Chest X-Ray Image Analysis

A Vision of Logic Programming

João Neves[1], Ricardo Faria[2], Victor Alves[2], Filipa Ferraz[2], Henrique Vicente[2,3], and José Neves[2](✉)

[1] Mediclinic Arabian Ranches, PO Box 282602, Dubai, United Arab Emirates
joaocpneves@gmail.com

[2] Centro Algoritmi, Universidade do Minho, Braga, Portugal
ricardo.mof@hotmail.com,
{valves, jneves}@di.uminho.pt, filipatferraz@gmail.com

[3] Departamento de Química, Escola de Ciências e Tecnologia, Universidade de Évora, Évora, Portugal
hvicente@uevora.pt

Abstract. Most cardiovascular diseases can be prevented by addressing behavioral risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol using strategies of the entire population. People with cardiovascular disease or high cardiovascular risk (due to the presence of one or more risk factors, such as hypertension, diabetes, hyperlipidemia or already established disease) need early detection and management using counseling and medication as appropriate. Now a leading cause of death. In fact, it reveals the centrality of prevention and how important it is to be aware of these situations. Thus, this paper will focus on the development of a decision support system to prevent these events to happen, centered on a structure based on Logic Programming for Representation and Knowledge Reasoning, complemented with a case-based approach to computation.

Keywords: Chest X-Ray images · Knowledge representation and reasoning
Logic programming · Case-based reasoning · Decision support systems

1 Introduction

The radiographic image is the result of using the X-Ray methods to visualize the inside of objects. These images are obtained with electromagnetic radiation in several wave ranges, which are selected accordingly to its usage. In the medical imaging field, the projectional radiography, as it is called, helps in diagnose, mainly the ones related to bones density or shape modifications. The chest X-Ray is a quick procedure, as well as easy, painless and non-invasive, and it allows to obtain images from the different structures within the chest area. With these images' records, it is possible to look for symptoms of several types of diseases, namely pneumonia, congestive heart failure, lung cancer, pulmonary fibrosis or sarcoid tissue.

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In this study, the X-ray images will be used to evaluate cardiovascular problems, disease that cause 31.5% of the overall deaths in the world every year [1]. Indeed, this work is focused on the development of a hybrid methodology for problem solving, aiming at the elaboration of a decision support systems to detect cardiovascular problems based on parameters obtained from chest *X-ray* images, like the Cardiac Width (Fig. 1(a)), the Thoracic Width (Fig. 1(b)) and the *Aortic Knuckle Perimeter* (*AKP*) (Fig. 1(c)) [2], according to a historical dataset, under a *Case Based Reasoning* (*CBR*) approach to problem solving [3, 4].

Undeniably, *CBR* provides the ability of solving new problems by reusing knowledge acquired from past experiences [3], i.e., *CBR* is used especially when similar cases have similar terms and solutions, even when they have different backgrounds [4]. Its use may be found in many different arenas, like in *Online Dispute Resolution* [5] or *Medicine* [6–8], just to name a few.

This article is subdivided into five sections. In the former one a brief introduction to the problem is made. Then a mathematical logic approach to Knowledge Representation and Reasoning and a *CBR* view to computing are introduced. In the third and fourth sections a case study is set. Finally, in the last section the most relevant attainments are described and possible directions for future work are outlined.

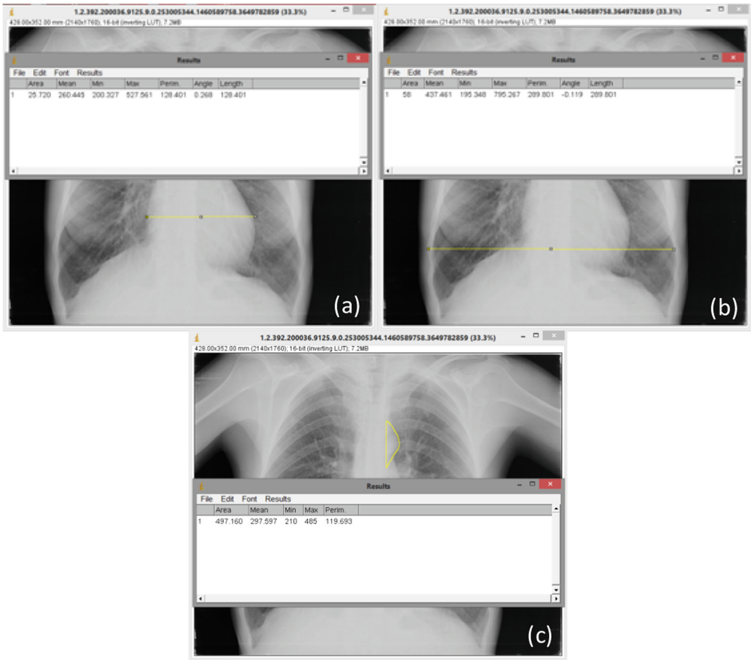

Fig. 1. The *Chest X-ray's* parameters considered in this study, i.e., *Cardiac Width* (a), *Thoracic Width* (b), and *Aortic Knuckle Perimeter* (c) [2].

2 Related Work

2.1 Knowledge Representation and Reasoning

Regarding the computational paradigm it were considered extended logic programs with two kinds of negation, classical negation, ¬, and default negation, *not* [9, 10].

An *Extended Logic Program* is a finite set of clauses as shown in Program 1.

$$\{$$

$$\neg p \leftarrow not\ p, not\ exception_p$$

$$p \leftarrow p_1 \wedge \cdots \wedge p_n \wedge not\ q_1 \wedge \cdots \wedge not\ q_m$$

$$?\left(p_1 \wedge \cdots \wedge p_n \wedge not\ q_1 \wedge \cdots \wedge not\ q_m\right)(n, m \geq 0)$$

$$exception_{p_1}$$

$$\ldots$$

$$exception_{p_j}\ (0 \leq j \leq k),\ being\ k\ an\ integer$$

$$\} :: scoring_{value}$$

Program 1. The Archetype of a Generic Extended Logic Program.

where the first clause of Program 1 depict the predicate's closure, "∧" denotes "*logical and*", while "*?*" is a domain atom denoting "*falsity*". The "p_i, q_j, and p" are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign "¬" [9]. Indeed, "¬" stands for a "*strong declaration*" that speaks for itself, and "*not*" denotes "*negation-by-failure*", i.e., a flop in proving a given statement, once it was not declared explicitly. According to this formalism, every program is associated with a set of "*abducibles*" [11, 12], given here in the form of *exceptions* to the extensions of the predicates that make the program, i.e., clauses of the form:

$$exception_{p_1}$$

$$\ldots$$

$$exception_{p_j}\ (0 \leq j \leq k),\ being\ k\ an\ integer$$

stands for data, information or knowledge that cannot be ruled out. The *invariants* or *restrictions*, i.e., clauses of the type:

$$?(p_1 \wedge \cdots \wedge p_n \wedge not\, q_1 \wedge \cdots \wedge not\, q_m)(n, m \geq 0)$$

allows one to set the context under which the universe of discourse has to be understood. Finally, the term $scoring_{value}$ denotes the relative weight of the extension of a specific predicate.

In order to model the universe of discourse in a changing environment, the breeding and executable computer programs will be ordered in terms of the *Quality-of-Information* (*QoI*) and *Degree-of-Confidence* (*DoC*) that stems out of them, when subject to a process of conceptual blending [13]. In blending, the structure or extension of two or more predicates is projected to a separate blended space, which inherits a partial structure from the inputs, and has an emergent structure of its own. Meaning is not compositional in the usual sense, and blending operates to produce understandings of composite functions or predicates, the conceptual domain, i.e., a basic structure of entities and relations at a high level of generality (e.g., the conceptual domain for journey has roles for traveler, path, origin, destination). Here it will be followed the normal view of conceptual metaphor, i.e., the system will carry structure from one conceptual domain (the source) to another (the target) directly. Now, the predicates whose extensions make an extended logic program (or theory that model the universe of discourse), i.e., i ($i \in \{1, \ldots, m\}$), the attributes of the mentioned predicates, j ($j \in \{1, \ldots, n\}$) and the respective values of the attributes j, i.e., $x_j \in [min_j, max_j]$ must be considered in order to compute a scoring function $V_j^i\left[min_j, max_j\right] \rightarrow 0 \cdots 1$, that gives the score predicate i assigns to a value of attribute j taking into account its domain, given in terms of *all* (*attribute exception list*, *sub expression*, *invariants*) productions. The former predicate generates a list of all possible value combinations (e.g., pairs, triples) as a list of sets defined by the domain size plus the invariants. The second predicate recourses through this list, and make a call to the third predicate for each exception combination. The third predicate denotes *sub expression* and is constructed in the same form. Thus, the *QoI* with respect to a generic predicate *K* is:

- 1 (one) when the information is *known* (*positive*) or *false* (*negative*);
- 0 (zero) if the information is *unknown*; and
- ϵ]0, 1[for situations where the extensions of the predicates that make the program include *exceptions* [14].

In order to measure the *QoI* that stems from a logic program or theory the *QoI* of each predicate are posting into a multi-dimensional space. The axes denote the logic program or theory, with a numbering ranging from 0 (at the center) to 1. Figure 2, shows an example of an extended logic program or theory *P*, built on the extension of 5 (five) predicates, $p_1 \ldots p_5$, where the dashed area stands for the respective *QoI*.

Regarding the *DoC*, it is a measure of one's confidence that the argument values of the terms that make the extension of a given predicate, with relation to their domains, fit into a given interval. The *DoC* is computed using $DoC = \sqrt{1 - \Delta l^2}$, where Δl denotes the length of the argument interval, which was set to the interval [0, 1], since the ranges

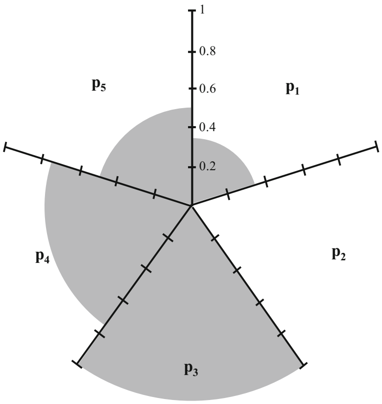

Fig. 2. A measure of *QoI* for the logic program or theory *P*.

of attributes values for a given predicate and respective domains were normalized, in terms of the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$, where the Y_s stand for themselves.

The universe of discourse is engendered according to the information presented in the extensions of such predicates, according to productions of the type:

$$predicate_i - \bigcup_{1 \le j \le m} clause_j(((A_{x_1}, B_{x_1})(QoI_{x_1}, DoC_{x_1})), \cdots$$
$$\cdots, ((A_{x_n}, B_{x_n})(QoI_{x_n}, DoC_{x_n}))) :: QoI_j :: DoC_j$$

where $\cup$, m and l stand, respectively, for *set union*, the *cardinality* of the extension of $predicate_i$ and the number of attributes of each clause [15]. On the other hand, either the subscripts of the QoI_s and the DoC_s, or those of the pairs (A_s, B_s), i.e., x_1, ..., x_l, stand for the attributes' clauses values ranges.

2.2 Case Based Computing

The CBR approach to computing is a technique for problem-solving grounded on the humans' decision-making process. Indeed, it stands for an act of finding and justifying a solution to a given problem based on the consideration of past similar situations, either using old solutions, or by reprocessing and generating new data or knowledge from the old ones [3, 4]. In *CB* the *cases* are stored in a *Case Base*, and those cases that are similar (or close) to a new one are used in the problem solving process. The typical *CB* cycle containing four steps, namely:

- Retrieve – The new case is defined and it is used to retrieve one or more cases from the *repository*, aiming to obtain cases with a higher degree of similarity to it;
- Reuse – The solutions of the similar cases found in the previous step were used to suggest a solution for the new problem;

- Revise – The suggested solution is tested by the user, allowing for its correction, adaptation and/or modification in order to found the solution for new problem; and
- Retain – The new problem and the correspondent solution is stored in the case *repository* [3, 4].

There are several examples of the use of CBR in Medicine, aiming to enhance the work of health experts and to improve the efficiency and quality of health care. In the literature it is possible to found review papers with different applications of *CBR* in medical context, such as disease diagnosis, classification, treatment and management [16, 17]. A recent study in the area of mental health care presents a *CBR* approach aiming to predict the effect of treatments of patients with anxiety disorders. Such approach showed 65% of correct predictions in the absence of similarity restrictions, while for scenario with similarity restrictions (i.e., under the condition that the prediction was based only on cases with a similarity of at least 0.62), the accuracy increased to 80% [6]. Another study presents a fuzzy ontology-based semantic *CBR* system to answer complex medical queries related to semantic understanding of medical concepts and handling of vague terms in diabetes diagnosis [7]. Other work combines *CBR* and multi-agent systems for the diagnosis, prognosis, treatment and therapeutic monitoring of gastric cancer. In the multi-agent architecture, the ontological agent type uses the knowledge domain in order to ensure proficiency in the extraction of similar clinical cases and provide treatment suggestions to patients and physicians. *CBR*, in turn, is used to memorize and to restore experience data aiming to solve similar problems [8].

Despite promising results, the current *CB* systems are neither complete nor adaptable enough for all domains. In some cases, the user cannot choose the similarity (ies) method(s) and is required to follow the system defined one(s), even if they do not meet their needs. Moreover, in real problems, the access to all necessary information is not always possible, since existent *CB* systems have limitations related to the capability of dealing, explicitly, with unknown, incomplete, and even self-contradictory information. To make a change, Neves *et al*. [2, 14] induced a different *CB* cycle that is depicted in Fig. 3. It takes into consideration the case's *QoI* and *DoC* metrics. It also contemplates a cases optimization process present in the *Case Base*, whenever they do not comply with the terms under which a given problem has to be addressed (e.g., the expected *DoC* on a prediction was not attained). The optimization process can use *Genetic Algorithms* [10], *Artificial Neural Networks* [18, 19] or *Particle Swarm Optimization* [20], generating a set of new cases which must be in conformity with the invariant:

$$\bigcap_{i=1}^{n} (\boldsymbol{B}_i, \boldsymbol{E}_i) \neq \emptyset \tag{1}$$

that states that the intersection of the attribute's values ranges for cases' set that make the *Case Base* or their optimized counterparts ($\boldsymbol{B}_i$) (being n its cardinality), and the ones that were object of a process of optimization ($\boldsymbol{E}_i$), cannot be empty (Fig. 3).

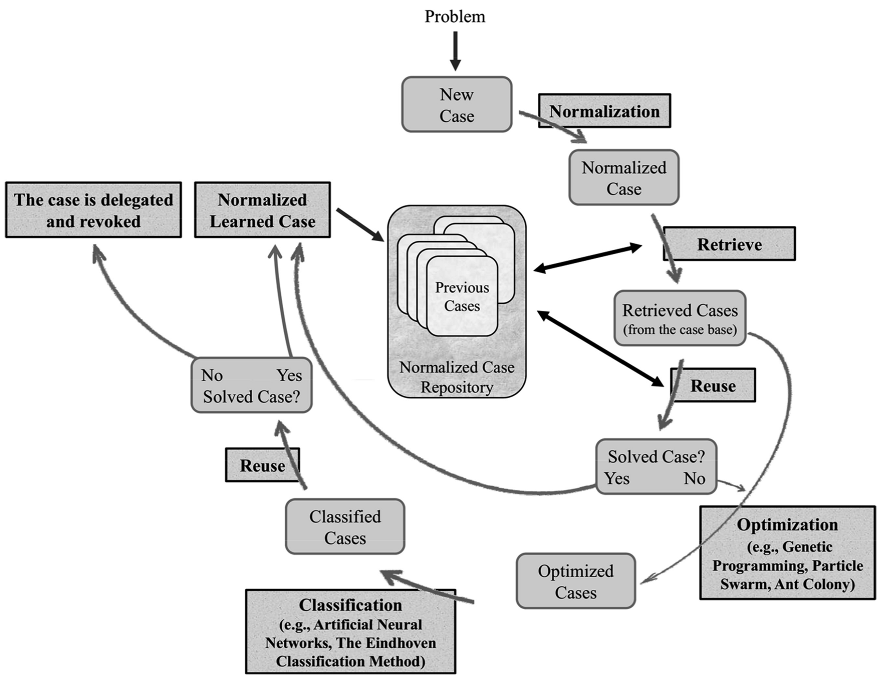

Fig. 3. The updated view of the *CB* cycle [2].

3 Case Study

Aiming to develop a predictive model to estimate the risk of cardiovascular diseases, a database was set, built on 542 health records of patients from a major health care institution in the North of Portugal. The patients included in this study aged between 18 to 97 years old, with an average of 56±16 years old. The gender distribution was 42.2% and 57.8% for male and female, respectively.

After having collected the data it is possible to build up a knowledge database given in terms of the extensions of the relations or predicates depicted in Fig. 4, which stand for a situation where one has to manage information aiming to access the cardiovascular disease predisposing. The software *imageJ* [21] was used to extract the necessary features from *X-ray* images (Fig. 1). In the database some incomplete and/or default data is present. For instance, the *Systolic Blood Pressure* in case 1 are unknown (depicted by the symbol ⊥), while the *Risk Factors* range in the interval [1, 2]. The *CTR* column is the *Cardiac Thoracic Ratio* computed using cardiac and thoracic width. The *Descriptions* column stands for free text fields that allow for the registration of relevant patient features.

Applying the algorithm presented in [2] to the fields that make the knowledge base for *Cardiovascular Diseases Predisposing* (Fig. 4), excluding at this stage of such a process the *Description* one, it is possible to set the arguments of the predicate ***c**ardiovascular **d**iseases **p**redisposing* (*cdp*) referred to below, whose extension denote the objective function with respect to the problem under analyze:

	Cardiovascular Diseases Predisposing									
Attributes of the Feature Vector:	#	Age	Systolic Blood Pressure	Cholesterol (LDL)	Cholesterol (HDL)	Triglycerides	Cardiac Thoracic Ratio	Aortic Knuckle Perimeter	Risk Factors	Description
Feature Vector Attributes:	1	64	⊥	128	47	203	0.45	124	[1, 2]	Description 1
	2	72	128	135	53	252	⊥	⊥	[2, 3]	Description 2
	…	…	…	…	…	…	…	…	…	…
	542	44	113	92	45	104	0.42	112	0	Description 542
Feature Vector Domains:		[18, 97]	[70, 200]	[50, 250]	[20, 90]	[90, 600]	[0.35, 0.65]	[102, 155]	[0, 4]	

Fig. 4. A fragment of the knowledge base for cardiovascular diseases predisposing assessment.

$$cdp : Age, S_{ystolic}B_{lood}P_{ressure}, Chol_{esterol_{LDL}}, Chol_{esterol_{HDL}}, Trigly_{cerides}, C_{ardiac}T_{horacic}R_{atio}, A_{ortic}K_{nuckle}P_{erimeter}, R_{isk}F_{actors} \rightarrow \{0, 1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth values *false* and *true*.

Exemplifying the application of the algorithm presented in [2] to a term (patient) that presents the feature vector Age = ⊥, SBP = 120, $Chol_{LDL}$ = 102, $Chol_{HDL}$ = 70, $Trigly$ = 130, CTR = [0.53, 0.56], AKP = 120, RF = [1, 2], one may have:

$$\{$$

$$\neg\, cdp\left(\left(\left(A_{Age}, B_{Age}\right)\left(QoI_{Age}, DoC_{Age}\right)\right), \cdots, \left(\left(A_{RF}, B_{RF}\right)\left(QoI_{RF}, DoC_{RF}\right)\right)\right)$$

$$\leftarrow not\ cdp\left(\left(\left(A_{Age}, B_{Age}\right)\left(QoI_{Age}, DoC_{Age}\right)\right), \cdots, \left(\left(A_{RF}, B_{RF}\right)\left(QoI_{RF}, DoC_{RF}\right)\right)\right)$$

$$cdp\underbrace{\left(\left(\left((0, 1)(1,\ 0)\right), \cdots, \left((0.25,\ 0.5)(1,\ 0.96)\right)\right)\right)}_{\substack{attribute`s\ values\ ranges\ once\ normalized\ and \\ respective\ QoI\ and\ DoC\ values}} :: 1 :: 0.86$$

$$\underbrace{[0, 1] \qquad \cdots \qquad [0, 1]}_{\substack{attribute`s\ domains \\ once\ normalized}}$$

$$\} :: 1$$

4 Computational Model

The framework presented previously shows how the information comes together and how it is processed. In this section, a soft computing approach was set to model the universe of discourse, where the computational part is based on a *CB* approach to computing. In present work the *CB* cycle proposed by Neves *et al*. [2, 14] (Fig. 3) was adopted. The main advantage of the new *CB* cycle relies on the fact that not only all the cases have their arguments set in the interval [0, 1], but it also caters for the handling of incomplete, unknown, or even self-contradictory data or knowledge. Thus, the *Case Base* given in terms of the following pattern:

$$Case = \{ < Raw_{data},\ Normalized_{data},\ Description_{data} > \}$$

In addition the proposed methodology also contemplates the optimization of the retrieved cases. *Artificial Neural Networks* (*ANNs*) were used in the optimization stage in the following way:

- The extremes of the attribute's values ranges, as well as their *DoCs* and *QoIs* are fed to the *ANN*; and
- The outputs are given in a form that ensures that the case may be used to solve the problem (*no* (*0*), *yes* (*1*)), and a measure of the system confidence on such a result is provided (Fig. 5).

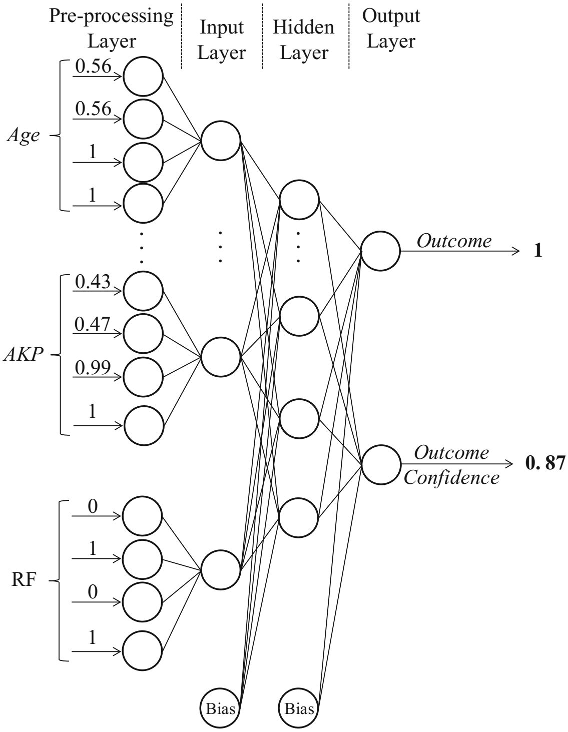

Fig. 5. A case's classification procedure based on *ANNs*.

When confronted with a new case, the system is able to retrieve all cases that meet such a case structure and optimize such a population, having in consideration that the cases retrieved from the *Case-base* must satisfy the invariant present in Eq. (1), in order to ensure that the intersection of the attributes range in the cases that make the *Case-base* repository or their optimized counterparts, and the equals in the new case cannot be empty. Having this in mind, the algorithm described in [2] is applied to the new case that presents the feature vector $Age = 62$, $SBP = 110$, $Chol_{LDL} = 105$, $Chol_{HDL} = 65$, $Trigly = 182$, $CTR = 0.43$, $AKP = [125, 127]$, $RF = \perp$, with the outcome:

$$cdp_{new\,case}(((0.56, 0.56)(1, 1)), \cdots, ((0, 1)(1, 0))) :: 1 :: 0.87$$

Now, the *new case* may be portrayed on the *Cartesian* plane in terms of its *QoI* and *DoC*, and by using clustering methods [22] it is feasible to identify the cluster(s) that intermingle with the *new one*. After the optimization process the *new case* is compared with every *retrieved case* from the cluster using a similarity function *sim*, given in terms of the average of the modulus of the arithmetic difference between the arguments of each case of the selected cluster and those of the *new case*. Thus, one may have:

$$\underbrace{\begin{array}{c} retrieved_{case_1}((((0.77, 0.77)(1, 1)), \cdots, ((0.25, 0.75)(1, 0.87))) :: 1 :: 0.81 \\ retrieved_{case_2}((((0.90, 0.90)(1, 1)), \cdots, ((0.5, 0.75)(1, 0.98))) :: 1 :: 0.85 \\ \vdots \\ retrieved_{case_j}((((0.69, 0.69)(1, 1)), \cdots, ((0.75, 1)(1, 0.97))) :: 1 :: 0.83 \end{array}}_{normalized\ cases\ that\ make\ the\ retrieved\ cluster}$$

Assuming that every attribute has equal weight, for the sake of presentation, the *dis (imilarity)* between new_{case} and the $retrieved_{case1}$, i.e., $new_{case \to 1}$, may be computed as follows:

$$dis^{DoC}_{new\ case \to 1} = \frac{\|1 - 1\| + \cdots + \|1 - 0.87\|}{8} = 0.15$$

Thus, the *sim(ilarity)* for $sim^{DoC}_{new\ case \to 1}$ is set as $1 - 0.15 = 0.85$. Regarding *QoI* the procedure is similar, returning $sim^{QoI}_{new\ case \to 1} = 1$. Thus, one may have:

$$sim^{QoI,DoC}_{new\ case \to 1} = 1 \times 0.85 = 0.85$$

i.e., the product of two measurements is a new type of measurement. For instance, multiplying the lengths of the two sides of a rectangle gives its area, which is the subject of dimensional analysis. In this work the mentioned product gives the overall similarity between the new case and the retrieved ones. These procedures should be applied to the remaining cases of the retrieved clusters in order to obtain the most similar ones, which may stand for the possible solutions to the problem. This approach allows users to define the most appropriate similarity methods to address the problem (i.e., it gives the user the possibility to narrow the number of selected cases with the increase of the similarity threshold).

The proposed model was tested on a real data set with 542 examples. Thus, the dataset was divided in exclusive subsets through the ten-folds cross validation [19]. In the implementation of the respective dividing procedures, ten executions were performed for each one of them. Table 1 presents the coincidence matrix of the *CB*

Table 1. The coincidence matrix for *CB* model.

Target	Predictive	
	True (1)	False (0)
True (1)	276	33
False (0)	19	214

model, where the values presented denote the average of 30 (thirty) experiments. A perusal to Table 1 shows that the model accuracy was 90.4% (i.e., 490 instances correctly classified in 542). Thus, from clinical practice perspective, the predictions made by the *CB* model are satisfactory, attaining accuracies close to 90%.

Based on coincidence matrix it is possible to compute different metrics in order to evaluate the performance of the model, namely *sensitivity*, *specificity*, *Positive Predictive Value* (*PPV*), *Negative Predictive Value* (*NPV*) [23]. The sensitivity and specificity of the model were 89.3% and 91.8%, while *Positive* and *Negative Predictive Values* were 93.6% and 86.6%. The *ROC* curve [23, 24] is shown in Fig. 6. The area under *ROC* curve (0.91) denotes that the model exhibits a good performance in the assessment of cardiovascular diseases predisposing, despite the presence of unknown and incomplete information in the knowledge database.

In some recent studies the problem of incomplete information was addressed. In this context, Abreu et al. [25] present a study to predict the overall survival of women with breast cancer using a clinical dataset with 847 cases and 25% missing values. The *k*-nearest neighbor algorithm was used as the imputation method. The model presents a prediction accuracy of 73%. In another study the referred authors compared the performance of three different imputation methods, i.e., mean/mode imputation, expectation-maximization algorithm and *k*-nearest neighbor algorithm. The sensitivity, specificity and accuracy range from 83.9% to 88.4%, 47.4% to 70.5% and 68.8% to 81.7%, respectively [26].

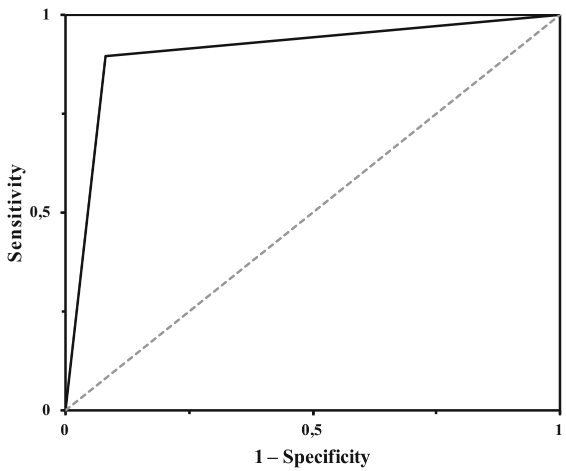

Fig. 6. The *ROC* curve regarding the proposed model.

5 Conclusion

CVD is one of the leading causes of death in the world. Adjusting lifestyle to minimize the prevalence of the risk factors can decrease the prevalence of CVD. Beyond just harming the individual who suffers from some form of *CVD*, it also affects everyone economically, environmentally, and socially. As healthcare and related costs increase, so do the budgets required by these programs. Thus, taxes will likely rise in order to keep up with the demand for government funding of these initiatives. Thus, this work aims at to minimize the impact of this situation, by presenting a *Logic Programming* based *Decision Support System* centered on a formal framework based on *LP* for knowledge representation and reasoning, complemented with a *CB* approach to computing that caters for the handling of incomplete, unknown, or even contradictory information. The proposed model is able to provide adequate responses once the overall accuracy is close to 90%. Indeed, it has also the potential to be disseminated across other prospective areas, therefore validating a universal attitude. In fact, the added values of the presented approach arises from the complementarily between *Logic Programming* (for knowledge representation and reasoning) and the computational process based on *Case Based* expertise.

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