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Dental Caries Degree Detection based on Fuzzy Cognitive Maps and Genetic Algorithm

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Abstract—**Dental caries is the most common infectious disease in humans, which affects 97% of the population in their lifetimes. In this article, fuzzy cognitive maps (FCMs) are applied to classify patients in terms of their personal risk of dental caries. Two approaches are discussed for developing FCMs. At first, causal relations between concepts and their weights are defined based on the domain experts. Then, these causal weights are determined by means of the real-coded genetic algorithm (RCGA) and historical data, without the intervention of experts. These two FCMs have been compared by categorizing 86 sample patients into two classes: 'carious' and 'healthy'. Although the conventional FCM has successfully categorized 67.44% of the cases in correct classes, the RCGA based FCM hits the 83.72% correct classification rate. Results show the efficiency of RCGA based FCM in comparison with the conventional FCM.**

Keywords-fuzzy cognitive maps; dental caries; real-coded genetic algorithm; patient classification

I. Introduction

The most efficient way of dental caries diagnosis is the clinical examination [1]; which requires the patient to refer to the dentist. This mostly happens when the sufferer feels intense dental pain. In the proposed research, a medical decision support system is developed; where patient is able to submit required information about his/her status and see the degree of being affected by the tooth decay. Moreover, some clinical guidelines are proposed for the treatment or prevention.

In order to construct this medical decision support system, fuzzy cognitive maps (FCMs) are used. Dental caries is a multifactorial dental disease, where these factors and their severity of influence on each other could not be limited into few number of rules and guidelines [2, 3]. Furthermore, dentists' opinions about some of these relationships between factors, may vary noticeably. On the other hand, by merging the concepts of the neural networks and fuzzy logic, FCM is an efficient method for modeling and analysis of the complex and dynamic systems. They are also able to eliminate the disagreements between experts' opinions about an issue, to a certain extent [4].

Recently, FCMs were applied in the numerous variant domains, such as medicine [4, 5], quadrotor control [6], image processing [7, 8] and etc. In the medical domain, a good number of researches were conducted using FCMs for decision support, classification, diagnosis and prediction of various diseases [4]. Recently Amirkhani et al. [8], have presented a new method based on FCM and its evolutionary-based learning capabilities for classifying mammography images. A hybrid approach based on FCM and possibilistic fuzzy c-means clustering algorithm is proposed in [9] for categorizing celiac disease (CD). In [9], to improve FCM efficiency and classification capability, a nonlinear Hebbian learning (NHL) algorithm is applied for adjusting the FCM weights. In another study [10], grading CD is performed based on the combination of FCM and support vector machine. FCMs were also applied in classification and prediction of different types of cancer: FCM with active Hebbian learning (AHL) algorithm was used for classification of intraductal breast lesions, which was applied on the data from 86 patients in [11]. Authors of [12] described all concepts and the weights of connecting links between them based on interval type-2 membership functions. In the field of odontology, Anuradha and Uma [13] applied AHL-FCM in oral tumor grading. Also, FCM-based decision-making system was developed for selecting proper dental implant abutment [14]. Moreover, the authors of [15] employed FCM for assessing periodontal disease. In this research, our aim is to apply FCM, in conjunction with genetic algorithm, for categorizing patients based on the risk of dental caries. The goal here is to develop a virtual medical visiting system for patients who can input their information and get to know whether they are in need for visiting the physician in order to prevent dental caries, before feeling severe dental pain.

This paper is structured in the following way. Section II presents an overview of the medical background of the dental caries. Section III is a brief review about FCMs. Section IV also discusses about the real-coded genetic algorithm (RCGA). Section V presents the material used in this project. Section VI also extends the method which is been applied. Section VII is where the overall results are discussed. And finally, section VIII is dedicated to the conclusion.

II. Medical Backgraound

A. Dental Caries

Dental caries is a multifactorial disease, which is the interaction of three main factors including teeth, microbes on the teeth's surface, microbial flora, and the diet. At first, bacteria are accumulated in a specific place on the teeth, creating the bacterial plaque. Then, if there is fermentable carbohydrate in the diet, the bacteria, by fermentation, create

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lactic acid, which leads to the dissolution of the dental hard tissues.

When this dissolution becomes intense, the dental cavity is formed and the bacterium penetrates into the hard tissue, resulting in a lesion of caries. Therefore, caries is the reflection of previous or ongoing microbial activity in the biofilms, rather than being a disease [1].

B. Symptoms of the caries

Clinically, the caries lesions appear to be a white chalky spot, a sign of the current bacterial activity, or a brown spot indicating the previous bacterial activity. If the biofilm is removed from the teeth surface, the activity stops. Of course, a stopped lesion may re-activates and progresses; in order to prevent dental damage, the patient should have regular oral check-ups [1].

C. Medical diagnosis

The first way for diagnosing caries is the medical examination. Radiography is also a valuable supplement. In the clinical examination, a caries lesion, as mentioned, is in the form of a white or brown spot. In radiography, the image is observed as a radiolucent area.

In diagnosis of the decay, accurate examination may not reveal superficial dissolution, specially at occlusal surfaces. While radiography can detect caries lesions on both occlusal and proximal surfaces [1]. The basic problem in diagnosis is that the patient has to be present for examination and radiography. Due to the lack of patient's knowledge about his/her oral condition, going to the dentist often happens after the severe pain was felt in the dental area.

D. Caries factors

According to a systematic review study on dental caries in children, 106 factors were mentioned to have significant impact on the prevalence of caries [2]. But in general, factors affecting tooth decay, extended for all ages, can be summed up to 22 factors.

Microbiological changes in oral biofilms lead to a disruption of the balance between the process of demineralization and remineralization. This balance is affected by the salivary flow, fluoride exposure and other preventive behaviors, such as brushing [16]. Patients, especially those with a high risk of dental caries development, should reduce the volume and frequency of sugars and carbohydrates intake [17].

One of the important factors, is the flow of saliva. As the dryness of the mouth (Xerostomia) increases, it helps the dental caries development. As the salivary flow increases, the metabolism of the Streptococcus mutans, bacteria responsible for tooth decay, decreases. Cigarette smoking, narcotics, some of the calmative drugs and oral breathing [18] lead to the lower salivary flow. Chewing gum leads to an increase in the saliva.

The proposed model, in addition to these, considers the history of dental caries, both in patient and patient's family, due to the effect of these factors on the level of the dental caries [3]. In the research conducted by Rodrigues and Sheiham [19], on 650 cases, family income and living standards were mentioned among the important factors affecting the rate of dental caries.

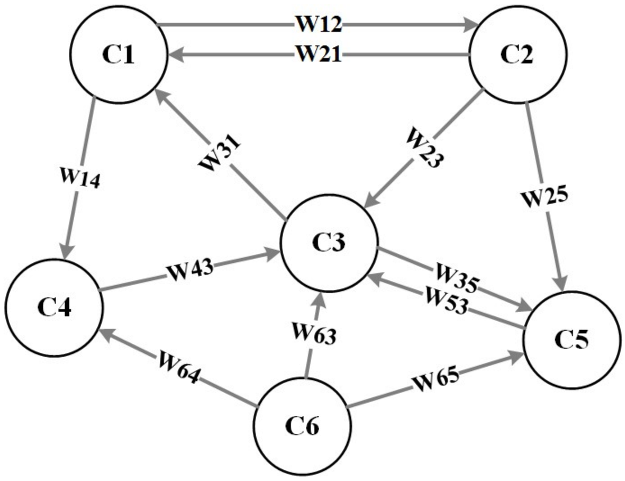

Figure 1. A simple FCM with 6 nodes and 12 edges

III. FUZZY COGNITIVE MAP

The FCM was first introduced by Kosko [20]. FCM is used for modeling a system by means of a set of nodes and edges between them. Nodes represent key concepts in the system and edges connecting them together are indicating the cause-effect relationship. The weight values of these connecting links are often normalized in the interval [-1, +1] and the values of concepts are usually in the interval [0, +1]. If the relationship between two concepts is inverse, the weight of the link is negative; if the relationship between them is direct, the weight value is positive. In a simple FCM, the definition of involving concepts, the relationship between them, the weight values and the initial state of the concepts are all defined by one or more domain experts.

Once the model is constructed, the concepts' values in every iteration is calculated using following equation:

$$A_i^{k+1} = f\left(A_i^k + \sum_{j=0, j\neq i}^{n} A_j^k W_{ji}\right) \tag{1}$$

Where A_i^{k+1} is the value of concept i in the iteration $k+1$, A_i^k is the value of concept i in the iteration k, A_j^k is the value of concept j in the iteration k and W_{ji} is the weight of the connecting link between these two concepts. The activation function f maps the input value into a specific interval [21]. Here the sigmoid function is used:

$$f_{sigmoid}(x) = \frac{1}{1+e^{-\lambda x}} \tag{2}$$

In this paper, considering the structure of the FCM and its convergence rate, we have considered $\lambda = 1$.

IV. REAL-CODED-GENETIC-ALGORITHM

One of the main disadvantages of the simple FCM model is the need for the experts, which takes time. Furthermore, experts' opinions may differ in terms of the relationship between concepts, which increases the difficulty of constructing the model.

The efficient solution for the mentioned problem is to use the optimization algorithms to determine the weights of relations, resulting in the elimination of the expert intervention [22]. The algorithms used so far include Hebbian-based algorithms, population-based evolutionary algorithms or a combination of them (hybrid) [4]. In [22] the authors have employed genetic algorithm to generate FCM models requiring only a single state vector as an input; resulting in elimination of human intervention. They have also shown the efficiency of RCGA in learning of various FCMs. Thus, RCGA is selected here in order to determine the weights matrix of the FCM.

A. The chromosome structure

In RCGA algorithm, every chromosome is a vector of decimal numbers; where the number of columns is equal to the number of drawable links. Assuming that no concept has relationship with itself, for an FCM with n concepts, the length of each chromosome equals to $n \times (n-1)$. Every array of the chromosome's vector is called a gene, where the amount of each gene is between -1 and +1. The structure of a chromosome here is as follows:

$$E = \left[w_{12}, w_{13}, \ldots, w_{n.n-1} \right] \tag{3}$$

Where w_{ij} is the weight of the relationship link between concept i and concept j.

B. Objective function

One of the most essential parameters related to the successful implementation of the genetic algorithm is the appropriate objective function. In the FCM-related applications, all the cost functions have a common property: they are an extension of the subtraction between the value of a concept, based on the dataset, and the value of that concept, obtained by the random weights. In fact, when the result of this subtraction tends to zero, the implemented FCM model with random weights (the candidate FCM) mimics the input data. The proposed fitness function is as follows:

$$fitness - function = \sum_{n=1}^{M} \left| \hat{A}_n - A_n \right|^2 \tag{4}$$

Where A_n is the value, obtained from the candidate FCM, for a specific concept (here, the concept of dental caries). $\hat{A}_n$ is the value for that concept obtained from the dataset and M is the number of records available in the dataset.

V. MATERIAL

The data is obtained from 86 patients. They were asked to answer questions related to the concepts affecting the level of dental caries. The responses were used as the initial values of the concepts. The examiner dentist was then asked to provide the result of the medical examination in forms of two conditions: "healthy" or "carious". "Healthy" means that the patient had 0, 1 or 2 cases of tooth decay. On the other hand, "carious" reveals that the number of tooth decay cases was 3 or more, per patient.

People in "healthy" condition, do not need to visit the dentist, they just have to keep the track of the certain check-up to monitor their teeth status. Those who are located in "carious" condition, have to visit the dentist as soon as possible, in order to prevent the development of their caries. The result of the medical examination on the 86 patients was 41 "carious" cases and 45 "healthy" ones.

VI. METHOD

Factors affecting caries include the amount of consuming sugar, the flow of saliva and etc. Some factors have indirect effect on dental caries, such as dental floss. These factors affect oral hygiene, which is itself a key factor affecting dental caries level. For this reason, the multi-layered FCM model, known as ML-FCM, was applied to represent this system. ML-FCM is composed of a main FCM where our goal concept (here, dental caries) is located in, and one or more lower branches, called leaves. Leaves add more levels of details to the concepts located in the immediate higher layer [23, 24].

In this model, in addition to the characteristics of the patient lifestyle, personal and familial backgrounds are also included. In the researches related to the FCMs in the medical field, few articles investigated the patient's personal-familial history [4].

A. The conventional FCM model

To construct the FCM model based on the experts' knowledge, first step is to determine the relationships between concepts, their direct or reversal effect and the weight values. Thus, three dentists are first asked to identify the relationships between concepts and to determine whether these links are direct or reverse. Then, in order to determine the weight values of the relationships, they are requested to describe the impact of concepts on each other, in terms of linguistic variables and IF-THEN rules. To describe these relationships, the terms "very high", "high", "medium", "low" and "very low" were used. For

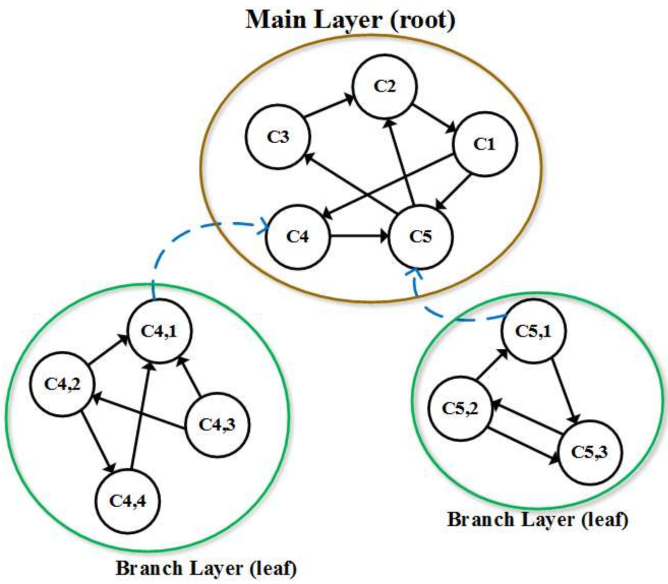

Figure 2. An example of ML-FCM structure

example, one of these rules is described as follows: If the amount of sweet consumption (C4) increases slightly (low), then the caries level (C9) will increase significantly (high).

In the next step, the words used by experts for each relationship are extracted and fuzzified through the membership functions. Then, the numerical value representing the weight of the relationship is de-fuzzified using the center of area (CoA) method. For example, the effect of concept C4 on concept C9 was answered by three experts like this:

According to the first expert, C4 has a "high" impact on C9; by the inference of the second expert, C4 has a "medium" effect on C9; and from the third one this effect is "very high" between C4 and C9. These three linguistic terms were aggregated and by applying CoA, the final numerical value was obtained and assigned to the w_49 weight value. This way, all the weights of the relations between concepts were extracted and the final FCM model was created.

B. The data-driven FCM model

In this model, in contrast with the previous model, the intervention of the domain experts is eliminated. Instead, the historical data is used to obtain the weight values. For applying RCGA, we must consider each layer of the FCM fully connected. Meaning that, all concepts are considered to have relationships with each other, except each concept on itself ($w_{ii} = 0$). After each iteration, the cost function is calculated with the new random population. Finally, the best chromosome is identified, which is the vector representing the optimum weight values for the FCM model.

VII. RESULTS

The FCM model, constructed to model the experts' knowledge, is applied on the dataset. The output of the grading system is extracted in a specific iteration, before the final convergence is reached. The best iteration to terminate the algorithm is selected considering the best accuracy. In Fig.4, blue circles indicate the "healthy" cases and the red squares represent "carious" cases. After mapping the cases into the new space, a threshold is needed to accomplish the classification. The chosen threshold must result in the lowest possible false-positive rate (FPR) and false-negative rate (FNR), which are the important benchmarks assessing the accuracy of the proposed medical decision system.

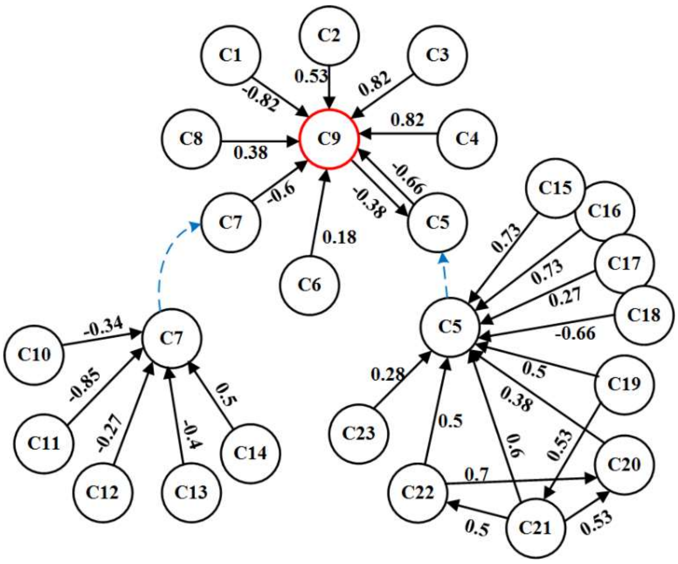

Figure 3. Final conventional FCM

TABLE I. DENTAL CARIES RISK FACTORS

Concept	Feature	Concept	Feature
C_1	Teeth gap	C_{13}	Calmative drugs
C_2	Historical caries	C_{14}	Chewing-gum
C_3	Soda	C_{15}	Brush frequency
C_4	Sweets	C_{16}	Floss
C_5	Dental hygiene	C_{17}	Fluoride
C_6	Spots on teeth	C_{18}	Brush time
C_7	Flow of saliva	C_{19}	Family education
C_8	Historical family caries	C_{20}	Living standards
C_9	Dental caries	C_{21}	Education
C_{10}	Oral breathing	C_{22}	Income
C_{11}	Salivary poverty	C_{23}	Fruits, veg and dairies
C_{12}	Cigarette		

The most efficient decision boundary to achieve the best accuracy is $T = 0.742$. According to T, in Fig. 4, true-positive rate (TPR) and specificity are 60.98% and 73.33%, respectively. Therefore, the TPR, which is the probability of detecting dental caries, finds out 60.98% of the cases who have the "carious" condition and misses the other cases. Table II represents confusion matrix, sensitivity and specificity of the FCM model, known as the truth table.

The data-driven FCM is then investigated. Because of the size of the dataset, leave-one-out cross-validation method (LOO-CV) is employed to evaluate the accuracy of the final model. According to this method, all cases are used to train the FCM model except one, which is then used as the test case. The LOO-CV method is repeated for all cases and the result is presented in Table II, indicating the reasonable accuracy of the system.

Due to the structure of the ML-FCM, RCGA algorithm is first used to define weight values in every leaf, separately. At last, the weight values of the root FCM are calculated. After these steps, FCM is applied on the dataset and the result is shown in Fig. 5. The most efficient threshold is defined as $T = 0.48$. Based on this threshold, sensitivity and specificity are

TABLE II. TRUTH TABLE OF THE CONVENTIONAL FCM MODEL

Conditions	Healthy	Carious	Accuracy (%)
Healthy	33	12	73.33
Carious	16	25	60.98

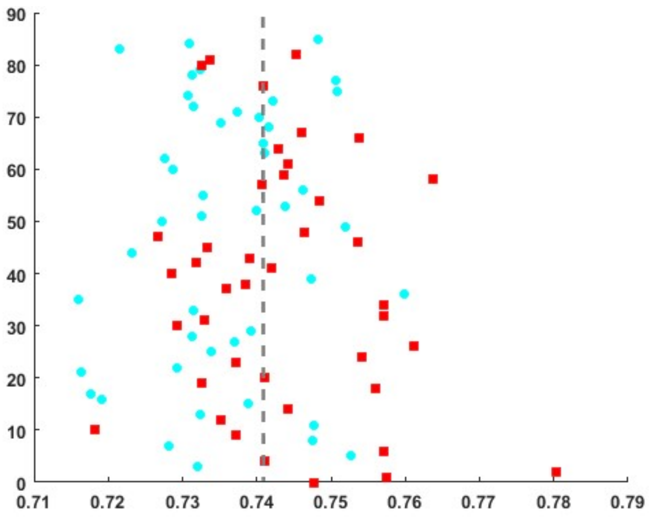

Figure 4. The result of the conventional FCM on 86 samples

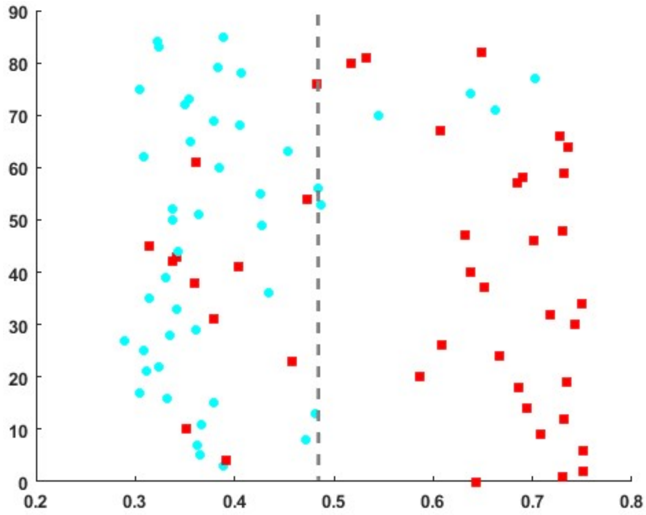

Figure 5. The result of the RCGA-FCM on 86 samples

equal to 75.61% and 91.11%, respectively. Table III reveals the higher TPR and specificity of the RCGA-FCM compared to the conventional FCM model.

Another important criterion for comparing the system performance of the proposed models is the receiver operational characteristic (ROC) curve. The ROC curve is achieved by moving the classification threshold throughout the model, explaining sensitivity changes versus specificity. The area under curve (AUC) is the parameter for measuring the system's reliability in correct classification of the dental caries cases [10].

Fig. 6 illustrates the ROC plots of the RCGA-FCM, conventional FCM and the random classification system, where the AUC is equal to 0.87, 0.67 and 0.5, respectively. Higher AUC of the RCGA-FCM compared to the two other systems, is a sign of the performance efficiency, which means this model is more reliable for categorizing the dental caries degree of the new patient case. It is worth mentioning that the length of the classification interval, where the dental caries concept falls, plays a very important role in determining system efficiency. The larger interval length expresses better differentiation of the grades. The RCGA-FCM model reveals a large interval in comparison with the conventional FCM model, stating higher accuracy and validity of the former model, regarding the convergence of the goal concept values in the new space.

VIII. CONCLUSION

The results of this study revealed that using RCGA algorithm led to a reasonable higher accuracy, nearly 16%, compared to the regular FCM model constructed by the experts' knowledge. Moreover, using this algorithm eliminated the intervention of the mentioned domain experts, resulting in simpler and easier model construction process. Although the dataset records are not adequate, the model classification accuracy is satisfactory. Extending the dataset to more records, will result in more efficient accuracy. Hence, we can improve the FCM by including more variables. Taking into consideration the radiographic images, some variables could be extracted, by means of the image analysis methods. Thus, the FCM model will become more comprehensive and extendable to the new patient cases.

TABLE III. TRUTH TABLE OF THE RCGA-FCM MODEL

Conditions	Healthy	Carious	Accuracy (%)
Healthy	41	4	91.11
Carious	10	31	75.61

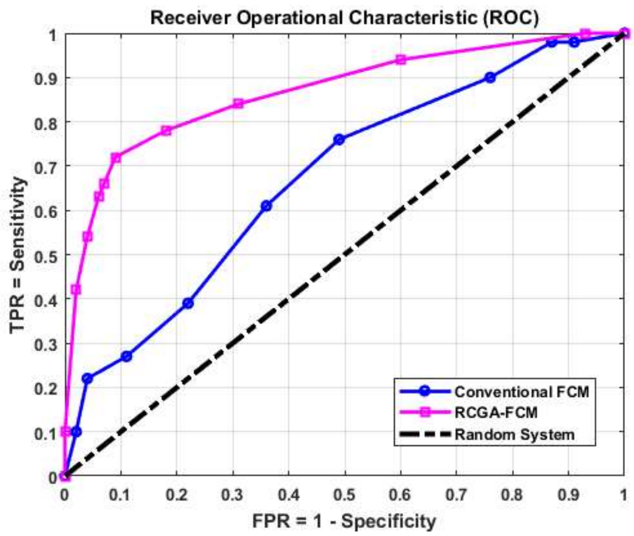

Figure 6. The ROC plot of the proposed models

REFERENCES

[1] S. C. White and M. J. Pharoah, *Oral radiology: principles and interpretation*.

[2] R. Harris, A. D. Nicoll, P. M. Adair, and C. M. Pine, "Risk factors for dental caries in young children: a systematic review of the literature.," *Community Dent. Health*, vol. 21, no. 1 Suppl, pp. 71–85, Mar. 2004.

[3] O. Chankanka *et al.*, "Longitudinal associations between children's dental caries and risk factors.," *J. Public Health Dent.*, vol. 71, no. 4, pp. 289–300, 2011.

[4] A. Amirkhani, E. I. Papageorgiou, A. Mohseni, and M. R. Mosavi, "A review of fuzzy cognitive maps in medicine: Taxonomy,

methods, and applications," *Comput. Methods Programs Biomed.*, vol. 142, pp. 129–145, 2017.

[5] A. Amirkhani, M. R. Mosavi, A. Naimi, "Unsupervised Fuzzy Cognitive Map in Diagnosis of Breast Epithelial Lesions," *in Proc. IEEE, 22nd Iranian Conference on Biomedical Engineering (ICBME 2015),* Tehran, Iran, pp. 111-115, 2015.

[6] A. Amirkhani, M. Shirzadeh, E. I. Papageorgiou, M. R. Mosavi, "Visual-based quadrotor control by means of fuzzy cognitive maps," *ISA Transactions*, vol. 60, pp. 128-142, 2016.

[7] M. Kolahdoozi, A. Amirkhani, M Maroufi, "Fuzzy cognitive maps and a new region growing algorithm for classification of mammography images," *in Proc. IEEE, 24th national and 2nd International Iranian Conf. on Biomedical Engineering (ICBME)*, Iran, 2017.

[8] A. Amirkhani, M. Kolahdoozi, E. I. Papageorgiou, M. R. Mosavi, "Classifying mammography images by using fuzzy cognitive maps and a new segmentation algorithm," DOI: 10.1007/978-3-319-77911-9_6, *Advanced Data Analytics in Health, Smart Innovation,* 2018.

[9] A. Amirkhani, M. R. Mosavi, E. I. Papageorgiou, K. Mohammadi, "A novel hybrid method based on fuzzy cognitive maps and fuzzy clustering algorithms for grading celiac disease," *Neural Computing and Applications*, DOI: 10.1007/s00521-016-2765-y, 2016.

[10] H. Nasiriyan-Rad, A. Amirkhani, A Naimi, K. Mohammadi, "Learning fuzzy cognitive map with PSO algorithm for grading celiac disease," in Proc. IEEE, *23rd Iranian Conference on Biomedical Engineering and 1st International Iranian Conference on Biomedical Engineering (ICBME),* 2016.

[11] A. Amirkhani, M. R. Mosavi, S. B. Shokouhi, F. Mohammadizadeh, "A novel fuzzy cognitive map based method for the differentiation of intraductal breast lesions," *in Proc. IEEE, 5th International Conference on BioMedical Engineering and Informatics (BMEI)*, China, pp 6-11, 2012.

[12] A. Najafi, A. Amirkhani, E. I. Papageorgiou, M. R. Mosavi, "Medical decision making based on fuzzy cognitive map and a generalization linguistic weighted power mean for computing with words," *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, 2017.

[13] K. Anuradha and K. P. Uma, "Histological grading of oral tumors using fuzzy cognitive map," vol. 10, no. 4, pp. 1695–1700, 2017.

[14] S. Lee, J. Yang, and J. Han, "Development of a decision-making system for selection of dental implant abutments based on the fuzzy cognitive map," *Expert Syst. Appl.*, vol. 39, no. 14, pp. 11564–11575, Oct. 2012.

[15] V. K. Mago, E. I. Papageorgiou, and A. Mago, "Employing fuzzy cognitive map for periodontal disease assessment," Springer, Berlin, Heidelberg, pp. 375–389, 2014.

[16] R. H. Selwitz, A. I. Ismail, and N. B. Pitts, "Dental caries," *Lancet*, vol. 369, no. 9555, pp. 51–59, Jan. 2007.

[17] S. U. Maheswari, J. Raja, A. Kumar, and R. G. Seelan, "Caries management by risk assessment: A review on current strategies for caries prevention and management.," *J. Pharm. Bioallied Sci.*, vol. 7, no. Suppl 2, pp. S320-4, Aug. 2015.

[18] S. F. Bakor, J. C. M. Pereira, S. Frascino, T. C. C. G. Ladalardo, S. S. N. Pignatari, and L. L. M. Weckx, "Demineralization of teeth in mouth-breathing patients undergoing maxillary expansion," *Braz. J. Otorhinolaryngol.*, vol. 76, no. 6, pp. 709–712, Dec. 2010.

[19] S. Rodrigues and A. Sheiham, "The relationships between dietary guidelines, sugar intake and caries in primary teeth in low income Brazilian 3-year-olds: a longitudinal study.," *Int. J. Paediatr. Dent.*, vol. 10, no. 1, pp. 47–55, Mar. 2000.

[20] B. Kosko, "Fuzzy cognitive maps," *Int. J. Man. Mach. Stud.*, vol. 24, no. 1, pp. 65–75, Jan. 1986.

[21] S. Bueno and J. L. Salmeron, "Benchmarking main activation functions in fuzzy cognitive maps," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 5221–5229, Apr. 2009.

[22] W. Stach, L. Kurgan, W. Pedrycz, and M. Reformat, "Genetic learning of fuzzy cognitive maps," *Fuzzy Sets Syst.*, vol. 153, no. 3, pp. 371–401, Aug. 2005.

[23] A. Christoforou and A. S. Andreou, "A framework for static and dynamic analysis of multi-layer fuzzy cognitive maps," *Neurocomputing*, vol. 232, pp. 133–145, 2017.

[24] N. Mateou, A. S. Andreou, C. Stylianou C, "A new traversing and execution algorithm for multilayered fuzzy cognitive maps," *IEEE World Congress on Computational Intelligence*, pp. 2216-2223, 2008.