**12 An Explainable Fuzzy Cognition Methodology for CAD diagnosis in Nuclear Medicine**

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# **Abstract**

Coronary Artery Disease (CAD) is one of the leading causes of mortality among cardiovascular diseases. This chapter demonstrates the DeepFCM multimodal framework that integrates clinical and imaging data with the application of Fuzzy Cognitive Maps (FCMs), which provide an interpretable structure for modeling expert knowledge and clinical relationships, and Convolutional Neural Networks (CNNs), where they extract high-level imaging features. Initially, the FCM model processes clinical data as input concepts. RGB-CNN, a CNN implemented from scratch, was trained on Polar Maps and generated a prediction for each instance. These predictions were inserted as an additional input concept, forming the multimodal model DeepFCM. Particle Swarm Optimization (PSO) was employed for the DeepFCM training to calculate the interconnections among concepts. To ensure interpretability, multiple explainability techniques were integrated. With graphical visualizations, the impact of each concept on the diagnosis was demonstrated. Gradient-weighted Class Activation Mapping (Grad-CAM) highlighted the most relevant image regions, and Llama 3.2-Vision provided textual explanations of the results. The dataset included 571 instances, where 248 correspond to pathological and 323 to normal. DeepFCM-PSO attained 77.59% accuracy, 0.22 loss, 78.05% sensitivity, 76.29% specificity, and 74.05% precision, where 10-fold cross-validation was applied.

Keywords: Coronary heart disease; Convolutional Neural Networks; Fuzzy Cognitive Maps

# **12.1 Introduction**

CAD is the leading cause of death from heart disease. The term implies the buildup of blood in a segment of the heart that has died or was injured because of a blockage in the coronary artery. CAD is a significant, life-threatening disease, and medical attention should be sought immediately. Conventional methods are often invasive and time-consuming, utilizing a process that is prolonged and less convenient for patients (Papandrianos, Feleki, Papageorgiou, et al. 2022).

Based on the literature review, CNNs have been developed for effective diagnosis of CAD, employing a range of methodologies, including both pre-trained architectures and models built from scratch. In the study (Papandrianos, Feleki, Papageorgiou, et al. 2022), the authors developed the RGB-CNN model for three-class classification in the diagnosis of CAD. 647 instances were included, with 134 cases referring to infarction, 251 cases to ischemia, and 262 to normal. Data augmentation techniques included rescaling, rotation, width shift range, height shift range, shear transformation, zooming, horizontal flip, and vertical flip. The RGB-CNN model obtained an accuracy of 91.86%, outperforming the pretrained networks, which scored an accuracy of 88.54%, 86.11% for VGG-16 and DenseNet-121, respectively. In the study (Apostolopoulos et al. 2020), the authors developed the pre-trained network VGG-16. A total of 216 patients were included in attenuation correction (AC) and non-attenuation (NAC) correction in stress and rest conditions. The AC and NAC images were rescaled to 150x150. Data augmentation was applied with the rotation technique by a maximum of 45 degrees. VGG-16 yielded an accuracy of 74.53%, sensitivity of 75%, and specificity of 73.43%. In the study (Bansal et al. 2024), the authors developed various pre-trained networks for the CAD classification. A total of 192 SPECT-MPI cases were included from an open dataset. The images were rescaled to a 256x256 pixel size. Data augmentation was applied, with the employment of shear transformations, horizontal flip, rotation, zoom, shift in width, height and fill mode. Early stopping was applied to stop the training process and prevent the model from overtraining. InceptionV3 outperformed all models with an accuracy of 96.88%, with the rest of the models attaining the following accuracy values, DenseNet201 (93.75%), Xception (90.63%), EfficientNetB5 (90.63%), and ResNet101V2 (84.38%). In the study (J. J. Chen et al. 2021), CZT SPECT myocardial perfusion images were analyzed with a three-dimensional CNN to classify whether the patient had CAD or not. A total of 979 gray-scale instances were included, which were rescaled to 70x70, where 601 instances correspond to healthy, and 378 instances to unhealthy. The proposed model attained accuracy, sensitivity, and specificity of 87.64%, 81.58%, and 92.16% accordingly, where five-fold cross-validation was applied. To interpret CNN results and identify the areas contributing to the respective prediction, Grad-CAM was utilized.

Furthermore, FCMs have been applied to a variety of CAD classification problems. In the study (Khodadadi et al. 2019), the authors constructed FCM for the effective diagnosis of ischemic stroke. A total of 110 instances were included, where 12 characteristics served as input concepts (age, blood pressure, LDL cholesterol, HDL cholesterol, diabetes, heart disease, family history, smoking, BMI, exercise, sex, stroke history) with 1 output (risk of stroke). For the FCM training process and the initialization of the weights, the non-linear Hebbian method was employed. The proposed model achieved an accuracy of 93.6% ± 4.5%, outperforming traditional machine learning methods, including support vector machines (86.0% ± 5.27%) and K-nearest neighbors (80.2% ± 5.33%). In the study (Apostolopoulos, Groumpos, and Apostolopoulos 2021), a State Space Advanced Fuzzy Cognitive Map (AFCM) model was developed for the CAD diagnosis. The dataset included 303 instances, including 116 healthy cases and 187 diseased cases. Nuclear medicine experts defined the system’s concepts and assigned linguistic values between them, and also established specific rules to enhance the model's knowledge. 30 input characteristics were included, such as typical angina pectoris, atypical angina pectoris, atypical thoracic pain, dyspnea on exertion, asymptomatic status, gender (male and female), and age categories (e.g., age < 40), among others. The experts also designated state concepts, which were grouped into Predisposing Factors, Recurrent Disease, Demographic Characteristics, and Diagnostic Tests. The AFCM model included a single output node with three states, utilizing a SigmoidN activation function, along with an activator concept. The proposed model AFCM, achieved 85.47% accuracy, 89.3% sensitivity, and 79.31% specificity, and it outperformed various machine learning models, where Chirp yielded 76.89% accuracy, and both AdaBoostM1 and Random Forest attained 74.58% accuracy.

Existing works on CAD do not employ explainability techniques and often employ single-modality data imaging or clinical data as their input data. This restricted feature set limited the ability of the model to represent the multiplicity of nature of coronary pathology and also limited its ability to be used in clinical practice. In this work, we attempt to tackle these limitations by applying the multimodal framework, named DeepFCM, that combines anatomical information from Polar maps, along with clinical data, with employing explainability techniques.

DeepFCM was first presented in (Feleki, Apostolopoulos, Papageorgiou, Moustakidis, et al. 2023) for diagnosing Non-Small Cell Lung Cancer (NSCLC). Clinical data, along with PET scans, were used as input concepts. RGB-CNN, a CNN developed from scratch and trained on the PET images. For every instance, RGB-CNN generated a prediction, where these predictions and clinical data (SUVmax, tumor diameter) formed the input concepts. As an explanation technique, a concept graph demonstrated the relationships between input and output concepts. This method yielded an accuracy of 94.71%. In (Feleki, Apostolopoulos, Papageorgiou, Papageorgiou, et al. 2023) DeepFCM was used for CAD diagnosis with clinical data and Polar Maps. It achieved an accuracy of 77.95%. The explainability framework was improved by comparing the inferred concept connections with both expert-initialized and randomly initialized weight structures. In (Feleki, Apostolopoulos, Moustakidis, Papageorgiou, et al. 2023) a subset of the most informative clinical features was selected and combined with Polar Maps, which reached an accuracy of 83.07%. Grad-CAM was used to interpret CNN outputs by highlighting important image areas. GPT-API was integrated to create human-readable explanations of the DeepFCM outputs. In (Feleki et al. 2024), the DeepFCM-PSO variant included the full set of clinical characteristics and PET images, which achieved 88.14% accuracy. Grad-CAM was used to identify malignant regions from RGB-CNN feature maps. GPT-API generated natural language explanations. In (E. Papageorgiou et al. 2025) DeepFCM-ELM was introduced by adding an Extreme Learning Machine (ELM) to the learning framework. The generated interconnections were demonstrated through the concept graph. Grad-CAM explained the CNN outputs, and GPT-API turned model predictions into clear language. DeepFCM-ELM reached an accuracy of 90.57%. A MDSS has also been developed by the EMERALD team (Samaras et al. 2024), which includes ML and FCM-based classification algorithms regarding CAD and NSCLC diagnosis, with various explainability techniques like graphical visualizations, textual explanations, Grad-CAM, SHapley Additive exPlanations (SHAP), and ablation heatmaps.

The current study experimented with the DeepFCM learning mechanism and developed important improvements to the PSO framework. These changes aim to navigate the solution space better and facilitate more accurate and stable solutions for CAD diagnosis. A significant innovation is the introduction of LLaMA 3.2-Vision, an open-source NLG model that does not depend on a limited number of tokens. The prompt for the NLG model was adjusted to generate clearer and more useful output for diagnosing CAD. This adjustment enables LLaMA 3.2-Vision to provide more precise and actionable insights that support the diagnostic process.

**12.2 Materials & Methods**

The dataset for this study was collected from the Clinical Sector of the Department of Nuclear Medicine at the University Hospital of Patras. The dataset includes 571 instances, with 248 cases classified as CAD-diseased and 323 as normal, by nuclear experts. Participants underwent gated-Singe Photon Emission Computed Tomography – Myocardial Perfusion Imaging (SPECT-MPI) and Invasive Coronary Angiography (ICA) within 60 days of the MPI procedure, determining their CAD diagnosis, which serves as the ground truth. The dataset included information on various patient attributes, which are binary normalized and used as input features for the FCM classification model and number twenty-two: (1) Sex, (2) Age, (3) Body Mass Index (BMI), (4) known CAD, (5) previous Acute Myocardial Infarction (AMI), (6) previous Percutaneous Coronary Intervention (PCI), (7) previous Coronary Artery Bypass Grafting (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) Electrocardiogram (ECG), and (22) Preliminary Expert Diagnosis.

In addition to clinical data, imaging data in the form of Polar Maps were also included. These images provide a visual representation of myocardial perfusion. We present an example, showcasing a normal instance alongside a pathological case in Figure 12.1.

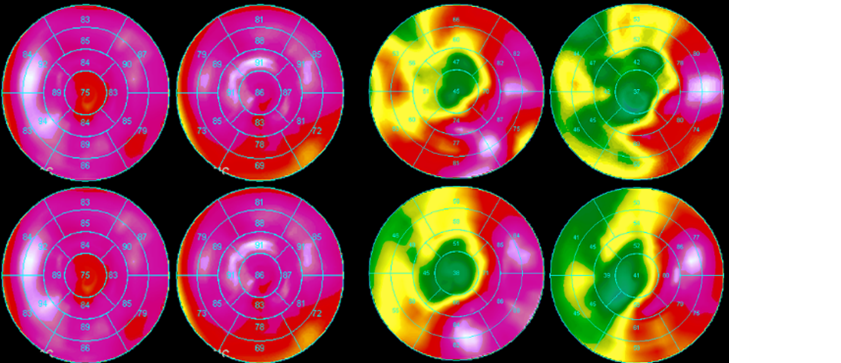


Figure 12.1. Representation of two Polar Maps instances (left), Normal (right), Pathological

# **12.3 DeepFCM methodology**

The clinical data are processed with normalization techniques and are processed as input concepts by a FCM. A CNN trained from scratch, named RGB-CNN, is trained on the Polar Map images and generates a prediction for each image instance. These CNN predictions are incorporated as an additional input concept, forming the proposed multimodal model DeepFCM. For the initialization of interconnections among input-output concepts, expert knowledge is utilized in the form of fuzzy sets. PSO is included in the DeepFCM training process to calculate the interconnections of concepts based on historical and expert knowledge, treating each weight matrix as a possible solution by minimizing the error function. A 10-fold cross-validation approach is applied to ensure the generalizability of DeepFCM-PSO results. By using the weight matrix attained in the training process, on the testing set, and comparing the DeepFCM-PSO predicted values to the actual dataset, performance metrics are calculated to evaluate the model's accuracy and effectiveness. The proposed model, DeepFCM-PSO, encapsulates transparent and understandable results, with the application of the following XAI methodologies: Grad-CAM and NLG with the Llama3.2-vision model, which can offer insights into the decision-making process.

In Figure 12.2, the methodological pipeline of the DeepFCM-PSO is demonstrated.

A diagram of a computer process

AI-generated content may be incorrect.

Figure 12.2. Demonstration of the methodological framework of the DeepFCM-PSO pipeline.

The steps of the proposed methodology are analyzed below:

**12.3.1 Clinical dataset**

*Step 1: Loading Clinical Dataset*

The clinical data are loaded into the system through an external file, presenting an overview of the patient's status. The clinical dataset involves twenty-two diverse parameters, including demographic information and CAD diagnostic features.

*Step 2: Data preprocessing*

* Data normalization: Regarding the clinical data of our research, we applied as a normalization technique to the Age and BMI characteristics the Min-Max technique (Papandrianos, Apostolopoulos, et al. 2022) to rescale their values into the spectrum [0, 1].
* Data shuffle: To improve generalization, the data were inserted into the model in a random order, to reduce any bias (Papandrianos, Feleki, Moustakidis, et al. 2022).

**12.3.2 Imaging dataset**

*Step 3: Loading Imaging Dataset*

The Polar Map images are two-dimensional (2D) circular representations summarizing the results of the three-dimensional (3D) tomographic slices.

*Step 4: Image Data Preprocessing*

* Data normalization: Rescaling of pixel values was applied to fit them into the range of [0, 1], to simplify the computational process.
* Data shuffle: Shuffling of the imaging dataset was applied to randomize the order of the instances.

*Step 5: RGB-CNN training*

A CNN represents an algorithm that includes input, hidden, and output layers. By employing diverse filters on input images, CNN can automatically extract features. Through an intricate learning process, it retains the most salient pixel values (Papandrianos, Apostolopoulos, et al. 2022).

RGB-CNN was implemented from scratch, and trained on Polar maps images, and generated a prediction for each instance. The following steps were applied.

* + Data augmentation: Data augmentation was applied to increase the size of the dataset, achieve generalization of instances, and handle overfitting (Shijie et al. 2017). The techniques that were utilized are the following: a width shift range with a value of 0.1, a height shift range with a value of 0.1, and a zoom range with a value of 0.1.
  + Define CNN architecture: An exploration was conducted with diverse architectures, varying the number of nodes in both convolutional and fully connected layers. Experimentation was conducted with different batch sizes, where a batch size of 16 yielded the best results. Moreover, the images were resized to a dimension of 300x300 pixels. The developed RGB-CNN model was constructed with three convolutional layers with 16, 32, and 64 nodes and two fully connected layers with 64 and 32 nodes, respectively. All layers included Rectified Linear Unit (ReLU) as an activation function, and the final fully connected layer included a sigmoid activation function. Adam optimizer was selected, along with the binary cross-entropy as a loss function.
  + Early Stopping: Additionally, early stopping was employed during RGB-CNN training to reduce redundant iterations by stopping the training process when the change between the validation error among consecutive epochs has a smaller value than a predefined threshold (Feleki, Apostolopoulos, Moustakidis, Papageorgiou, et al. 2023) (Heckel and Yilmaz 2020). The maximum number of epochs was set to 300.
  + Extract CNN predictions: The final fully connected layer of the RGB-CNN model consists of a single node, whose binary output (1 or 0) indicates the presence or absence of CAD. For each instance, RGB-CNN generates predictions.

*Step 6: FCM-based classifier*

FCMs are computing tools that are a combination of fuzzy logic and neural networks. FCMs have been introduced by Kosko (Kosko 1986) as an advanced version of cognitive maps with the application of fuzzy causal functions. FCM is a fuzzy diagram that transforms a system into concepts, where each concept represents a variable, a state, or a characteristic of a system. FCMs consist of several nodes that demonstrate variables, where relationships among the nodes rely on the range [-1, 1]. The value of an interconnection expresses the strength of the relation (Feleki, Apostolopoulos, Moustakidis, Papageorgiou, et al. 2023; E. I. Papageorgiou et al. 2005; Feleki, Apostolopoulos, Papageorgiou, Papageorgiou, et al. 2023). In our study, a FCM is initially constructed using the 22 previously described clinical characteristics as input concepts.

*Step 7: Integration of clinical data along with CNN predictions*

The predicted values for each image instance derived from the RGB-CNN model along with the clinical data, formed the input concepts for the proposed model DeepFCM.

*Step 8: Validation process*

To ensure the reliability of our proposed model and prevent overfitting (Brownlee 2018) (Papandrianos, Apostolopoulos, et al. 2022) K-fold cross-validation was employed, where represents the number of batches used to divide the dataset. In our study, was set to 10, where nine folds were employed for training and one fold for testing in each iteration. This process was repeated until every fold had been used once as the testing set.

*Step 9: Initialization of interconnections by nuclear experts*

In our study, we utilize clinical characteristics along with CNN predictions as input concepts to the proposed model, DeepFCM. When an FCM is applied for decision-making, it can be effectively constructed either by leveraging expert domain knowledge or by employing a random initialization of concept weights. In our study, experts assigned linguistic values for each input-output interconnection, in the form of fuzzy sets. Fuzzy sets have a degree of uncertainty, in contrast to traditional binary logic, where statements are strictly true or false (Zadeh 1965). Membership Functions (MFs) define fuzziness within a fuzzy set. The triangular MF was selected by the nuclear experts to represent linguistic values (Kreinovich, Kosheleva, and Shahbazova 2020). Nuclear experts assigned linguistic values (Very Weak, Weak, Medium, Strong, Very Strong) to define the impact of each input concept on the presence of CAD. These values were transferred to numerical values within the range [-1,1], following the main aspects of fuzzy logic as defined in (E. I. Papageorgiou et al. 2005; E. I. Papageorgiou and Salmeron 2013). When expert-defined values were not provided, interconnections were randomly initialized within the range [-1, 1].

The calculation of the weights in the FCM model, which constitutes causal relationships among concepts, is a crucial step in FCM learning. To enhance the dynamic capabilities of FCMs and update the weights based on the available data, learning algorithms were proposed and have been used in previous studies (E. I. Papageorgiou and Salmeron 2013). Based on the literature on FCM learning algorithms, the most commonly used are evolutionary and population-based algorithms, which find great applicability in various disciplines, including medicine.

*Step 10: Integration of PSO as a learning technique for the DeepFCM training process*

In this study, Particle Swarm Optimization (PSO) was employed for the calculation of the weight matrix, which includes the total set of interconnections among concepts. PSO is known for its application to various optimization problems (E. I. Papageorgiou et al. 2005; H. Chen et al. 2020). It emulates the collective behavior observed in swarms, where a group of particles, each representing a potential solution, is randomly initialized within the search space. These particles then move through space, adapting their positions based on both their own experiences and the successes of their neighbors, converging toward a collective solution.

The PSO approach enables DeepFCM to effectively learn the interconnections among concepts by exploring the solution space starting from initial weighted values initially defined by nuclear experts. This guides the model toward semantically meaningful relationships, but also allows refining of these connections based on the historical data, resulting in a more accurate and interpretable representation of the decision-making process.

*Application of XAI techniques:*

For transforming the DeepFCM into an interpretable tool, several approaches were applied. Firstly, through the DeepFCM graph, the relationships among input and output concepts are demonstrated, highlighting the most impactful factors for the diagnosis (Feleki et al. 2024).

Also, Grad-CAM is employed to understand the decision-making process of CNNs (Selvaraju et al. 2020). It identifies the most influential pixel regions in an input image that contribute to the classification outcome. Grad-CAM utilizes the generated feature maps from the last convolutional layer of the CNN, since these layers maintain important spatial information. By calculating the gradient of the target class, Grad-CAM assigns importance weights, allowing it to highlight the regions of the image that most influenced the model’s prediction.

*Application of Natural language Generation method to interpret DeepFCM and RGB-CNN results into human-understandable language*

As an additional technique, Natural Language Generation (NLG) was employed to translate the numerical results of the DeepFCM-PSO framework into clear, human-readable textual explanations. This was accomplished using the open-source language model Llama 3.2-Vision (Chi et al. 2024; Fedorov et al. 2024). Leveraging its multimodal capabilities, Llama 3.2-Vision processed the weight values produced by DeepFCM, the clinical characteristics, and the predictions from both the DeepFCM and CNN models, in order to provide insights into the DeepFCM and RGB-CNN predictions.

# **12.4 Results**

In this section, we demonstrate the DeepFCM-PSO classification performance and its integration into the developed MDSS (Feleki et al. 2024; Samaras et al. 2024) for the diagnosis of CAD, along with the provided XAI techniques. Table 12.1 presents a comparison across various models, with DeepFCM-PSO, both with randomly initialized weights and expert-guided initialization, and FCM-PSO, which is based solely on clinical data, also under the same initialization strategies for the interconnection among concepts. We also include the performance metrics attained from RGB-CNN, which relied exclusively on Polar Map imaging data.

The following evaluation metrics were included: accuracy, loss, sensitivity, specificity, and precision. DeepFCM-PSO was also evaluated using 10-fold cross-validation to ensure generalization of the performance estimation. We also computed the standard deviation of each performance metric across the ten folds.

Table 12.1 demonstrates that DeepFCM-PSO achieves higher classification performance when expert knowledge is used to initialize the interconnections among concepts, compared to relying on random initialization. Moreover, the results demonstrate that combining clinical and imaging data leads to more accurate and reliable CAD diagnosis, reinforcing the value of a multimodal approach in medical decision support systems, since FCM-PSO and RGB-CNN, which are based on clinical data and imaging data, respectively, attained lower performance metrics.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Loss | Sensitivity | Specificity | Precision |
| FCM-PSO (random weights) | 72.65%±3.86% | 0.25%±0.04 | 70.71%±6.41% | 78.51%±9.76% | 72.94%±4.46% |
| FCM-PSO (expert knowledge) | 73.24%±3.22% | 0.28%±0.03 | 70.96%±9.19% | 77.84%±9.67% | 70.65%±4.86 |
| RGB-CNN | 74.58%±5.25% | 0.45±0.04 | 81.71%±5.59% | 70.48%±9.51% | 72%±7.85% |
| DeepFCM-PSO (random initialization) | 75.49%±6.3% | 0.24±0.06 | 71.75%±10.95% | 77.58%±10.04% | 70.69%±9.76% |
| DeepFCM-PSO (expert knowledge) | **77.59%±4.34%** | **0.22±0.04** | **78.05%±9.55%** | **76.29%±8.31%** | **74.05%±7.68%** |

Table 12.1. Comparison of performance metrics between DeepFCM-PSO models initialized with expert knowledge and random initialization, alongside single-modality models based solely on clinical and imaging data

Table 12.2 presents an analysis of the relationships between clinical characteristics associated with CAD and the model output, as captured by the DeepFCM-PSO framework. The first column lists each input–output relationship. The second column displays the corresponding linguistic value, as defined by expert nuclear cardiologists. These linguistic terms were transformed into numerical ranges using the triangular membership function, as shown in the third column. The fourth column includes the interconnection weights generated by DeepFCM-PSO when initialized with expert knowledge, while the fifth column provides the weights obtained through random initialization within the interval [–1, 1]. This comparative structure allows for the evaluation of the effect of expert-guided initialization on the interpretability and consistency of the resulting fuzzy cognitive map.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Relationship | Suggested linguistic value | Transformed to a range of values | DeepFCM-PSO (expert knowledge) | DeepFCM-PSO (random initialization) |
| Sex→Output | Very Weak | [0, 0.3] | 0.25±0.09 | -0.46±0.22 |
| Age→Output | Very Weak | [0, 0.3] | 0.28±0.11 | -0.2±0.29 |
| BMI→Output | Weak | [0.15, 0.5] | 0.31±0.08 | -0.22±0.31 |
| known CAD→Output | Strong | [0.5, 0.85] | 0.66±0.12 | 0.37±0.17 |
| previous AMI→Output | Very Weak | [0, 0.3] | 0.17±0.12 | 0.19±0.3 |
| previous PCI→Output | Weak | [0.15, 0.5] | 0.38±0.09 | 0.14±0.2 |
| previous CABG→Output | Weak | [0.15, 0.5] | 0.33±0.11 | 0.13±0.24 |
| previous STROKE→Output | Medium | [0.35, 0.65] | 0.4±0.08 | 0.02±0.34 |
| Diabetes→Output | Strong | [0.5, 0.85] | 0.7±0.09 | 0.21±0.25 |
| Smoking→Output | Medium | [0.35, 0.65] | 0.47±0.06 | -0.02±0.28 |
| Hypertension→Output | Medium | [0.35, 0.65] | 0.38±0.06 | -0.15±0.22 |
| Dyslipidemia→Output | Medium | [0.35, 0.65] | 0.44±0.1 | -0.21±0.19 |
| Angiopathy→Output | Medium | [0.35, 0.65] | 0.51±0.09 | 0.16±0.26 |
| Chronic Kidney Disease→Output | Weak | [0.15, 0.5] | 0.32±0.09 | 0.12±0.28 |
| Family History of CAD→Output | Weak | [0.15, 0.5] | 0.26±0.06 | -0.11±0.24 |
| Asymptomatic→Output | -Strong | [-0.85, -0.5] | -0.79±0.06 | -0.17±0.23 |
| Atypical Symptoms→Output | Very Strong | [0.7, 1] | 0.75±0.05 | -0.18±0.16 |
| Angina Like→Output | Strong | [0.5, 0.85] | 0.63±0.04 | 0.05±0.23 |
| Dyspnoea on Exertion→Output | Medium | [0.35, 0.65] | 0.48±0.09 | -0.01±0.26 |
| Incident of Precordial Pain→Output | Strong | [0.5, 0.85] | 0.61±0.1 | 0.05±0.34 |
| ECG→Output | Medium | [0.35, 0.65] | 0.29±0.4 | 0.17±0.28 |
| Expert\_Diagnosis\_Binary→Output | Very Strong | [0.7, 1] | 0.86±0.09 | 0.34±0.26 |
| CNN\_prediction→Output | Strong | [0.5, 0.85] | 0.64±0.1 | 0.25±0.16 |

Table 12.2. Generated interconnections among input-output concepts with and without expert knowledge

Table 12.2 demonstrates that the interconnection weights generated by the model closely match the initial relationships suggested by nuclear medicine experts, with only minor differences noted. These small differences are seen as reasonable adjustments based on the data. In contrast, when the interconnection weights were initialized randomly, without incorporating expert knowledge, the resulting values showed considerable deviation from expert-defined ranges. The absence of domain-specific priors caused the training process to explore the solution space without constraints, increasing the risk of convergence to local minima and producing suboptimal and less interpretable outcomes. Although the development of DeepFCM-PSO, with and without expert knowledge, achieved similar overall performance, the DeepFCM initialized by expert knowledge developed more meaningful and clinically interpretable weight structures. This result highlights DeepFCM's ability to incorporate domain expertise in its learning process, resulting in clearer and more understandable decision-making.

For the application of DeepFCM-PSO, through the developed MDSS, we refer to a patient with a medical history of known CAD, diabetes, smoking, hypertension, and dyspnoea on exertion, where the expert predicted that this patient is pathological. Given these risk factors, both DeepFCM-PSO as a multimodal approach and the CNN based solely on image prediction classified this instance as pathological. As illustrated in Figure 12.3 DeepFCM-PSO predicted the instance as pathological with a high probability score of 98.55%, while the CNN, based solely on imaging data, predicted it as pathological with a probability score of 55.47%.

The DeepFCM-PSO graph further demonstrates the key contributing factors influencing the CAD diagnosis. The most impactful clinical indicators regarding CAD multimodal diagnosis include known CAD (weight: 0.51), diabetes (0.62), smoking (0.34), hypertension (0.68), dyspnea on exertion (0.58), expert diagnosis (0.51), and the CNN prediction (0.56).

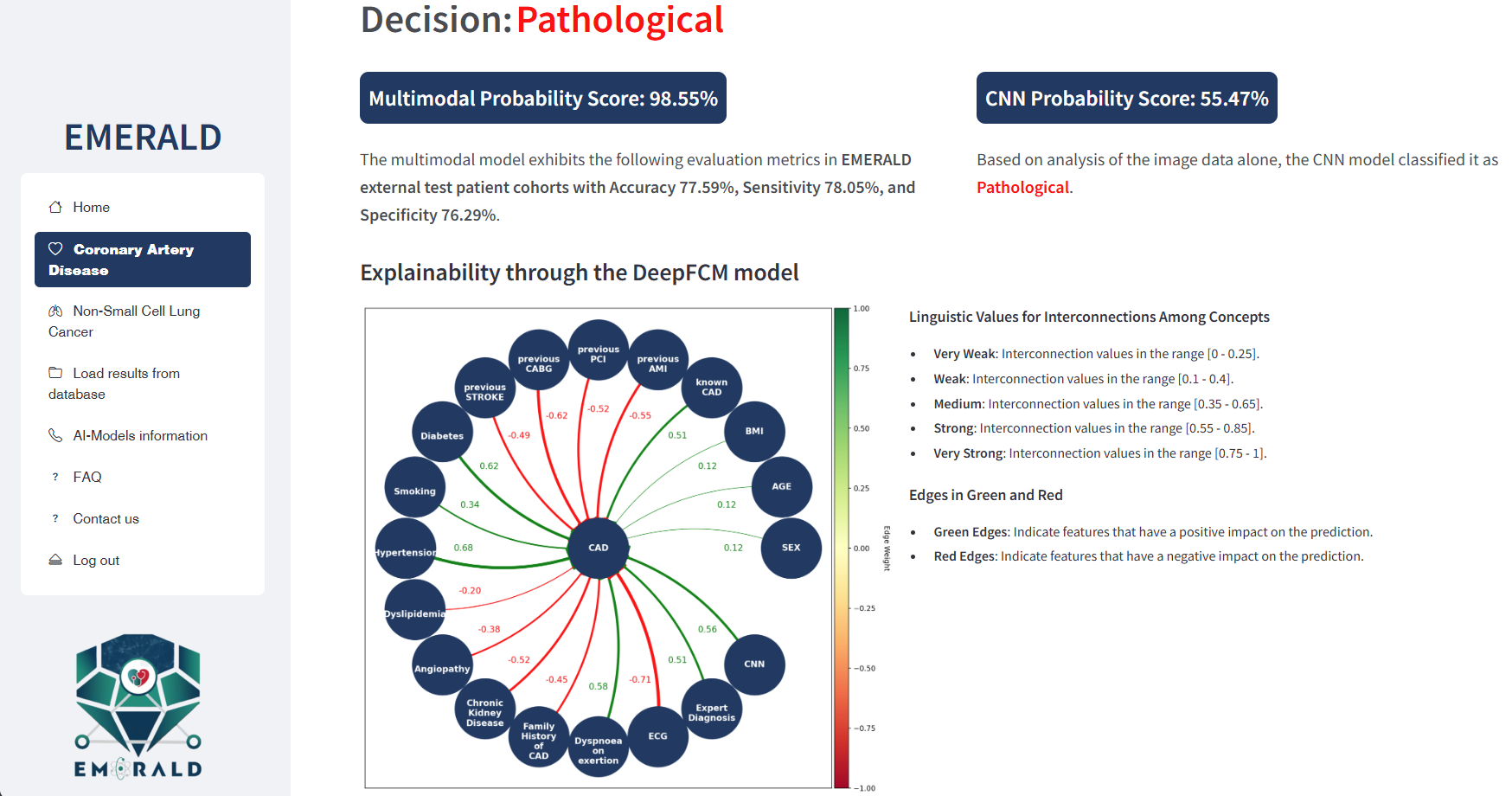


Figure 12.3. DeepFCM-PSO prediction for CAD multimodal diagnosis.

For the interpretation of the RGB-CNN predictions, the Grad-CAM technique was employed. The JET colormap from the OpenCV library was utilized, where red represents the most influential pixel areas, and blue regions indicate pixel regions with lower impact.

In Figure 12.4, we present the Grad-CAM application, where the left panel displays the original Polar Map image of the patient, which provides a visual representation of myocardial perfusion in both AC and NAC formats for stress and rest conditions.

The Grad-CAM heatmap effectively identified the most critical areas in the original image that contributed to the model’s decision, where red represents high-impact pixel regions, and blue defines low-impact.

A close-up of a screenshot of a computer screen

AI-generated content may be incorrect.

Figure 12.4. Grad-CAM application to the Polar map image.

To further enhance explainability, we integrated NLG using the open-source Llama3.2-vision model to translate DeepFCM's numerical outputs into human-understandable textual explanations. We constructed a prompt that includes the clinical variables, the Polar image of the specific instance, the generated weight values, the RGB-CNN prediction based on the image, and the DeepFCM-PSO multimodal predicted output, along with specific guidelines for the structure of the response.

The constructed prompt is utilized as input to the open-source model Llama 3.2-Vision, enabling it to translate the reasoning behind DeepFCM-PSO’s decision-making process. In Figure 12.5, we present the Llama 3.2-Vision’s response for this instance. The response effectively detects and analyses the most influential clinical features, leveraging the weight values from the DeepFCM-PSO graph. Additionally, it provides a detailed analysis of the pathological regions detected in the uploaded polar map image.

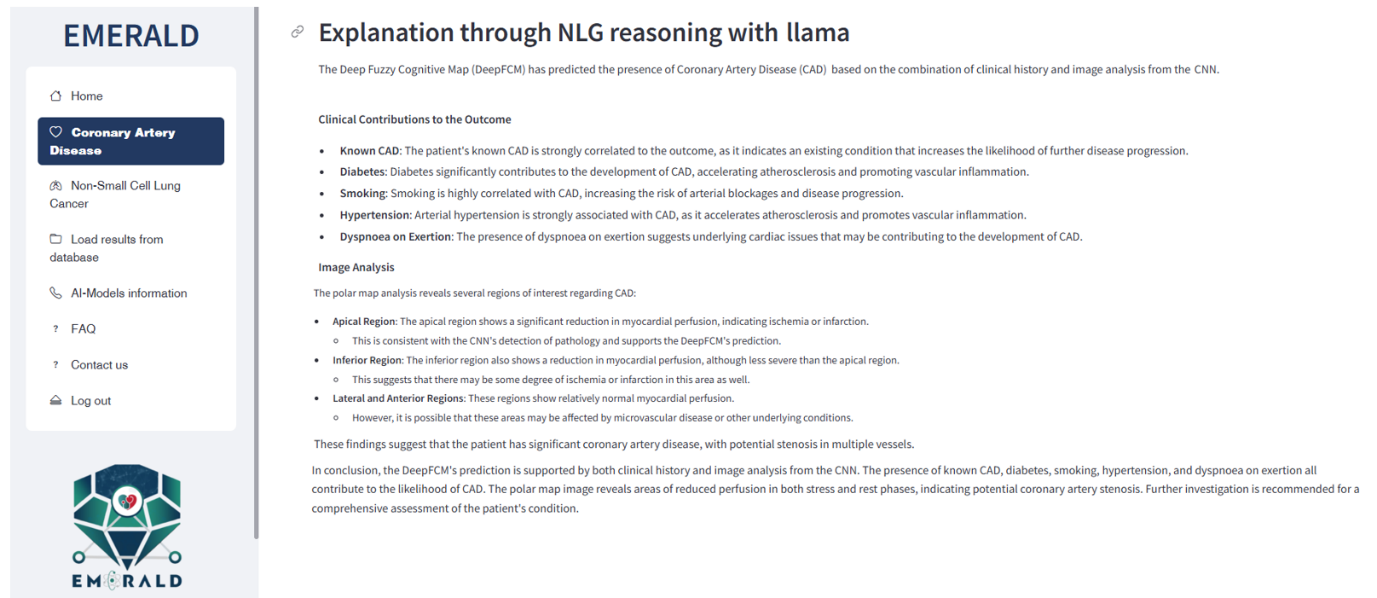


Figure 12.5. Llama 3.2-Vision response for a CAD multimodal instance.

# **12.5 Conclusions**

The proposed model, DeepFCM-PSO, has proven to be a reliable and interpretable multimodal diagnostic model for CAD diagnosis. By incorporating expert-driven interconnections and explainable AI methodologies, DeepFCM-PSO enhances prediction accuracy and also provides transparency of the decision-making process. The model attained high performance metrics, with an accuracy of 77.59%, a loss of 0.22, a sensitivity of 78.05%, a specificity of 76.29%, and a precision of 74.05%, validated through a 10-fold cross-validation process. Furthermore, a comparative evaluation highlights that DeepFCM-PSO, particularly with expert-guided initialization, outperforms random weights initialization and achieves superior classification performance compared to single-modality methods such as FCM-PSO and RGB-CNN, which rely on clinical and imaging data, respectively. These results highlight the effectiveness of incorporating multimodal models in critical domains such as healthcare, where integrating diverse data sources can enhance diagnostic accuracy and decision-making reliability.

The proposed DeepFCM-PSO system demonstrated effectiveness and interpretability in diagnosing CAD. To ensure transparency, several XAI techniques were included in the MDSS. Graphical visualizations demonstrated the weighted influence of each feature on the CAD diagnosis. Grad-CAM also highlighted the most important areas in the Polar map images, which helped explain the RGB-CNN's predictions. Additionally, Llama3.2-Vision, an open-source language model, was used to translate the DeepFCM, and RGB-CNN predictions into textual explanations. With these XAI techniques, DeepFCM-PSO provides a data-driven and transparent decision support system that builds trust in AI-assisted medical evaluations.

For future work, we aim to employ alternative learning methods in the DeepFCM training process and enhance the XAI techniques to further enhance the explainability of the results, while preserving high diagnostic accuracy. By advancing explainability methodologies, DeepFCM will contribute to a more interpretable and trustworthy AI-assisted decision-making framework in medical applications.

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