A Fuzzy Cognitive Map learning approach for coronary artery disease diagnosis in Nuclear Medicine

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Abstract. Coronary artery disease (CAD) is the primary cause of death and chronic disability, among cardiovascular conditions worldwide. Its diagnosis is challenging and cost-effective. In this research work, Fuzzy Cognitive Maps with Particle Swarm optimization (called FCM-PSO) were used for CAD classification (healthy and diseased).. In particular, a new DeepFCM framework, which integrates image and clinical data of the patients is proposed by employing the FCM-PSO method enhanced by experts' knowledge along with an efficient attention Convolutional Neural Network to improve diagnosis. The proposed method utilizes 571 CAD instances and achieved 77.95±5.58 accuracy, 0.22±0.05 loss, 76.98±8.27 sensitivity, 77.39±7.13 specificity and 73.97±0.09 precision, implementing a 10-fold cross validation process. The results extracted from the proposed model demonstrate the model's efficiency which outperforms traditional machine learning algorithms. An essential asset of the proposed Deep-FCM framework is the explainability as it offers nuclear physicians meaningful causal relationships between clinical symptoms and the diagnosis, helping them in decision-making regarding CAD.
Keywords: Fuzzy Cognitive Maps, Particle Swarm Optimization, Classification, Coronary artery disease.

1 Introduction

Obstructive Coronary Artery Disease (CAD) is the most frequent type of cardiovascular disease, and it occurs when at least one of the coronary arteries are blocked, which leads to the reduction of blood inserting into the myocardium, causing stenosis. CAD is a life-threatening disease. It requires early appropriate diagnosis and treatment to improve a patient's condition and deflect death. Consequently, it is crucial to detect the existence of stenosis and the danger of its advancement [1].

With respect to the previous studies regarding Fuzzy Cognitive Map (FCM) implementation for medical data classification, the following research studies have been analyzed. Papageorgiou et al in [2] developed a FCM model for brain tumor characterization utilizing the Activation Hebbian Algorithm, which utilizes initial experts' knowledge. The proposed model defines the degree of tumor abnormality, with only qualitative data as input. The model achieved 90.26% and 93.22% accuracy for brain tumor of low-grade and high-grade, accordingly and outperformed other intelligent techniques. Nasiriyan-Rad et al. in [3] presented a new method for grading Celiac disease (CD) with the combination of FCM and Support Vector Machine (SVM), with Particle Swarm Optimization (PSO) for enhancing the results. The performance of the proposed model was compared against the fuzzy rule-based Bayesian Networks (BN), where FCM-SVM model performed better achieving accuracy of 87%, 86% and 8% for each of three possible CD grades. Papageorgiou et al. in [4] introduced a new approach for FCM learning, utilizing ensemble-based learning approaches, which is based on non-linear Hebbian learning (NHL) for autism classification. The proposed model outperformed in contrast to FCM models that support their training procedure on Hebbian-based learning algorithms, with 89.41% accuracy while data driven NHL extracted 79.62%. Papageorgiou et al. in [5] presented FCMs for decision making in medical domain, regarding thyroid diagnosis. The developed model achieved 89.80% accuracy, regarding thyroid diagnosis. Carvajal et al in [6] aimed to develop a General Type (GT2) Fuzzy Logic (FL) classifier for pulse levels and optimize the general type-2 membership functions parameters with the usage of Ant Lion Optimizer a metaheuristic algorithm. The dataset includes 4240 patients acquired from the Framingham Database and the hold out method is applied for the splitting of training and testing data. The GT2 FL classifier outperforms with average 99% accuracy for all experiments than interval-type-2 and type-1 fuzzy classifiers. Guzman et al in [7] aimed to develop a type-2 fuzzy system with triangular membership for the classification of blood pressure. The model attained 99.408% classification rate with type-2 fuzzy system utilizing triangular membership functions, where the type-1 classifier in previous study reached 98%. Miramontes et al in [8] proposed a dynamic parameter adaptation with the inclusion of the Bird Swarm algorithm (BSA) based on type-2 fuzzy systems. The proposed model achieved 97% classification accuracy and performed better compared to other methodologies. Hoyos et al in [9] proposed a clinical decision-support system based on Fuzzy Cognitive Maps architecture to classify patients that suffer from dengue. The developed model compared to other machine learning approaches and outperformed with 89.4% accuracy, while providing analysis of factors and explainability of decision of results.

The contribution of this research is the development of a DeepFCM model utilizing Particle Swarm as an optimization technique for the provision of an automatic classification tool that diagnoses CAD non-invasively and is based on both image and clinical risk factors. The classification problem is two-class, and it is devoted to the presence of CAD. The added value of this research is the proposal of an explainable tool that provides interpretability, which is an important factor in sensitive areas like healthcare, compared to machine learning approaches, where they are known as "black boxes". The FCM presents analysis of relationships among features, where we can detect signs of CAD before the clinical diagnosis and recommend precautionary treatment to avoid complications and mortality [9].The results show our model's high consistency and robustness, denoting that the proposed model can be adjusted in nuclear medicine domain and assist in decision making, as far as CAD diagnosis is concerned.

2 Material and Methods

2.1 CAD dataset

The corresponding dataset consists of 571 instances, where 248 cases are classified as pathological and 323 are as normal. Of the total dataset, 79.68% were male and regarding patients' age, they ranged from 32 to 90. Concerning Body Mass Index (BMI) is in spectrum of 16.53, which falls into underweight category to 87.2 which is categorized as extremely obese.

The patients underwent gated-SPECT-MPI (Single Photon Computed Tomography-Myocardial Perfusion Imaging) and Invasive Coronary Angiography (ICA) after 60 days of MPI procedure. This process shapes a patient's status regarding the CAD diagnosis and the result is utilized as ground truth in our study.

The dataset of this study was obtained from the Clinical Sector of the Department of Nuclear Medicine of the University Hospital of Patras from 16/2/2018 to 28/02/2022. Dataset acquisition is authorized by the ethical committee of University Hospital of Patras. All patients were given authorization for their results to be obtained anonymously. The performed methods agree with the Declaration of Helsinki.

The available dataset contains information about patient's status like age, sex, BMI, and furthermore medical characteristics like diabetes, previous CAD condition, etc. The features used as input by FCM classification model, after binary normalization are twenty-two: (1) Sex, (2) Age, (3) BMI, (4) known CAD,(5) previous AMI, (6) previous PCI, (7) previous CABG, (8) previous STROKE, (9) Diabetes, (10) Smoking, (11) Hypertension, (12) Dyslipidemia, (13) Peripheral Angiopathy, (14) Chronic Kidney Disease, (15) Family History of CAD, (16) Asymptomatic,(17) Atypical Symptoms, (18) Angina-like, (19) Dyspnea on Exertion, (20) Incident of precordial pain, (21) ECG, and (22) Preliminary Expert Diagnosis.

Furthermore, polar map images were used for CAD diagnosis, implementing an efficient VGG method, which provides an output, called CNN prediction.

2.2 Methodology

2.2.1 Fuzzy Cognitive Maps

FCMs were introduced by Kosko [10] in 1986 and they are an advanced version of cognitive maps. Cognitive maps contain a typical system with set of nodes/concepts and connections between the concepts that describe cause and effect relationships. In the interest of overcoming the binary logic, Kosko developed FCMs, evolved versions of CMs, which consist of fuzzy rules for the calculation of concepts. The FCM architecture which is similar to an Artificial Neural Network, is a soft computing tool that mimics the human process of making decisions [11] [2]. FCM utilizes all the accessible knowledge and translates it in the form of concepts and interconnections between them. Concepts represent the characteristics/states of the examined system whereas interconnections denote the cause-effect relationships with the rest of the concepts. Whether an interconnection has positive or negative value depends on the kind of connection. More specifically, the interconnections between the concepts are the weighted links of the FCM and are in the range [-1, 1] [2] [3].

In functional terms, FCM involves a set of concepts and a weight matrix. With reference to the links between the concepts, they display the direction and the effect of each node with the rest of the nodes. The connection can be positive or negative or have zero value. The construction of an FCM involves the definition of concepts and the equation of calculating the future values of concepts according to historical data. The fundamental equation for computing FCM concepts is eq. (1). To normalize the predicted value of concepts into a specific range, a transfer function is used. Generally, the sigmoid, or the trivalent function is preferred.

$$A_i^{(K+1)} = f\left(A_i^{(K)} + \sum_{i,j}^{N} w_{ij} A_j^{(K)}\right) \tag{1}$$

where, $A_i^{(K+1)}$ is the value of the concept iteration (k+1) and $A_j^{(K)}$ is the concept at the iteration k and *f* is the sigmoid function.

The strength of FCMs in general is that they consider the last state of each concept to calculate the future value. Regarding FCM learning, it is based on the construction of a weight matrix, utilizing unsupervised techniques with Hebbian adaptation, supervised with the inclusion of evolutionary algorithms and gradient methods. Well-known methods of FCM learning using historical data are RCGA and PSO.

2.2.2 Design of FCM model using experts' knowledge

The FCM model consists of 23 concepts which are clinical features, with one output regarding CAD presence, which consists of two classes, pathological and normal. The 22 input features indicate personal characteristics and clinical symptoms of patient status. All concepts' values have value 0 or 1, depending on whether they suffer from each disease, with the exception of Age and BMI, where their values are normalized and their values are rescaled into the spectrum of [0,1]. Nuclear Experts assigned linguistic values (represented by fuzzy sets) on the interconnections between inputs and output concepts. Table 1 gathers the fuzzy relationships among some of the most influential concepts with respect to the output. In particular, the following fuzzy sets were defined: very weak (VW), weak (W), medium (M), strong (S) and very strong (VS). For each linguistic value we assigned a specific range of values as it is reported in the literature [12], in order to perform FCM learning considering the respective ranges. For the fuzzy sets Very Weak (VW) and Weak (W) we determined the ranges to be [0 - 0.3] and [0.15 - 0.5] accordingly. Also, for Strong (S) and Very Strong (VS) we assigned the values to be randomly selected from [0.5 – 0.85] and [0.7 – 1] accordingly. Concerning the negative linguistic values, we adjusted the provided values according to the positive ones. For the rest of the relationships, where no experts' knowledge is provided, they take random values within the range [-1, 1].

Table 1. Presentation of extracted ranges for the relationship between input concepts with input concepts and with output obtained from nuclear experts.

Relationships	Assigned by experts	Relationships	Assigned by experts

Sex>>Output	M	Hypertension>>Output	M
		Dyslipidemia>>Output	M
AGE>>ECG	W	Angiopathy>>Output	M
BMI>>Output	W	Chronic Kidney Disease	W
Known CAD	S	Family History of CAD>>Output	W
previous AMI>>Output	VW	Asymptomatic>>Output	-S
previous PCI>>Output	W	Atypical symptoms>>ECG	VS
previous CABG>>Output	W	Atypical Symptoms>>ECG	M
Previous Stroke>>	M	Angina Like>>Output	S
Diabetes>>Output	S	Dyspnea on exertion>>Output	M
Smoking>>Output	M	Incident of precordial pain>>Output	M
		Expert_Diagnosis_Binary>>Output	VS

2.2.3 Learning FCM with Particle Swarm Optimization

Particle Swarm Optimization (PSO) [13] is an optimization methodology that was introduced in 1995 [3]. PSO utilizes a small number of parameters [3]. Regarding FCM learning, PSO is applied for the adjustment and calculation of relationships among the concepts. The definition of weight matrix, which consists of the relationships among all concepts is a crucial step and determines FCM's performance. The ideal state of the interconnections with output concepts is to rely within the suggested linguistic values provided by experts and also the produced weight matrix to be in a steady state. In general, PSO is utilized for the minimization of objective function by implementing the following steps. Initially a swarm of particles is being generated, where their values of position and velocities are assigned randomly and are evaluated from the objective function. The produced weight matrix of every particle is evaluated and if produces better results than the rest particles, velocity and position are updated. The weight matrix that globally minimizes the objective function of the corresponding particle is the winner particle [14]. Applying PSO to FCM learning improves FCM's performance and intensifies FCM ability to classify correctly. The application of PSO improves the FCM's ability to adjust the weight matrix correctly with optimization techniques, and as a result, FCM will not be supported only on historical data and bias related to bias will be avoided.

2.2.4 DeepFCM

In our model we added input predictions from image data representing CAD cases, to improve FCM's performance. For this reason, we trained an attention-based VGG19 network with the Polar Map images. This modified version includes attention blocks and branch-diverging (BD) paths to improve performance. The attention blocks aim to focus on important image regions during feature extraction by multiplying the features with a weight mask that highlights regions of interest. This is achieved by creating a small CNN that takes the features as input and outputs a mask that is then used to weigh the original features. The BD paths, on the other hand, aim to capture more diverse features by creating multiple branches that diverge from the main CNN path and then recombine the features later in the network. This helps the model to learn more complex patterns and improves its generalization capabilities. Finally, the model is trained to classify images into different categories using the categorical cross-entropy loss function and the Adam optimizer.

After making predictions on new images, the model's outputs are supplied to the FCM model. In this context, the FCM uses the predicted probabilities as input, along with clinical data, to make the prediction. By combining both imaging and clinical data, this approach provides a comprehensive and integrated approach to diagnosis, potentially improving accuracy and reducing the need for invasive tests.

Combining both predicted probabilities and clinical data, our proposed model named DeepFCM utilizes FCM methodologies and PSO as an optimization tool and Deep learning capabilities to correctly classify CAD cases. DeepFCM is an explainable method providing interpretability, clarification, and transparency of results to reduce complexity and scalability of other methods.

2.2.5 Methodological framework

This study aims to implement an FCM model, where PSO is applied as optimization technique with the usage of clinical and image data to classify CAD instances into pathological and normal and offer an automatic decision-making tool to nuclear medicine experts. In order to conclude to the final structure of our model a thorough exploration has been conducted with different techniques and various approaches for the initialization of weight matrix and for the overall methodology. Our proposed model DeepFCM has demonstrated remarkable performance and impressive capabilities, while providing interpretability and explainability.

With the acquired clinical data and prediction probabilities a transformed dataset has been generated. Data preprocessing techniques are applied for the normalization of values. For the stability and generability of results 10-fold cross validation is performed to the corresponding dataset. FCM utilized PSO as an optimization technique since its results are efficient with respect to??. With the application of PSO, along with the suggested linguistic values obtained from nuclear experts, the optimal weight matrix has been attained, which consists the produced interconnections among input-input and input-output concepts and the training procedure has been concluded. Regarding the testing dataset, the produced weight matrix is utilized and the predicted values from the DeepFCM framework are compared with the actual values of the output of the testing for the comparison metrics to be computed.

In Figure 1, we demonstrate the total process of our proposed methodological framework. The developed DeepFCM model is provided on GitHub [*https://github.com/AnnaFeleki/FCM-PSO-learning*].

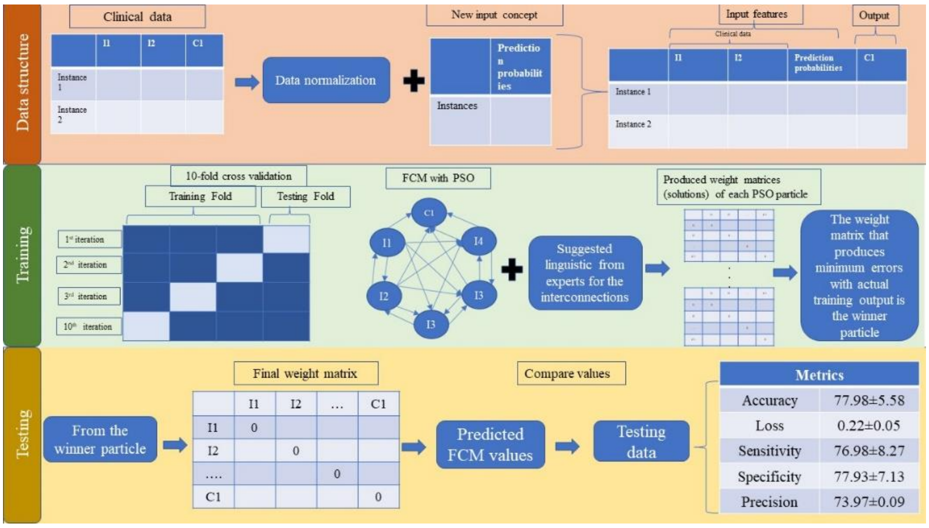


Fig. 1. Proposed methodological framework of our proposed model DeepFCM.

3 Results

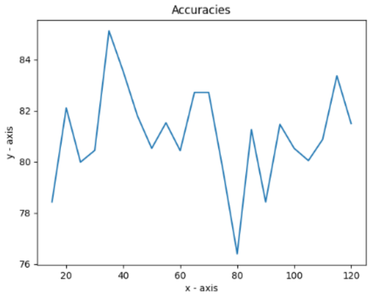
To conclude to the proposed architecture, various experiments were performed, and a comparison was conducted with different approaches regarding initial values for weight matrices. For comparison purposes, traditional machine learning algorithms were also applied to the provide dataset to evaluate each model's metrics. In all experiments 10-fold cross validation was performed, to confirm its consistency.

For model evaluation and performance testing, the selected metrics are accuracy, loss, sensitivity, specificity, and precision. Accuracy is the fraction between the correct instances with all instances. A small loss is desirable denoting a less huge deviation in predicted results, compared to actual values [14]. Sensitivity and specificity represent the percentage of true positives and true negatives, respectively [14]. Precision indicates the ratio of the number of true positives to the total number of positive predictions [15].

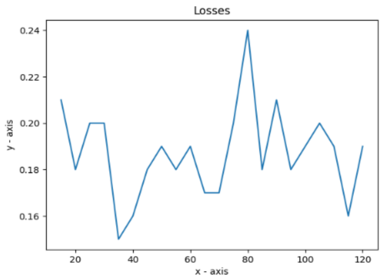
We followed the inspection of the equilibrium point's exact position, where the FCM presented a steady state by experimenting with different epochs. The epochs tested are in the range 15 to 120. The results regarding accuracy and loss for the examined number of epochs are depicted in Figure 2. It is observed that the best value for the epochs and the equilibrium point for the proposed FCM is 35, which is achieved in the position of the highest accuracy and the lowest loss.

Figure 2. Performance of proposed model with different epochs, regarding (a) Accuracy (b) Loss

(a) Accuracy



(b) Loss



The values of the performance metrics for the proposed FCM model, for each run, are illustrated in Table 3. The spectrum of the initial interconnections of concepts with the output was given by experts. The proposed ranges was inserted in the code while the weights matrices were initialized with the corresponding spectrum for each concept. The results concerning the most robust metrics were extracted after 10-fold cross validation is applied. It is concluded that the FCM model achieved sufficient performance, in terms of accuracy and sensitivity. For comparison reasons, the previous experiment was repeated, but this time, with randomly produced relationship between the input and output concepts, within the range [-1, 1]. The produced values of the same metrics are presented in Table 3. Additionally, for a further in-depth evaluation of the proposed model a comparative analysis has been made between the proposed FCM and robust machine learning algorithms such as Bayes, Random Forest, Decision Tree and Neural Network in their default specifications. Regarding Neural network architecture we experimented with different network configurations, for example number of nodes, number of layers, optimization algorithms, and activation functions. The optimal parameters of the final model were 3 three hidden layers with 16-32-64 nodes each layer, 16 batch size, Adam optimizer and sigmoid activation function. The extracted results are demonstrated in Table 3. The reason we developed machine learning algorithms for our dataset is to compare the metrics of methodologies that have demonstrated efficient performance on structure data.

Table 3. Comparison of results of FCM-PSO with traditional machine learning algorithms

Models	Accuracy	Loss	Sensitivity	Specificity	Precision
			Clinical Data		
FCM-PSO with random weights	72.9 ± 6.39	0.27 ±0.06	64.89 ±11.7	80.11±8.96	70.05±0.07
FCM-PSO with suggested weights	74.98±5.95	0.25±0.06	74.96±7.29	74.6±15.34	75.01±0.04

Clinical Data and polar map Images					
DeepFCM with suggested weights	**77.95±5.58**	**0.22±0.05**	**76.98±8.27**	**77.39±7.13**	**73.97±0.09**
DeepFCM with random weights	65.91±4.42	0.36±0.04	71.01±5.96	68.36±9.97	65.63±5.65
Bayes	75.45±5.57	0.24±0.05	81.26±5.29	69.54±8.28	78.51±0.07
Random Forest	78.87±3.42	0.22±0.03	74.26±5.46	83.37±5.48	76.43±0.05
Decision Tree	74.13±4.23	0.26±0.04	72.34±6.14	75.82±6.14	73.43±0.05
Neural Network	78.57±5.49	0.28±0.02	78.08±6.7	79.28±6.16	73.5±0.09

Comparing the results provided in Table 3, we conclude that the proposed DeepFCM model utilizing the weights suggested by experts outperforms the model that employed the random values considering the CNN output from trained model. In this case, the proposed DeepFCM model exceeded in terms of efficiency when utilizing historical data and additional knowledge from experts.

In Table 4, we gather the range of values for every relationship between input and output concept, that were i) suggested by nuclear experts, ii) produced from the DeepFCM learning approach with values suggested by experts, along with predicted probabilities. The first column demonstrates the suggested weights from experts for the connection of every input concept with the output, with the exception of some Nan values. On this occasion, a random value could be selected from the range [-1, 1]. The second column presents the produced weight for the interconnection between input and output concepts for the FCM learning model, whose initial values are provided from the suggested ranges displayed in the first column.

The weights produced from DeepFCM model utilizing experts' values of weights are close to the values suggested by experts, and do not present large deviation, with contrast to those interconnections randomly initialized as Nan, in which large deviations were observed.

Table 4. Presentation of extracted ranges for the relationship between input concepts and output produced from model with random weights and from model that utilized experts' opinions.

Suggested interconnections	Weights from experts	Produced weights by DeepFCM
Sex>>Output	[0.35-0.65]	[0.49±0.09]
Age>>Output	Nan	[-0.35±0.39]
BMI>>Output	[0.15-0.5]	[0.3±0.11]
known CAD>>Output	[0.5-0.85]	[0.66±0.07]
previous AMI>>Output	[0-0.3]	[0.16±0.08]
previous PCI>>Output	[0.15-0.5]	[0.32±0.12]
previous CABG>>Output	[0.15-0.5]	[0.29±0.09]
previous STROKE>>Output	[0.35-0.65]	[0.47±0.1]

Diabetes>>Output	[0.5-0.85]	[0.69±0.11]
Smoking>>Output	[0.35-0.65]	[0.49±0.07]
Hypertension>>Output	[0.35-0.65]	[0.48±0.1]
Dyslipidemia>>Output	[0.35-0.65]	[0.51±0.1]
Angiopathy>>Output	[0.35-0.65]	[0.48±0.06]
Chronic Kidney Disease>>Output	[0.15-0.5]	[0.38±0.14]
Family History of CAD>>Output	[0.15-0,5]	[0.34±0.06]
Asymptomatic>>Output	[-0.85 - -0.5]	[-0.66±0.07]
Atypical symptoms>>Output	[0.7-1]	[0.83±0.08]
Angina like>>Output	[0.5-0.85]	[0.67±0.06]
Dyspnea on exertion>>Output	[0.5-0.85]	[0.6±0.08]
Incident of precordial pain>>Output	[0.35-0.65]	[0.67±0.11]
ECG>>Output	Nan	[-0.16±0.57]
Expert_Diagnosis_Binary>>Output	[0.7-1]	[0.89±0.07]
CNN output>>Output	[0.5-0.85]	[0.7±0.15]

4 Discussion

We propose a DeepFCM model for CAD diagnosis. It achieves high accuracy and also exceeds traditional machine learning algorithms. Moreover, it utilizes historical data or/and expert's opinions, with prediction probabilities extracted from trained VGG-19. Regarding the first model, the interconnections of concepts with the output CAD concept were initialized randomly with numbers in the range [-1, 1]. Concerning results, FCM is a transparent and explainable tool, since it produces interconnections between every input concept and the output CAD concept, with meaningful influences among them, which is a great advantage, in comparison to Random Forest, Bayes, Decision Tree and Neural Networks that are characterized as black-boxes [14].

We experimented with different DeepFCM learning methods to determine the optimal. For example, we developed FCM with random values from a spectrum [-1, 1] for the initial values of interconnections and furthermore we did not utilize the prediction probabilities from CNN to evaluate and DeepFCM performed better comparison with the rest of the experiments. It is demonstrated that the doctor-in-the-loop approach yields better results and makes the system more informative and explainable. In addition, the integration of a CNN for offering an extra input to our system benefits the model, because it leverages the feature extraction capabilities of the CNNs in CAD screening.

The developed code can be implemented producing results effortlessly providing nuclear experts with an autonomous decision-making tool for patient's health, regarding CAD diagnosis.

5 Conclusions

In this research study, the DeepFCM model achieved remarkable results, providing an integral tool that can assist decisions in nuclear medicine. In future work, the authors intend to implement state equations for FCM learning and obtain nuclear experts' opinions that entail certain conditions regarding patient's characteristics. Furthermore, we plan to extend our work by improving FCM's performance with random values for initial interconnections. Last but not least, we intent to insert to our proposed model DeepFCM image data and perform image classification with the application of Fuzzy Cognitive Maps, along with clinical data and prediction probabilities obtained from image data and develop a hybrid method.

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