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# Aid decision algorithms to estimate the risk in congenital heart surgery

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ABSTRACT

*Background and objective:* In this paper, we have tested the suitability of using different artificial intelligence-based algorithms for decision support when classifying the risk of congenital heart surgery. In this sense, classification of those surgical risks provides enormous benefits as the a priori estimation of surgical outcomes depending on either the type of disease or the type of repair, and other elements that influence the final result. This preventive estimation may help to avoid future complications, or even death.
*Methods:* We have evaluated four machine learning algorithms to achieve our objective: multilayer perceptron, self-organizing map, radial basis function networks and decision trees. The architectures implemented have the aim of classifying among three types of surgical risk: low complexity, medium complexity and high complexity.
*Results:* Accuracy outcomes achieved range between 80% and 99%, being the multilayer perceptron method the one that offered a higher hit ratio.
*Conclusions:* According to the results, it is feasible to develop a clinical decision support system using the evaluated algorithms. Such system would help cardiology specialists, paediatricians and surgeons to forecast the level of risk related to a congenital heart disease surgery.



## 1. Introduction

Congenital heart diseases (CHDs) are among the most common congenital anomalies, becoming a major global health problem. The 28% of the most critical congenital anomalies are heart defects, causing high rates of morbidity and mortality in neonates [1,2]. If these anomalies are not discovered and treated appropriately in an early stage, children will have a low quality of life and they can even die in the course of time [3].

A CHD is an abnormality that appears in the intrauterine life which in many cases is only detected during the birth and, in the worst cases, much later. These defects can affect the heart walls, valves, arteries and veins, hindering prenatal diagnosis. Congenital heart defects can change the normal flow of blood through the heart [4,5].

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**Table 1 – A worldwide reported birth prevalence of the CHD subtypes (per 1000 live births)[5].**

| Congenital heart diseases | Value |
|---|---|
| Ventricular septal defect (VSD) | 2.62% |
| Atrial septal defect (ASD) | 1.64% |
| Persistent ductus arteriosus (PDA) | 0.87% |
| Pulmonary stenosis (PS) | 0.50% |
| Tetralogy of Fallot (TOF) | 0.34% |
| Coarctation of aorta | 0.34% |
| Transposition of great vessels (TGA) | 0.31% |
| Aortic stenosis (AoS) | 0.22% |

The prevalence of CHDs varies widely among studies worldwide; in Europe, it was reported as 8 per 1000 live births/year [2]. The most commonly reported incidence of congenital heart defects in the United States is between 4 and 10 per 1000 live births [6]. Table 1 shows reported birth prevalence of the eight most common CHD in the world.

Many symptoms and signs can be associated to CHDs, such as cyanosis, heart failure, murmurs, aortic regurgitation, rapid breathing, short of breath and faint (during exercise), among others [4]. CHDs the medical diagnosis is complex because there are a lot of variables to assess. Furthermore, cardiologists require extensive knowledge and many years of practice before carrying out an adequate diagnostic process. In order to achieve an accurate diagnose, which would allow an appropriate intervention, the use of new technologies has been added to medical practice, e.g.: perinatal echography, decision support systems (diagnosis, treatments), etc.

In order to get the best classification rate of the risk in congenital heart surgery we have compared four different methods of classification. The classification of the risk has been based on the Risk Adjustment for Congenital Heart Surgery: RACHS-1, which has been taken as gold standard; this risk measure is based on the categorization of surgical interventions, palliative or corrective, which is used to compare the mortality among hospitals. The diseases are assigned to six risk categories (being six the most complex and one the least complex), according to the expected mortality rate predicted for each disease [7].

Within computer science, the field of artificial intelligence offers algorithms that are currently applied to multiple environments, due to their ability to provide computer programs that perform intelligent tasks as learning, recognition or classification. From the different techniques used in artificial intelligence, those related to classification, such as artificial neural networks (ANN) or decision trees, have been used in medical research showing good performance in clinical diagnostic tasks [8–10].

The objective of our work is to achieve a system for classifying the risk of paediatric cardiac surgery independent of RACHS-1 method by means of different machine learning techniques with pre-surgical and post-surgical input data, allowing clinical experts to have better understanding and prior knowledge of the mortality and the risks associated to a patient undergoing surgery because of a CHDs. This could improve plans of care for each service (intensive care unit, hospitalization, etc.) according to the complexity associated to each patient.

This paper is organized as follows: next we present a survey of works related to the use of classification tools to aid in medical diagnosis; secondly, we explain learning and classification methods used in our research; then, we describe clinical data used, the experiments developed and their results; finally, our conclusions and a final discussion are presented.

## 2. Background

The used of machine learning in any area of medicine as a tool to support decision making and, in particular, in diagnostic tasks has been increasing in the last years. For instance, in neurology, artificial neural networks are used to determine the accuracy of diagnoses that identify typical postural sway patterns for balance disorders [11]; in urology, a multilayer perceptron has been proposed to help urologists in diagnosis of patients with dysfunctions in the lower urinary tract [12]; predicting mortality in patients with strokes [13] and predicting length of hospital stay [14]. Different types of ANN have been used such as those based on radial basis functions [15]. Artificial intelligence classifiers have also been used in oncology and breast cancer diagnosis [10,16,17]; for pulmonary diseases [18]; in haematology [19] and cardiology [20–23]. Decision trees have been also widely used both to represent and to carry out making decision processes. One example is the decision tree used to build a diagnostic model for appendicitis patients [24]. Decision trees are also used in classification of admitted patients according to their critical condition [25], in decision support for early diagnosis of congestive heart failure [26] or in the assessment of risk factors of coronary heart events [27]. Despite we found a large volume of research related to the use of neural networks and decision trees in the diagnosis of heart diseases in adults, only a few were found for CHD diagnosis. For example, in paediatric diagnosis, Reategui proposed a model by integrating case-based reasoning with neural networks [28]. Chowdhury applied a multilayer perceptron with a backpropagation learning algorithm to predict different categories of neonatal disease diagnosis [29].

Classification algorithms are widely used to extract information from datasets. The criteria used to evaluate the classifiers are principally accuracy, computational complexity, robustness, scalability, integration, comprehensibility and stability [30]. There are various classification algorithms and each of them provides different benefits depending on the task and the types of data set on which they are used. The use of ANN provides features such as adaptability, fault tolerance and good classification even when the data presents noise [31]. These characteristics allow neural networks algorithms to recognize complex patterns and then to generate an output assigning a specific category to a given input developing a classification or clustering process. Decision trees (DT) are considered one of the most popular techniques for classifying and they consists on four steps: (1) building tree, (2) stopping of growing the tree (adjusting the information in our database), (3) pruning for making it simpler and leaving only the most important nodes and (4) selection of the optimal tree [32]. Processing is basically a search similar to that in a binary search tree (although DT may not be binary) [33]. Essentially the goal is to find the optimal decision tree by minimizing the generalization error. DT is very used due to its easy understanding and rules generation.

We try to cover most of the algorithms that are widely used in medical applications. We will analyse a multilayer perceptron (MLP) and a radial basis function network (RBFN) as examples of supervised ANN; self-organizing map (SOM) as an example of unsupervised networks and a decision tree as example of algorithm based on rules. In order to train the ANN MLP, we have used backpropagation (BP), developed by Rumelhart [34]. The BP algorithm trains a network for a given set of input data with known outputs (classifications). When each input of the sample set is presented to the network, the network compares the output associated to that input, estimating the difference, or error, between the two values. Based on that error, the connection weights between neurons of each layer are adjusted, from the input layer to the output layer.

## 3. Methods

### 3.1. *Data set*

The children heart disease database used in this study consists on 2432 cases gathered from Cardiovascular Foundation of Colombia. The attributes represent information such as age, gender, weight, diagnosis, surgical intervention and health condition after surgery. Appendices A and B show a list of the variables used, which are classified, into four types: basic data, health history, surgical intervention and post-surgical intervention. The input variables (87) present heterogeneous types of data: text, numbers, ranges, and continuous data, etc. We faced some typical medical database troubles: lack of information (missing values) and data entry mistakes. For instance, data like age and weight were outside of the range, e.g., one of them was 800 kg and another one was registered as a 109 year-old.

Different methods have been suggested for dealing with the missing data problem; a commonly used one is the imputation procedure. This practice can be based on a statistical model for the data distributions, such as the Gaussian Mixture Models (GMMs) and the formulation for Maximum-Likelihood (ML) [35,36]. The simplest method is ignoring cases with missing data. Nonetheless, it is necessary to avoid ignoring data that may affect to classification tasks. Bearing in mind these ideas above and referring to our work, we have replaced the missing attribute values (approximately 10%) by giving the average of all known values of that same attribute.

Other essential pre-processes are data normalization and discretization within a uniform range. This is to prevent large number data from overriding smaller ones and the precipitated saturation of the hidden nodes [37]. One technique used is to scale input and output variables ($Z_i$) in an interval [$\lambda_1$, $\lambda_2$] corresponding to the range of the transfer function:

$$x_i = \lambda_1 + (\lambda_1 - \lambda_2)\left(\frac{z_i + z_i^{\min}}{z_i^{\max} - z_i^{\min}}\right) \tag{1}$$

where $x_i$ is the normalized $z_i$ value, while $z_i^{max}$ and $z_i^{min}$ are the maximum and minimum $z_i$ values in the database. We have used discretization to transform data of some variables like: weight and age (Tables 2 and 3).

**Table 2 – Weight's range.**

| Weight range | Value |
|---|---|
| 0.6–3 kg | 1 |
| 3.1–6 kg | 2 |
| 6.1–9 kg | 3 |
| 9.1–12 kg | 4 |
| 12.1–15 kg | 5 |
| >15.1 kg | 6 |

**Table 3 – Age range according to Jenkins [38].**

| Age range | Value |
|---|---|
| <30 days | 1 |
| 31 days until 1 year old | 2 |
| >1 year old | 3 |

The age was clustered according to Jenkins [38], who created three groups (Table 3) for allowing a refined understanding of differences in mortality among patients undergoing congenital heart surgery, as would typically be encountered within a paediatric population [38]. Chronologically, in our database, children category covers from birth to adolescence (18 years old). The gender variable was encoded (0, 1 where 0 = male and 1 = female).

The list of variables (diagnostic signs) asplenia, polyasplenia, Down's syndrome, Marfan syndrome, DiGeorge syndrome, dysmorphic syndrome, dextrocardia, pre-operative mechanical ventilation, kidney failure, hypoxia, arrhythmia, congestive heart failure and cardiac output have these values: 0 = absent; 1 = present. Hypertension and pre-operative infection present these values: 0 = no and 1 = yes. The rest of coding are shown in Appendices A and B.

The RACHS-1 classification used by the different international associations of congenital cardiac surgery provides a high security level, which allows the predictive method provide highly reliable results [39]. This is used as a basis for pre-sorting patients according to their risk. The RACHS-1 is used to classify the surgical procedures into six categories of complexity [38], from 1 to 6, being 1 the least complex and 6 the most. This type of classification allows surgical groups to compare their results against the predicted mortality in each risk category. RACHS-1 can be understood as a quality improvement or a benchmarking tool.

We have clustered the risk RACHS-1 (that we have used as a gold standard) into three categories (low, medium and high complexity) as follows: 1 and 2 as 1 (low), 3 and 4 as 2 (medium) and 5 and 6 as 3 (high complexity), because the data that belong to the highest complexity represented only 2.96% out of total data.

### 3.2. *Aid decision algorithms*

#### 3.2.1. *Multilayer perceptron (MLP)*

A supervised ANN is characterized by a learning process which is performed and controlled by an external agent (a supervisor training master) who determines the answer the network should generate. The multilayer perceptron (MLP) is one of the most popular supervised ANN models due to its architecture

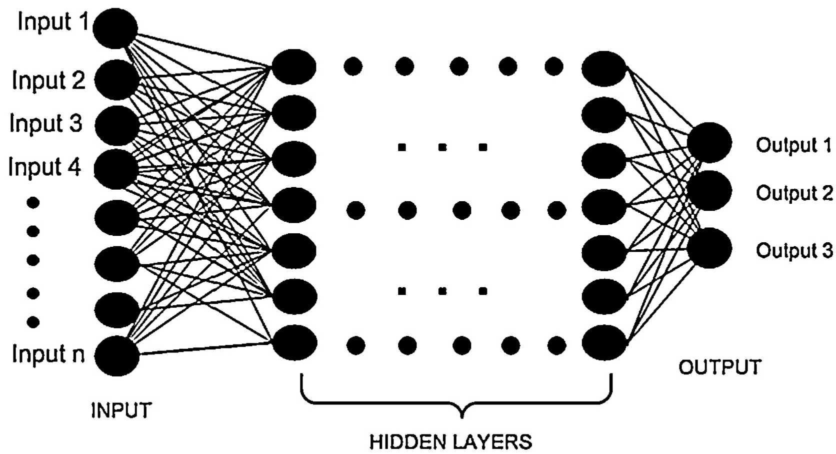


**Fig. 1 – Structure of implemented multilayer perceptron.**

and simple algorithm [40]. A MLP consists on an input layer that receives the values of the variables, one or more hidden layers where the adjustment processes are carried out and the output layer [16,41].

For the construction of the architecture of our MLP (Fig. 1) we followed the next steps:

(1) Input Layer. Inputs correspond to each of the medical variables from the patients who underwent surgery.
(2) Hidden layers. In this part all the researchers have faced the question: which is the appropriate number of hidden neurons? Referring to the number of hidden layers involved in the efficiency of learning and generalization of the network. There is no rule, so that optimal number must be estimated each problem. However Liu and He [42] used the following formula for calculating the number of hidden neurons:

$$N_h = \lfloor J * (K-1)/(I+J+I) \rfloor \quad (2)$$

where $N_h$ represents the numbers of hidden nodes, $J$ is the number of output nodes, $I$ is the number of input nodes and K is the number of training samples. Applying the formula (2) to our work, we obtain 37.5 hidden nodes. Experimentally, we have divided the neurons on five hidden layers with seven neurons on each.
MLPs typically use sigmoid transfer functions in the hidden neurons. This function reduces an infinite input range into a finite output range. Sigmoid function are characterized by the fact that their slopes must approach zero [37].
(3) The output layer has as many neurons as the number of classifications sets. In our case it corresponds to three nodes, one for each set classified.

### 3.2.2. *Self-organizing map (SOM)*

These unsupervised learning systems developed by Kohonen [43] do not require a vector of desired outputs. SOM have the property of creating spatially organized internal representations of various input features. They are composed of two layers: the first one is the input layer which consists of $n$

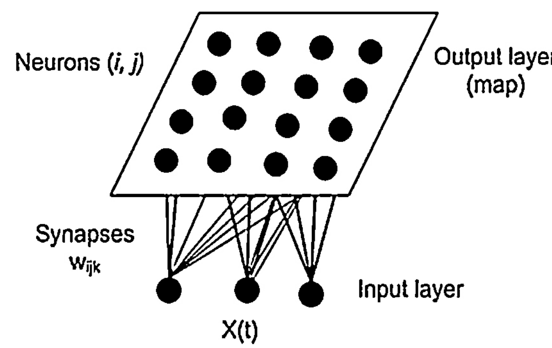


**Fig. 2 – Structure network self-organizing maps.**

neurons and the second layer ($m$ neurons) which is responsible for carrying the procedures out. In our implementation $n$ and $m$ values are 87 and 9, respectively. All the input neurons are connected with the second layer neurons through synaptic weights ($w_{ij}$) (Fig. 2). Each neuron in the second layer is assigned to one weight vector having the same dimension as the input vectors.

This algorithm presents competitive learning, that is to say that the neurons compete to be the closest one to the input value. The Euclidian distance (3) is usually used to measure the similarity between the input value and the neurons' weights in order to select the winning neuron. Then, that winner neuron and its neighbours' weights are updated.

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})}^{2} \quad (3)$$

where $x_{ik}$ is the data value at the *ith* data member of the sample and $n$ is the number of dimensions to the sample vectors.

### 3.2.3. *Radial basis function networks (RBFN)*

RBF neural network is another type of supervised ANN architecture that is aimed at solving specific problems,

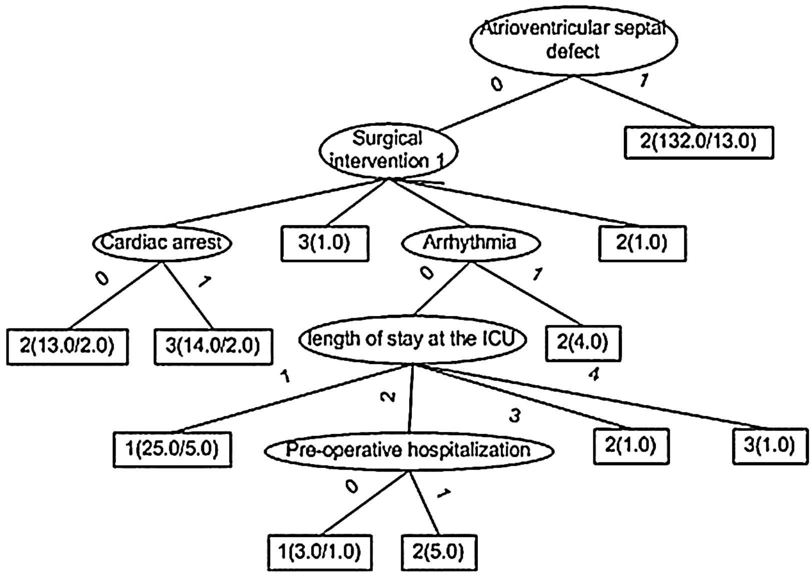


**Fig. 3 – Part of the structure of our decision tree C4.5.**

**Table 4 – Parameters used in our experimentation.**

| | Value |
|---|---|
| **MLP backpropagation** | |
| Hidden layer | 5 |
| Learning rate | 0.3 |
| Momentum | 0.2 |
| Training time (epoch) | 700 |
| **SOM** | |
| Learning rate | 1 |
| Trainign time (epoch) | 1000 |
| Tolerance parameter | 0.001 |
| **RBF** | |
| ClusteringSeed | 1 |
| MinStdDev | 1 |
| NumClusters | 2 |
| TmaxIts | 1 |
| **Decision Tree C4.5** | |
| Confidence factor | 0.25 |
| Seed | 1 |
| Number folds | 3 |
| MinNum obj | 2 |

e.g. optimization and adjustment to non-linear functions. They were introduced by Broomhead in 1998. This type of ANN has got a mixture of the previous two; it can use two methods for learning, hybrid (with an unsupervised phase and a supervised phase) and fully supervised method.

It consists on three layers: input, hidden and output layer [44]. The input layer transmits the signals to the hidden layer and it does not process them. This means that the connections of the input layer to the hidden layer do not have associated weights. Each neuron on the hidden layer represents a single radial basis function with a width and an associated centre position [45]. In the output layer the activation and transfer function is linear: for a pattern $n$, $X(n)$=(($x_1(n)$, $x_2(n)$, $\ldots x_p(n)$)) the output associated to each $k$ element of the output layer is obtained as follows:

$$y_k(n) = \sum_{n=1}^{m} w_{ik} z_i(n) + \mu_k \quad \text{for } k = 1, 2, 3, \ldots, r \tag{4}$$

where $w_{ik}$ are weights associated to the $k$ element of the output layer and $i$ element of the hidden layer; that weights each output $z_i(n)$, $\mu_k$ is a term called threshold and is associated to each element in the output layer.

Despite of that, the architecture is similar to the MLP. The main difference is that the neurons in the hidden layer, which are two in our experimentation, compute the Euclidean distance between the synaptic weights vector (centroid) and the input values (as SOM networks do), and over that distance a radial basis function is applied. The most commonly used is the Gaussian function.

$$\phi(r) = \ell^{\left(\frac{-r}{2}\right)} \tag{5}$$

That is, it has a different activation function for the hidden layer (radial functions of non-linear character with its own gravitational centres) and the output layer (linear functions).

### 3.2.4. *Decision trees*

Decision trees are methods in which different alternatives that occur when analysing a problem are represented with the objective of determining the optimal decisions sequence that must be performed in order to classify an input sample. In this work, we use the algorithm C4.5, proposed by Quinlan, to improve the algorithm ID3 [46] and it is considered a standard model in supervised classification. The C4.5 has advantages such as its intuitive structure that is closer to clinical reasoning and therefore it can be more readily interpreted [47]. In addition, it performs implicitly variable screening or

**Table 5 – Confusion matrix risk category.**

| | Low complexity | Medium complexity | High complexity |
|---|---|---|---|
| **MLP backpropagation** | | | |
| Low complexity | 1181 | 0 | 1 |
| Medium complexity | 2 | 1176 | 0 |
| High complexity | 0 | 0 | 72 |
| **SOM** | | | |
| Low complexity | 1004 | 176 | 2 |
| Medium complexity | 193 | 957 | 28 |
| High complexity | 2 | 42 | 28 |
| **RBF** | | | |
| Low complexity | 1152 | 24 | 6 |
| Medium complexity | 38 | 1130 | 10 |
| High complexity | 1 | 28 | 49 |
| **Decision tree** | | | |
| Low complexity | 1002 | 178 | 2 |
| Medium complexity | 239 | 926 | 13 |
| High complexity | 8 | 44 | 20 |

**Table 6 – Accuracy percentages of each algorithm.**

| Algorithms | MLP | RBF | SOM | DT |
|---|---|---|---|---|
| Correctly classified instances | 2429 | 2325 | 1989 | 1948 |
| Incorrectly classified instances | 3 | 107 | 443 | 484 |
| Accuracy percentage | 99.87% | 95.60% | 81.79% | 80.09% |

featuring selection [48]. Algorithm C4.5 is based on criteria gain ratio, due to this way, it avoids that the variable with the largest number of possible values could be beneficial in the selection. In addition, it also incorporates a pruning procedure for decreasing the overall tree size and decreasing the estimated error rate [49]. A heuristic approach is used for pruning, which is based on the statistical significance of splits.

The basic construction of C4.5 is:

(1) The input node is in the top of the tree. It considers all samples and selects the most important attributes.
(2) The attributes are passed to subsequent nodes, called "branch nodes" which eventually end in leaf nodes that give decisions.
(3) Rules are generated by showing the path from the origin node to the leaf nodes [50]. In this work, we have high dimensionality (eighty seven variables) and it is very difficult to handle data, because the tree can reach a considerable size, which could get complicated the analysis. In Fig. 3 we can observe a part of the decision tree used.

## 4. Experiments and results

In the experimentation process we have used the parameters shown in Table 4 for each implemented method. The classifiers have been designed, trained and tested using WEKA (Waikato Environment for Knowledge Analysis), a tool developed at the University of Waikato (New Zealand) under GPL license [51].

First of all, we implemented ANNs and the decision tree with the data previously mentioned. The corresponding parameters were empirically established (Table 4).

We have used cross validation which consists on: given a number n, data are divided into $n$ parts and, for each part, a classifier is trained with the $n-$A-1 remaining parts [52]. We use a 10-fold cross-validation, this way we do the division into 10 subsets. A single subset is retained as dataset for validation the model and the remaining subsets are used as training.

The classification of the results is displayed by means of the confusion matrix associated to each case. In a confusion matrix, each column represents the number of classifications for each class, while each row represents the instances in the actual class (risk category). Table 5 shows the confusion matrix associated to each classifier implemented.

The number of correctly classified instances is the sum of the diagonal of the matrix and everything out of that diagonal is an incorrect classification. The outcomes correspond to the classification of complexity (risk) in paediatric cardiovascular surgery, which are: low complexity, medium complexity and high complexity. Therein, the complexity is classified according to the expected mortality rate and the complications among groups of patients within a single dataset. It means that low complexity presents less mortality and complications than high complexity. As it is shown in Table 6, the best classification results were obtained with MLP, which presents three samples erroneously classified.

From the results detailed in Table 6, it is possible to notice that ANNs have a strong capability to accurately classify the risk of congenital heart surgery. The accuracy of the MLP is slightly higher that the others. The RBFN also presents good results in the classification; its accuracy is almost the same than the MLP. However RBFN shows a limitation because it is more sensitive to dimensionality and it has greater difficulties if the number of units is large [53]. One of the advantages of unsupervised classifiers is their ability to handle large datasets detecting isolated patterns within them. In this work, the SOM and decision tree show less accuracy than MLP and RBFN. In spite of that, decision trees have their advantages, such as setting out the problem so that all options are analysed. In our work this is not the best alternative since it has a low success rate, which could be due to the large number data.

## 5. Discussion

We have studied the use of classifiers based on neural networks and decision trees for the development of a system for classifying the risk of paediatric cardiac surgery as an alternative method to RACHS-1. The classification can be useful to predict mortality previous to surgery (using pre-surgical variables) and to anticipate care after surgery and associated risks (mortality, complications, etc.) with the use of post-surgical variables. A suitable classification of risk allows clinical staff to improve the plan of care and thus reduce the risk of death and complications.

To give a more comprehensive approach to the applicability of these type of tools as well as to ease their generalization and use in different hospitals, we have also tested the algorithms using just pre-surgical data with the same parameters in Table 4. We have obtained the following results: 82% accuracy for the MLP, 77% accuracy using RBFN, 83% accuracy in SOM and 80% of accuracy for DT. Through these results, the methods provide valuable information for predicting mortality in surgical interventions according to the classification of risk, and to prepare the care before and during the surgical procedure. In addition, it could be useful if it is used to plan the post-surgical care and long-term monitoring with the inclusion the post-surgical variables that offer better result (Table 6). This aspect provides added value in relation to social and corporate responsibility, allowing hospitals to have a better distribution of resources.

## 6. Conclusion

One of the biggest challenges in medicine is dealing with individuals who have the same disease but with different manifestations, which makes diagnosis difficult. This is the case of congenital heart disease; patients are grouped according to their pathology to facilitate predicting the surgical results (mortality, complications, etc.) and post-surgical; these results are used for comparisons among different health institutions and establish risk stratification. So far, with the information available, we consider that risk stratification and classification algorithms, as artificial neural networks and decision trees, are useful tools for the assessment of surgical outcomes in congenital heart disease.

In this paper, we present a decision support system to classify the risk of paediatric cardiac surgery within three categories (low, medium, and high). In order to get the best accuracy, we have assessed four different algorithms: a multilayer perceptron; a self-organizing map; a radial basis function network and a decision trees (C4.5). We have applied cross validation to assess the generalization of the classification. Evaluation of accuracy was similar among multilayer perceptron and radial basis function network 99.87% and 95.60%, respectively. On the other hand, the accuracy was lower in self-organizing map and decision tree, 81.79% and 80.09% respectively. These results prove that the aid decision algorithms evaluated can be useful to help doctors in their decisions related to the risk estimation in congenital heart diseases.

## Acknowledgment

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## Appendix A. Variables database I part

**Basic data**
Age [1–3]
Gender [0,1]
Health insurance [1–7]
Surgery's date (month) [1–12]
Weight [1–6]

**Health history**
Asplenia [0,1]
Polysplenia [0,1]
Down's syndrome [0,1]
Marfan syndrome [0,1]
DiGeorge syndrome [0,1]
Dysmorphic [0,1]
Pre-operative mechanical ventilation [0,1]
Kidney failure [0,1]
Hypoxia [0,1]
Arrhythmia [0,1]
Congestive heart failure [0,1]
Dextrocardia [0,1]
Cardiac output [0,1]
Pulmonary hypertension [0,1]
Pre-operative infection [0,1]
Diagnosis 1
Diagnosis 2
Diagnosis 3

**Health history**
Pre-operative hospitalization [0,1]
Diagnosis number [1,6]
Diagnosis 4
Diagnosis 5
Diagnosis 6

## Appendix B. Variables database II part

**Surgical intervention surgical**
Intervention number [1–6]
Surgical intervention 1
Surgical intervention 2
Surgical intervention 3
Surgical intervention 4
Surgical intervention 5
Surgical intervention 6
Atrial septal defect (ASD) [0,1]
Ventricular septal defect (VSD) [0,1]
Atrioventricular septal defect (AVSD) [0,1]
Surgery time [0,3]
Cardiac arrest [0,1]
Extracorporeal circulation [0,1]
Other surgery [0,1]

**Post-surgical intervention**
Time using pre-operative mechanical ventilation [1,6]
Post-operative complications [0,1]
Erythrocytes requirements [0,1]
Cryoprecipitable [0,1]
Bleeding [0,1]
Cardiac arrest [0,1]
Post-surgery complete atrioventricular block [0,1]
arrhythmia [0,1]
Artificial cardiac pacemaker [0,1]
Cardiac tamponade [0,1]
Cardiac output [0,1]
Post-operative congestive heart failure [0,1]
Post-operative hypertension [0,1]
Peripheria arterial disease [0,1]
Atelectasis[0,1]
Pleural Effusion [0,1]
Chylothorax [0,1]
Pneumothorax [0,1]
Subcutaneous emphysema [0,1]
Tracheostomy [0,1]
Pulmonary edema [0,1]
Post-operative hypoxia [0,1]
Pulmonary hypertension [0,1]
Diaphragmatic paralysis [0,1]
Respiratory Infections [0,1]
Fever [0,1]
Culture [0,1]
Antibiotic treatment for more than 5 days after hospital discharge [0,1]
Post-operative surgical wound infection [0,1]
Mediastinitits [0,1]
Endocarditis [0,1]
Sepsis [0,1]
Dialysis [0,1]
Spasm[0,1]
Hypoxic encephalopathy [0,1]
Reoperation because of bleeding [0,1]
Diaphragmatic plication [0,1]
Mediastinal lavage [0,1]
Sternal banding [0,1]
Intensive care unit re-hospitalization [0,1]
Length of stay before surgery [1,4]
length of stay at the intensive care unit [1,4]
First thirty days survival [0,1]

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