattern	Three fuzzy values (no evidence, localized, generalized)
C17: Radiologic evidence of complicated pneumonia	Their presence indicates serious infection worse prognosis and possible need for more aggressive therapeutic techniques.	Two fuzzy values (presence, absence)
C18: pH	It is an **indicator** that reflects the effectiveness of mechanism for regulating the **acid-base status** of the organism. It can be calculated by arterial blood gas analysis.	Three fuzzy values **Acidosis** <7.35 **Normal** 7,35 – 7,45 **Alcakalosis** >7.45
C19:pO2	The **partial pressure of oxygen** in the arterial blood is an early indicator of respiratory failure. Low values of pO_2 demand oxygen therapy	Two fuzzy value (**normal** 70-100mmHg **hypoxia** is every value under normal)
C20: pCO2	The **partial pressure of carbon dioxide** is also an indicator of respiratory failure. Hight values of pO_2 demonstrate hypoventilation and posible need for NIMV or MV.	Three fuzzy values **normal** 35-45mmHg **hypocapnia** <35 mmHg **hypercapnia** >45mmHg
C21: sO2%	**Oxygen saturation** (so_2%) is the fraction of the hemoglobin molecules in a blood sample that are saturated with oxygen at a given partial pressure of oxygen. Normal saturation is 95%-100%.	Two fuzzy values **normal** >95% **hypoxia** <95%
C22: WBC	**White blood cells.** Marked **leukocytosis**(>$10x10^3$/μl) with **leftward shift** (increased absolute number of neutrophils> $7,710^3$/μl) is more often seen in bacterial pneumonia caused by Streptococcus pneumoniae, Haemophillus influenzae.	Three fuzzy values **Normal** 4,3 - $10x10^3$/μl **leukocytosis**>10x 10^3/μl **leukopenia**<1000/ μl
C23: Immunocompromise	**Immunodeficiency** is a condition of altered mechanical and cellular defense mechanism of organism.	Two fuzzy values (presence, absence)
C24: Comorbidities	**Comorbidities** include conditions and diseases of individual associated with increased rate of pneumonia. Most frequently they are: COPD, bronchiectasis, asthma, congestive heart disease etc)	Two discrete values (presence=1, absence=0)
C25: Age	Patient age is a serious factor for assessment severity of pneumonia according to CURB-65 scale.	Three fuzzy (Young, middle age, older)
C26: Sputum culture	A valid expectorated **sputum** specimen can be obtained from about 40% of patients with pneumonia.	Negative or positive (-1, 1)
C27: Bronchial secrets culture	The necessary material can be obtained by: endotracheal aspiration, bronchoalveolar lavage (BAL) bronchoscopically with protected brush(PBB).	Negative or positive (-1, 1)
C28: Blood culture	A positive culture of blood definitively establishes the etiologic diagnosis of pneumonia.	Negative or positive (-1, 1)
C29: Pleural Fluid culture	**Pleural effusion** is excess fluid that accumulates in the pleural cavity, the fluid-filled space that surrounds the lungs.	Negative or positive (-1, 1)
C30: Mantoux	The **Mantoux test** is a diagnostic tool for tuberculosis.	Negative or positive (-1, 1)
C31: Gram stain (gram (+) gram (-)	**Gram staining** is used to differentiate bacterial species into two large groups (Gram(+) and Gram(-)) based on the chemical and physical properties of their cell walls.	Positive or negative
C32: Urinary antigen test	Urinary antigen test for detection Streptococcus pneumoniae and Legionella pneumophilla.	Positive or negative
C33: Sensitivity of pathogen – no of resistances	**Antibiotic resistance** is the ability of a microorganism to withstand the effects of antibiotics.	Three discrete values (Resistant, sensitive, intermediate)
D1: Severity of infection	The degree of severity of pulmonary infection	Four fuzzy values (low, moderate, med. Severe, severe)

Some fuzzy sets of the input variables as well as the fuzzy sets of the output decision concept D1 are illustrated in the following Table 2.

Table 2: Fuzzy sets describing “dyspnea” concept



The 34 identified concepts (Table 1) keep relations with each other, in order to characterize the process of assessing infectious diseases and to provide a first front-end decision about the prediction of pulmonary infection. After the determination of fuzzy sets, each expert was asked to define the degree of influence among the concepts and describe their interrelationship using an IF—THEN rule.

To illustrate how numerical values of weights are produced, the experts' suggestions indicate the interconnection between concept C_4 (fever) and decision concept D1 (severity of infection)) at the next example:

1st expert:

IF a small change occurs in the value of concept C_4, THEN a medium change in value of concept D1 is caused. *Infer:* The influence from C_4 to D1 is positive medium.

2nd expert:

IF a small change occurs in the value of concept C_4, THEN a small change in value of concept D1 is caused. *Infer:* The influence from C_4 to D1 is positive weak.

3rd expert:

IF a very small change occurs in the value of concept C_4, THEN a very small change in value of concept D1 is caused. *Infer:* The influence from C_4 to D1 is positive very weak.

Using the SUM technique the above three linguistic weights (medium, weak, very weak) are aggregated. Then the "centroid" defuzzification method is implemented to calculate the numerical value of the weight. The crisp weight of 0.32 has been produced and assigned to this interconnection.

The same approach was used to determine all the weights of the FCM. A weight matrix **E** gathering the initially suggested weights of all the interconnections among the concepts of the FCM model was produced. This weight matrix **E** is used in the simulation process of FCMs, constituting an essential part in the inference process. Fig. 2 illustrates the FCM model for predicting pulmonary infection with the numerical values of weights.

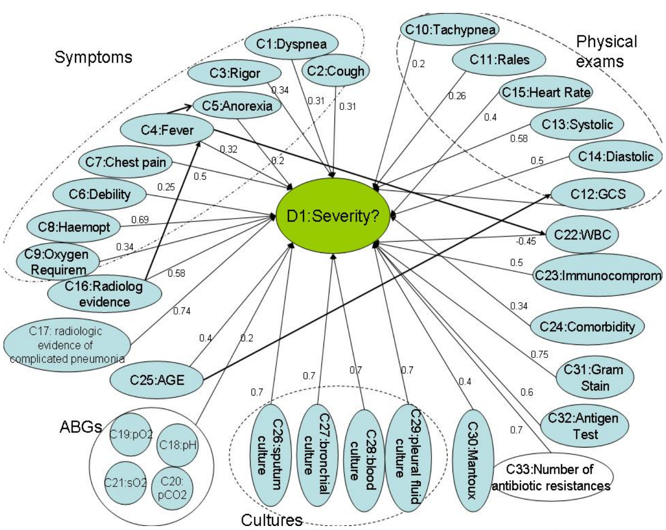


Figure 2. The FCM model for predicting the severity index of pulmonary infection

This is the first step in the development of an expert system module that will help in the decision making process, through the design of the knowledge representation and the design of reasoning with FCM to automate the decision making process.

III. Simulations and Results

After construction of FCM tool for the approach of assessing infectious diseases, a number of scenarios have been introduced and the decision making capabilities of the technique will be presented by simulating these scenarios and finding the predicted outcomes according to the available data.

In each of the test scenarios we have an initial vector Ai, representing the presented events at a given time of the process, and a final vector **A_f**, representing the last state that can be arrived at.

For the interpretation of the results, an average only for the output value of the decision concept D2 is computed according to the following criteria:

$$R(x) = \begin{cases} 0, x \le 0.5 \\ \dfrac{x-0.5}{0.5} \times 100\%, x > 0.5 \end{cases} \qquad (3)$$

where 0 represents the characteristic of the represented process by the concept is null, and 1 represents, the characteristic of the process represented by the concept is present 100%. The final value of decision concept applying this criterion is denoted by **AD_f**. This criterion can be modified according with the expert judgment.

The algorithm used to obtain the final vector **A_f** (where the last value of vector is the value **AD_f**) is the following:

(1) Definition of the initial vector *Ai* that corresponds to the elements identified in Table 1.

(2) Multiply the initial vector *Ai* and the matrix **E** defined by experts, as indicated in the previous section.

(3) The resultant vector is updating using Eqs. (1)–(2).

(4) This new vector is considered as an initial vector in the next iteration.

(5) Steps 2–4 are repeated until $\mathbf{A}^{t} - \mathbf{A}^{t-1} \le e = 0.001$.

The FCM performance is illustrated by means of simulation of the two scenarios in case of medium risk and high risk of pulmonary infection.

First Scenario: For this scenario, an immunocompromised patient (A_{23}=1) has been considered, with high Fever (A_4=0.7), loss of appetite (A_5=1), high systolic blood pressure (A_{13}=0.7), with radiologic evidence present in chest x-rays (A_{16}=1) and small number of WBCs (A_{22}=0.4), and negative sputum culture (-1) and negative antigen (-1). Thus the initial concept vector is: **A**=[0 0 0 0.7 1 0 0 0 0 0 0 0 0.7 0 1 0 0 0 0 0 0 0.4 1 0 0 -1 0 0 0 0 0 -1 0 0].

After FCM inference, the system converges at the thirteen simulation step as in the following state vector named final concept vector:

A1_f=[0 0 0 0.7000 0.7163 0 0 0 0 0 0 0 0.7000 0 0 1.0000 0 0 0 0.7660 0 0.4000 1.0000 0 -1.0000 0 0 0 0 0 -1.0000 0 0.8427].

The calculated value of decision concept (C34) is D1_f=0.8427, which following the above criterion in eq. (3) corresponds to the 68.54% of severity, thus means that the severity of infection is high according to the related fuzzy sets describing the decision concept of severity of infection.

Second Scenario: For this scenario, an old patient (A_{25}=0.8) has been considered, with low fever, with altered mental status (A_{12}=0.4), with high oxygen requirements

(A_9=0.8), and normal number of leukocytes-WBC (A_{22}=0), and positive sputum culture (A_{26}=1), negative blood culture (A_{28}=-1) and negative gram stain (A_{30}=-1). Thus the initial concept vector is **A**2=[0 0 0 0.3 0 0 0 0 0 0.8 0 0 0.4 0 0 0 0 0 0 0 0 0 0 1 0 0 0.8 1 0 -1 0 0 -1 0 0 0].

After FCM inference process the final concept vector is reached at 12 simulation steps:

A2_f=[0 0 0 0.3000 0.6845 0 0 0 0.8000 0 0 0.5596 0 0 0 0 0 0 0 0.7086 0 0 1.0000 0 0.8000 1.0000 0 -1.0000 0 0 -1.0000 0 0 0.7724]

The decision of the model is about the degree of severity. The final value of decision concept is D1_f=0.7724, which following the above criterion, corresponds to the 54.47% of severity risk, thus means that the severity of pulmonary infection is medium according to the related fuzzy sets.

If we continue with different scenarios, where random values have been selected and if more than eight nodes are stimulated initially, then the output value of decision concepts is approximately 0.90 which means that the calculated severity of pulmonary infection is above 90%, thus means that all those cases have a severe mode of pulmonary infection. This is a system limitation in this approach and in future work we will direct our research in order a more advanced process based on FCM tool predicts the severity of infection with no this limitation in the number of initially stimulated concepts.

The analysis of these cases leads to the sophisticated evaluation of diverse possible causes and to the assumption of preferences within the space of concepts. Should we consider (while making diagnosis) causes common for all symptoms that are weakly activated or the other with strong activation level? However, our preliminary experiences shows that it is much easier for a doctor to find even few mutually independent causes but strongly associated with the observed symptoms, than a single common cause of all symptoms. This is enhanced by the use of FCMs.

We have tested our system using data taken from real medical cases. Unfortunately, the presentation of the set of all contributed parameters and the entire FCM decision support module fall out beyond the scope of this paper. Therefore we decided to present only a part of it as in the Fig. 2. Some limitations of the FCM-DSS could be: (a) If not enough information-knowledge is available, the approach could not be more efficient than other decision making methods and should be complemented by other methods, and (b) the outcomes may be dependent on the attentiveness of the analysts about the knowledge extraction methods.

IV. Conclusion

The computational intelligent approach used in this work focuses on fuzzy cognitive map technique for the estimation of medical outcomes and resource utilization. The decision support system of FCM was designed with a view to help medical and nursing personnel to assess patient status, assist in making a diagnosis, and facilitate the selection of a course of therapy. In the presented research, we have proposed the FCM model for medical decision support for the process of predicting infectious diseases. The presented solution has been raised by some of the requirements imposed by the targeted application: the causal association of disease symptoms, signs, laboratory tests, that seem to be crucial for the right medical diagnosis. We have also sketched in this paper the exemplary problem of medical diagnosis and its simulation using the proposed solution.

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