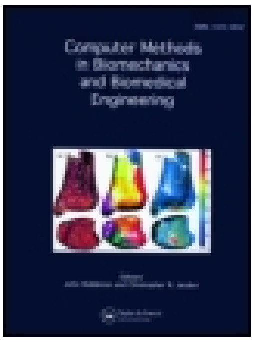

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Non - invasive modelling methodology for the diagnosis of coronary artery disease using fuzzy cognitive maps

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ABSTRACT
Cardiovascular diseases (CVD) and strokes produce immense health and economic burdens globally. Coronary Artery Disease (CAD) is the most common type of cardiovascular disease. Coronary Angiography, which is an invasive approach for detection and treatment, is also the standard procedure for diagnosing CAD. In this work, we illustrate a Medical Decision Support System for the prediction of Coronary Artery Disease (CAD) using Fuzzy Cognitive Maps (FCM). FCMs are a promising modeling methodology, based on human knowledge, capable of dealing with ambiguity and uncertainty and learning how to adapt to the unknown or changing environment. The newly proposed MDSS is developed using the basic notions of Fuzzy Cognitive Maps and is intended to diagnose CAD utilizing specific inputs related to the patient's clinical conditions. We show that the proposed model, when tested on a dataset collected from the Laboratory of Nuclear Medicine of the University Hospital of Patras achieves accuracy of 78.2% outmatching several state-of-the-art classification algorithms.

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Coronary Artery Disease; fuzzy cognitive maps; decision support system; machine learning

Introduction

Coronary artery disease (CAD) is one of the most common causes of death worldwide. CAD develops when the major blood vessels (coronary arteries) supplying the heart with blood, oxygen, and nutrients become damaged or diseased. The non-invasive accurate diagnosis of CAD is a challenging task. The standard diagnostic tests and factors affecting the risk of CAD do not guarantee reliable diagnosis. The enormous number of factors contributing to the existence of CAD and the complex connections between them makes it difficult for the doctors to handle the information. Hence, a Medical Decision Support System (MDSS) could provide a second opinion on the matter and possibly improve the accuracy of the final decision.

Developing Decision Support Systems is one of the most notable and vital efforts, while their application helps in solving daily problems in diverse areas. Examples of applications are found in the health, security and telecommunications sectors (Jaspers et al. 2011).

Fuzzy Cognitive Maps (FCM) is a promising modeling methodology, based on human knowledge. They are capable of efficiently integrating human knowledge for system modeling (Kosko 1992), dealing with ambiguity and uncertainty, and learning how to adapt to the unknown or changing environments, thus, achieving a better performance.

The proposed MDSS makes use of clinical data, doctor's opinions and suggestions and promotes the collaboration between the physicians. Its target is to model human knowledge and experience to deal with the diagnosis of CAD.

This work aims to enhance and to further develop an already proposed Medical Decision Support System for the diagnosis of Coronary Artery Disease. The first proposal (Apostolopoulos et al. 2017) was published in 2016. The already proposed model suffered major drawbacks, the most serious of which was its inability to treat the input variables in a dynamic way, with respect to the interconnections between them. In this work, we intend to overcome some limitations and evaluate the model in real-environment data.

Related work

Diagnosing the Coronary Artery Disease (CAD) in a non – invasive way is not a new challenge (Sintchenko et al., 2007). Several works and proposals are proposed over the years to achieve high accuracy

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(Acharya et al., 2017). The majority of the proposals apply data mining and machine learning techniques to a variety of datasets. Pattern recognition methods are also utilized to obtain information from medical images, such as ECGs or Myocardial Perfusion Imaging. We illustrate few characteristic recent works. A summary of every technique and dataset that was employed can be found in (Alizadehsani et al. 2019).

Most of recent research works utilize large number of patients. A Hybrid system of rough set and neural network has been proposed by An (An and Tong 2005). A research work proposed by Ordonez (Ordonez 2006) that uses association rules, instead of decision rules for heart disease prediction was proposed. Rajkumar and Reena (2010) used decision tree and Naïve Bayes algorithms on the public University of California Irvine (UCI) dataset and reached an accuracy of 52.33%. The aim of (El-Bialy et al. 2015) is to apply an integration of the results of the machine learning analysis applied on different data sets targeting the CAD disease. Other works include techniques such as the Bayesian model and decision trees, support vector machines (Lapuerta et al. 1995), and the naive Bayes classifier (Kampouraki et al. 2009).

Babaoğlu et al. (2010) employed data form exercise tests and Support Vector Machine (SVM) for the classification task and achieved 81.46% accuracy for the diagnosis of CAD. Different feature selection methods such as filter method (Setiawan et al. 2009), genetic algorithm (Arabasadi et al. 2017), and numerical and nominal attribute selection have been used for artery stenosis disease prediction. For the diagnosis of coronary artery disease based on evidence, Setiawan et al. (2009) have developed a fuzzy decision support system. The CAD data sets obtained from the University of California Irvine (UCI) are utilized.

In this work, we will illustrate the process of cooperating with the doctors in order to develop a medical decision support system that meets their needs and their way of thinking, when trying to overcome medical dilemmas. Furthermore, our proposed MDSS, as well as the most popular classification algorithms, will be trained and tested on a dataset of patients.

Materials and methods

The basic aspects of fuzzy logic and fuzzy cognitive maps

The term fuzzy cognitive map was introduced by Kosko (1986) to portray a cognitive map with two noteworthy characteristics: (a) Causal connections between the nodes are fuzzy and uncertain, and (b) The framework behaves in a dynamical way, where the impact of alteration in one concept influences other concepts, which, in turn, can influence the output. The FCM structure is comparable to that of an Artificial Neural Network, where concepts are spoken to by neurons and causal connections by weighted joins interfacing the neurons.

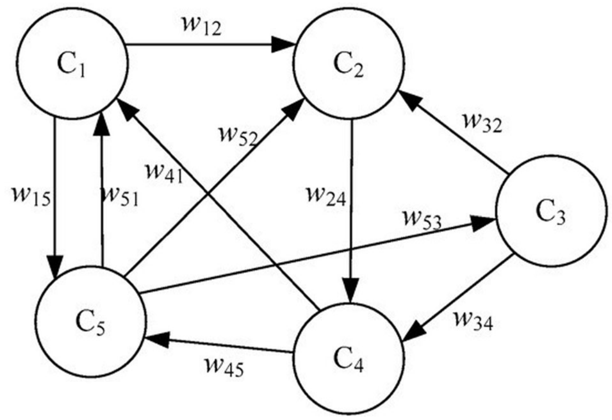

Figure 1. A graphical representation of a Fuzzy Cognitive Map.

A Fuzzy Cognitive Map is a representation of a belief system in a given domain. It comprises of concepts (C) representing key concepts of the real system, joined by directional edges of connections (w), which represent causal relationships between concepts. Each connection is assigned a weight wij, which quantizes the strength of the causal relationship between concepts Ci and Cj (Dickerson and Kosko 1994).

A positive weight demonstrates an excitatory relationship, i.e., as Ci increments, Cj also increments, whereas a negative weight shows an inhibitory relationship, i.e., as Ci increments, Cj diminishes. In its graphical frame, FCM provides a visualization of knowledge as a collection of “circles” and “arrows”, which are relatively simple to imagine and control. Key to the apparatus, is its potential to permit connections among its nodes, empowering its application that alters over time. It is especially suited for use in soft-knowledge domains where knowledge is presented qualitatively (Peng and Wu 2017).

Figure 1 (Papageorgiou et al. 2006) shows a Fuzzy Cognitive Map consisting of several concepts; some of them are input concepts, whereas the rest are decision (output) concepts. Fuzzy interactions between the concepts are also portrayed. The main objective of building a fuzzy cognitive map around a problem is for it to be able to predict the outcome by letting the relevant nodes interact.

The concepts C_1, C_2, … C_n, represent the drivers and constraints of importance to the issue under consideration. The link strength between two nodes C_i and C_j, as denoted by W_{ij}, receives values within the space of (-1,1). The concept values of nodes C_1, $C_2 \ldots$, C_n represent the state vector V. The function describing the system involves letting the vector V evolve. The state vector V is passed repeatedly through the FCM connection matrix W. This involves multiplying V by W, and then transforming the result as follows:

$$\boldsymbol{V} = f(\boldsymbol{V} + \boldsymbol{V} \cdot \boldsymbol{W}) \tag{1}$$

$$V_i(t+1) = f\left[V_i(t) + \sum_{\substack{j=1 \\ j \neq i}}^{N} V_j\ (t) \cdot W_{ji}\right] \tag{2}$$

where $V_i(t)$ is the value of concept C_i at step t, V_j (t) is the value of concept C_j at step t, Wji is the weight of the interconnection from concept C_j to concept C_i and f is the threshold function that normalizes the result of the multiplication in the interval [0, 1], (Papageorgiou et al. 2006). It is worth noting that in the particular study, the diagonal of the weight matrix (W) is filled with zeros, since each concept affects other concepts and not itself.

Equation 1 could be re-written in a more compact form, as expressed below:

$$\boldsymbol{V} = f(\boldsymbol{V}\boldsymbol{W}^*) \tag{1b}$$

Where $\boldsymbol{W}^* = \boldsymbol{W} + \boldsymbol{I}$ (**I** is the nxn identity matrix). We use the function:

$$\mathrm{f}_{(\mathrm{x})} = \tanh(\mathrm{k} * \mathrm{x}) \tag{3}$$

In the above function, x is the value of V_i at the equilibrium point. After experiments, the value of k was selected to be one (k = 1). The utilization of the specific function, along with equation 1b raises some problematic transformations, given specific input vectors. The mentioned strategy, although yielding good results in the particular study, should be further discussed to circumvent some limitations, which are discussed in the discussion section.

Development of the decision support system using fuzzy cognitive maps

The creation and advancement of the FCM is based generally on the human's contribution with knowledge and on the experts' gathered information and encounter. We select the depiction of the framework to be made not by a unique expertise, but by a bunch of specialists, to portray the framework as more dispassionately as possible. The specialists portray the system's behavior as a set of ideas, in each of which, they allot its concepts. Besides, they portray the existing relations among these ideas as cause and impact relations among the concepts.

The experts' procedure for a developing Fuzzy Cognitive Map is the following:

1. The specialists discuss and define the number and type of the concepts, which will be able to describe the main features of the system, and which will constitute the Fuzzy Cognitive Map.
2. Each specialist, in separate, defines the interaction of each system concept, according to his opinion.
3. Each specialist, in separate again, decides about the type of interaction among the concepts, namely if there will be a positive interaction $W_{ij}>0$, a negative interaction $W_{ij}<0$ or no interaction of the concept C_i to the concept C_j.
4. Then, the connectivity degree between two concepts is defined, namely the exact value of the weight W_{ij}.

Each interconnection partners the relationship between the two concepts and decides the review of causality between the two concepts. The causal interrelationships among concepts are ordinarily defined utilizing the variable impact, which is deciphered as a verbal variable of values within the universe U = [-1,1]. Utilizing ten etymological factors, the specialists portray in detail the impact of one concept on another and perceive between distinctive degrees of impact. At that point, the etymological factors proposed by the specialists for each interconnection are aggregated utilizing the Centre of Sums (COS) method (Hellendoorn and Thomas 1993). It is worth noting that in the particular example, no conflicting weights were assigned. In essence, all three experts agreed on the positive or negative impact of each variable.

Hence, generally etymological weight is delivered, which is defuzzied with the Centre of Gravity method (Runkler 1996). Hence, numerical weight for W_{ij} is produced. Utilizing this strategy, all the weights of the FCM are inferred.

Coronary artery disease

According to World Health Organization, 50% of deaths in European Union are caused by cardiovascular diseases, while 80% of premature heart disease and strokes can be prevented (Mendis 2015). The

American Heart Association (AHA), created a new set of central Strategic Impact Goals, in 2011, to drive organizational priorities for the current decade: "By 2020, to improve the cardiovascular health of all Americans by 20%, while reducing deaths from CVDs and stroke by 20%" (WHO 2018).

Cardiovascular diseases, including strokes, affect all ages, men and women, and all social groups. Cardiovascular and stroke incidents are the top cause of death in developed countries. 1 out of 10 men, aged 50-59, has a "silent" coronary disease and is at risk of having a heart attack without any warning (Montalescot 2013).

Coronary Artery Disease is caused when the atherosclerotic plaques load, namely fill, in the lumen of the blood vessels of the heart, which are named coronary arteries, and they obstruct the blood flow to the heart. This results to a decreased provision of oxygen and nutritional substances to the cardiac tissues (Montalescot 2013). In general, the stenosis of >70% of the vessel's diameter is considered abnormal (Willerson et al. 2007).

A unique feature of the disease, which must be taken into consideration, is that it typically reveals only one symptom, that of chest pain. This symptom might be random and it is not considered to be the decisive factor, except for cases where the chest pain is typical and continuous (American Heart Association 2017).

Factors that contribute to an increased risk of suffering from the particular disease have to be taken into consideration to reach to reliable diagnosis. Medical experts suggest that four groups of factors lead to the decision. Those are predisposing factors (e.g., gender, age, family history), intercurrent diseases (e.g., diabetes), diagnostic tests (e.g., stress echo) and of course, the type of pain (e.g., typical angina, atypical angina). In accordance with those groups, the proposed model utilizes every possible available data. For each person, even the most experienced and capable, the process of evaluating many factors that have inner connection, is very difficult. Hence the results of the diagnostic tests are occasionally overestimated.

The proposed model

The concepts of the FCM

One main difference of our proposed system in comparison with other techniques, is that it trusts the doctor's opinion on specific diagnostic tests and their results. It shall not try to diagnose CAD by interpreting the results of the tests (i.e., making use of measurements derived from the tests). The intrepretation of a diagnostic biomarkers derived from the tests is performed by the experts, who follow specific guidelines to define if a test should be considered normal, abnormal or ambiguous.

Three physicians-experts were pooled to define the number and type of parameters-factors affecting Coronary Artery Disease. Those factors are shown in Table 1.

The factor of typical angina will be excluded from the proposed MDSS, due to the fact that it leads to a straightforward diagnosis of CAD and no further examination is required. This method is a major diferrence between the particular model and models of related research. More specifically, most of the CAD datasets and models incorporate the typical angina, which automatically increases the accuracy.

Factors such as gender, age and diagnostic tests require different handling when taking absolute values and that is the reason "Normal" situations (e.g., young age, normal diagnostic tests) were separated from abnormal ones.

Development of the weight table

Each variable affects with its corresponding weight the variable of the output. However, there are also internal relations among these variables. The reader should note that the ability for each expert to define its own internal connections has not been predicted by this specific system. The rules presented above are rules proposed by all three doctors. These inter-relations are demonstrated in Table 2.

The possible variables that an interconnection weight can take are:

- VW (very weak): the relation between the concept Ai and Aj is very weak
- W (weak): the relation between the concept Ai and Aj is weak
- M (medium): the relation between the concept Ai and Aj is medium
- S (strong): the relation between the two concepts is strong
- VS (very strong): the relation between the two concepts is very strong
- The highest Possible (THP)

Accordingly, the affection of the rules illustrated in Table 2 will be translated into equal weight – rules. For example, the rule "The weight of Scintigraphy is greatly increased" will be translated into a change of the weight from M (Medium) to (VS) Very Strong. If the weight is already Very Strong and the doctor

Table 1. The concepts of the FCM.

Attributes		Values
(N/A)	typical angina pectoris	yes, no
A1	atypical angina pectoris	yes, no
A2	atypical thoracic pain	yes, no
A3	dyspnea on exertion	yes, no
A4	Asymptomatic	yes, no
A5	gender – male	yes, no
A6	gender – female	yes, no
A7	age <40	yes, no
A8	age [40-50]	yes, no
A9	age [50-60]	yes, no
A10	age >60	yes, no
A11	known cad	yes, no
A12	previous stroke	yes, no
A13	peripheral arterial disease	yes, no
A14	Smoking	yes, occasionally, no
A15	arterial hypertension	yes, no
A16	Dyslipidemia	yes, no
A17	Obesity	yes, relatively, no
A18	family history	yes, no
A19	Diabetes	yes, no
A20	chronic kidney failure	yes, no
A21	electrocardiogram normal	yes, no
A22	electrocardiogram abnormal	yes, no
A23	echocardiogram normal - doubtful	yes, no
A24	echocardiogram abnormal	little, abnormal, definitely abnormal
A25	treadmill exercise test normal	yes, no
A26	treadmill exercise test abnormal	abnormal, definitely abnormal
A27	dynamic echocardiogram normal	yes, no
A28	dynamic echocardiogram abnormal	doubtful, abnormal, definitely abnormal
A29	scintigraphy normal - doubtful	yes, no
A30	scintigraphy abnormal	little, abnormal, definitely abnormal
A31	prediction of infection	zero, small, medium, rel. large, large, very large

Table 2. Forever standing relationships between concepts.

Rule	Attributes Affected - Affection
If woman	Age [40 50] – sharply reduced impact, Age [50 60] – medium reduced impact, Diagnostic Tests – average increase at the weights of normal and medium decrease at the weights of abnormal ones.
If Definitely Abnormal Scintigraphy	The weight of Scintigraphy is significantly increased
If ECG is Normal and Scintigraphy is Normal	The weights of both tests are relatively increased
If previous Stroke	Negate the Gender Discrimination and de-activate the attribute from the system
If Known Cad	Negate the family history affection

suggests a further increase, then a mathematic procedure to handle with this will be implied.

In Table 3, the doctors' opinions of the weights associating each attribute with the diagnosis concept (A31) are presented. We present an example of the linguistic values the doctors proposed. The linguistic values of the weight are aggregated and transformed into one numerical value, by following the aforementioned method (COS), as presented in Table 4. The developed network is shown in Figure 2.

Mathematical procedure

Applying equation (2) and utilizing the final numerical table of weights, a specific value for the output concept is calculated.

Equation 2, when fed with a specific vector V, which represents the initial state of the system, and when the weight vector is applied, is reaching to a steady-state. Each element of the vector describes the final state of each attribute. The last element is the summary of each attribute's affection on the prediction.

For a certain new case, inserted as an input to the above system, the final state of Vector V is a unique number in space [-3, 6], before the application of the normalization function f (eq. 3). The space [-3,6] reflects the sum of the disturbances caused by the input concepts to the output concept. Specifically, the value -3 reflects the maximum possible negative contribution, which is established when only the negative concepts are activated (e.g., 39 year old female patient, with normal diagnostic tests). Accordingly, the value of 6 represents the maximum possible positive contribution, in case of a 80 year old male patient, with atypical angina and dyspnea on exertion, with every positive predisposing factor included and with all tests being positive.

This number reflects the probability of this case to be suffering from the disease. We can use the normalization function to transfer this number in space [0,1].

Fuzzification of the output

The potential values "Zero Probability", "Small Probability", "Medium Probability", "Relatively Large

Table 3. Example of weight definition by doctors.

Attribute	Doctor 1	Doctor 2	Doctor 3
A28	-M	-M	-M
A9	-VW	-W	0
A29	(-)THP	(-)VS	(-)S
A30	THP	THP	THP

Table 4. Defuzzied weight values.

Attributes		Weights
A1	Atypical Angina Pectoris	0.35
A2	Atypical Thoracic Pain	0.2
A3	Dyspnea on exertion	0.25
A4	Asymptomatic	−0.35
A5	Gender – Male	0.3
A6	Gender - Female	−0.5
A7	Age <40	−0.75
A8	Age [40-50]	−0.25
A9	Age [50-60]	0.1
A10	Age >60	0.4
A11	Known CAD	0.35
A12	Previous Stroke	0.1
A13	Peripheral Arterial Disease	0.1
A14	Smoking	0.1
A15	Arterial Hypertension	0.1
A16	Dyslipidemia	0.15
A17	Obesity	0.2
A18	Family history	0.1
A19	Diabetes	0.4
A20	Chronic Kidney Failure	0.15
A21	Electrocardiogram Normal	−0.4
A22	Electrocardiogram Abnormal	0.35
A23	Echocardiogram Normal - Doubtful	−0.35
A24	Echocardiogram Abnormal	0.42
A25	Treadmill Exercise Test Normal	−0.75
A26	Treadmill Exercise Test Abnormal	0.6
A27	Dynamic Echocardiogram Normal	−0.44
A28	Dynamic Echocardiogram Abnormal	0.625
A29	Scintigraphy Normal - Doubtful	−0.85
A30	Scintigraphy Abnormal	0.7
A31	Prediction of infection	

Probability”, “Large Probability”, and “Very Large Probability” must be derived from a certain space. In this work we chose those spaces to be:

- If $V_{31} \in [-1,0]$ then “Zero Probability”
- If $V_{31} \in (0,0.25]$ then “Small Probability”
- If $V_{31} \in (0.25,0.5]$ then “Medium Probability”
- If $V_{31} \in (0.5,0.75]$ then “Large Probability”
- If $V_{31} \in (0.75,1]$ then “Very large Probability”

Results

Dataset of the study

The database utilized in this work consisted of 303 patient cases, recorded at the Department of Nuclear Medicine of the University Hospital of Patras, in Greece. The majority of instances were recorded during the last 8 years. All the patient cases had been pointed to Surgical Coronary Angiography. For every instance, therefore, there is a final medical report confirming or denying the presence of CAD. In order for a doctor to characterize an instance as healthy or disease, the stenosis of the coronary artery is the only criterion, which is obtained by the above mentioned invasive diagnostic test. Stenosis equal or above 70% were labelled as diseased, whereas below 70% were labelled as healthy. The data used for the experiments was anonymous.

The dataset contains 116 healthy cases and 187 diseased cases, while it consists of 266 male instances and 37 female ones. The attributes are corresponding to the factors affecting the diagnosis of CAD, as described above. The factors include: the type of symptom (atypical angina, atypical thoracic pain, dyspnea on exertion, asymptomatic), age, gender, predisposing factors and recurrent diseases (Known Cad, Family History, Obesity, Diabetes, Arterial Hypertension, Dyslipidemia, Kidney failure, Peripheral Arterial Disease) and the results of the diagnostic tests (ECG, Dobutamine Stress Test, Stress Echo, Treadmill Exercise Test and Scintigraphy).

The medical reports regarding the diagnostic test were translated into numeric values with the appropriate staging. The medical staff supervised this process. The attributes regarding the patient’s history and condition (i.e., smoking) were also in need of some processing in order to turn the linguistic values (i.e., “smoker”) into zeros and ones.

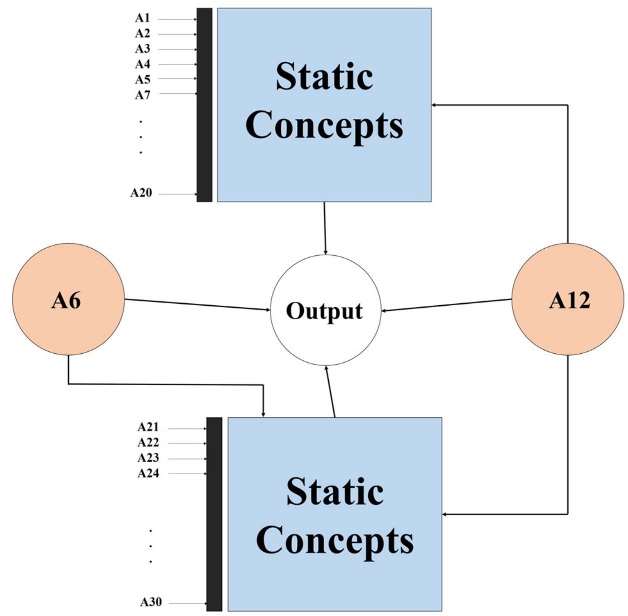

Figure 2. The graphical representation of the proposed Fuzzy Cognitive Map.

Table 5. Confusion Matrix.

	Disease (D+)	No disease (D-)	Total
Test Positive	TP = 157	FP = 36	193
Test Negative	FN = 30	TN = 80	110
Total	187	116	303

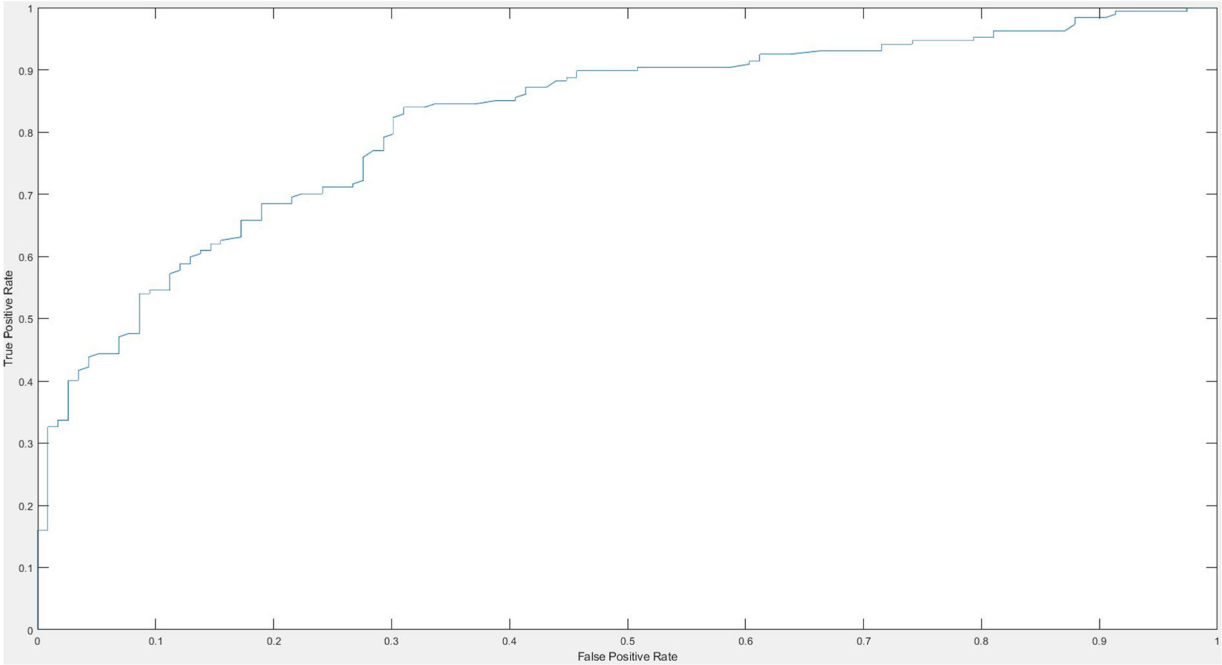

Figure 3. Receiver Operating Characteristics Curve for the results of the evaluation.

Activation function

In order to evaluate the system using real labelled data, we have to force the system to classify every instance in "diseased" or "healthy". One second option was to ignore instances corresponding to the fuzzy outputs "Medium Probability" (or 0.5) hence, considering this zone as a grey one, and therefore instructing the MDSS not to classify those instances.

However, as all of the classifiers we use are following the same procedure (no grey zones), the proposed MDSS will classify every instance. Through the mathematical procedure, all instances' output receives a number in space **(1-,1),** due to the normalization function.

Evaluation criteria and results

We extensively evaluate our system, therefore, more criteria besides accuracy will be employed. The evaluation criteria of the system will be the following: (a) Accuracy based on the whole dataset, (b) True Positives, (c) False Positives, (d) False Negatives, (e) True Negatives, (f) sensitivity, (g) specificity, (h) Negative Predict Value (NPV) and (i) Positive Predict Value (PPV). We consider the proposed MDSS seriously problematic, if the false negatives are exceeding an acceptable medical threshold. In case of CAD, a false negative advises the doctor and the patient ignore a possible fatal disease. Therefore, our gravest marker will be a trade-off favoring the False Negatives and maintaining the accuracy close to the accuracy obtained when objectively choosing the threshold. The results are illustrated in Table 5.

The confusion matrix corresponds to sensitivity of 83.96%, specificity of 68.97%, PPV of 81.34% and NPV of 72.73%. The overall accuracy is 78.21%. The ROC curve is depicted in Figure 3.

Considering the fact that the proposed MDSS was not trained on the dataset, the results are more than encouraging. The results show that the system provides good sensitivity and NPV, as well as PPV. However, its specificity is average. That is due to the high number of False Positives. This derives from the database itself, as it does not contain an equal amount of Diseased and Healthy patients.

Comparisons

The dataset was also utilized to make training and predictions by classification algorithms and methods. Two methods of making use of the dataset for training and testing were used (5-fold cross-validation and 70%-30% train and test data). The cross – validation was chosen to be 5-fold. The Neural Network contains 10 hidden layers of 100 nodes and is trained for 120 epochs, with a batch size of 32 and an initial learning rate of 0.01. Other Neural Networks with alterations on the pre-mentioned parameters were tested and excluded due to inefficiency. The Support Vector Machine (SMO) has the following parameters: Complexity Parameter (c) is set at 1.0, the value of epsilon is set at 1E-12, the batch size is 32 and the

Table 6. Classifier Results.

Classifier	Accuracy (5-fold – cross validation)	Accuracy (70-30)
Coarse Tree	63.4	65.5
Linear Discriminant	70.3	70.9
Logistic Regression	70.6	68.9
Linear SVM	70.0	72.2
Cubic SVM	68.0	69.5
Medium Gaussian	73.3	70.9
Coarse Gaussian	62.7	61.6
Medium KNN	67.7	68.2
Cubic KNN	66.3	68.9
Ensemble Bagged Trees	68.3	68.2
Ensemble Subspace Discriminant	71	71.5
Neural Network	72.6	71.42
Support Vector Machine (SMO)	72.93	71.42
AdaBoostM1	74.58	75.82
Chirp	76.89	72.52
Spaarc	72.93	74.72
Random Forest	74.58	71.42

calibrator method is tuned to Logistic. AdaBoostM1 meta classifier is trained for 50 iterations, with a batch size of 32 and the decision classifier Decision Stump is selected. Chirp is trained with a batch size of 32. Random Forest was trained for 100 iterations with a bag size of 20%, and batch size 32. Spaarc was trained with a batch size of 32.

In Table 6 we present the results of the classifiers, trained and tested on the dataset of the study. Several other classifiers were trained, but their results fell far below 60% at either 5 fold cross-validation or data split, and were not examined extensively. The results demonstrate that the proposed model, archives at least 2% better accuracy compared to the best accuracy obtained from the experiments (that is with Chirp Classifier).

Discussion

In this paper a challenging problem of the medical profession is considered and studied using engineering theories.

The proposed decision support system achieves its aim under the conducted experiments. In the total database, a 78.2% accuracy is acceptable, taking into consideration that the proposed model does not require training.

There are some drawbacks the proposed system has to overcome in future research. The main issue is the fact that all the concepts are directly affecting the output concepts, regardless of their different nature. This is not scientifically accepted. The second issue is the fact that seldom was the output triggered by every possible concept. That is due to missing data on certain diagnostic tests. For this reason, applying the same normalization function to every new instance is not actually placing the values to the desired space. Recent advances in FCM proposed by Mpelogianni et al. (2018), and by Groumpos & Stylios (2018) may be utilized to overcome those issues. That research is left for the future.

Moreover, an in-depth analysis of the mathematical expressions in the core of the model, reveals some potential issues. The equation (2), written in a more compact form, yields:

$$\boldsymbol{V_i}(\boldsymbol{t}+1) = \boldsymbol{f}\left[\sum{}^{j=1^{N}}\boldsymbol{V_j}\ (\boldsymbol{t}) \cdot \boldsymbol{W}^{*}_{\boldsymbol{ji}}\right] \tag{2b}$$

The utilization of the hyperbolic tangent function may sometimes map a non-zero initial vector V to a zero vector, following equation 2b. This unstable condition may be caused given a specific combination of the input vector and the weight matrix containing negative and positive weights. To investigate this issue further, we repeated the experiments observing the outputs of each iteration step. Although the particular dataset did not contain such data as to raise this issue, it is not eliminated. In fact, a potential assignment of input vectors including missing data (e.g., some of the concepts A11-A20 set to zero) could activate this situation. This is not valid for similar CAD datasets, however, it is scientifically possible. A possible solution to this issue involves either dealing with a high-dimensional problem, or reconsidering the activation function. The latter approach, although mathematically correct, is not acceptable from a medical point of view due to the fact that it does not solve the actual problem. Any non-zero input vector mapped to zero following equation 2b, is problematic, regardless of the activation function. Future research should be directed towards unstable (or medically undesirable) situations, involving fixed points affecting the stability of the system, following the remarks of Harmati and Kóczy (2019).

Disclosure statement

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