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A robust neuro-fuzzy classifier for the detection of cardiomegaly in digital chest radiographies

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Abstract

We present a novel procedure that automatically and reliably determines the presence of cardiomegaly in chest image radiographies. The cardiothoracic ratio (*CTR*) shows the relationship between the size of the heart and the size of the chest. The proposed scheme uses a robust fuzzy classifier to find the correct feature values of chest size, and the right and left heart boundaries to measure the heart enlargement to detect cardiomegaly. The proposed approach uses classical morphology operations to segment the lungs providing low computational complexity and the proposed fuzzy method is robust to find the correct measures of *CTR* providing a fast computation because the fuzzy rules use elementary arithmetic operations to perform a good detection of cardiomegaly. Finally, we improve the classification results of the proposed fuzzy method using a Radial Basis Function (RBF) neural network in terms of accuracy, sensitivity, and specificity.

Keywords: Cardiomegaly; fuzzy classifier; Radial Basis Function neural network; chest image radiographies.

Clasificador robusto neuro-difuso para la detección de cardiomegalia en radiografías digitales del tórax

Resumen

Presentamos un nuevo procedimiento que determina de forma automática y fiable la presencia de cardiomegalia en radiografías torácicas. El *CTR* muestra la relación entre el tamaño del corazón y el tamaño del tórax. El esquema propuesto utiliza un clasificador robusto difuso para encontrar los valores correctos del tamaño del tórax y los límites del corazón derecho e izquierdo para medir el agrandamiento del corazón para detectar cardiomegalia. El método propuesto utiliza operaciones clásicas de morfología para segmentar los pulmones proporcionando baja complejidad computacional y el método difuso propuesto es robusto para encontrar las medidas correctas del *CTR* proporcionando un cálculo rápido porque las reglas difusas usan operaciones aritméticas elementales para desempeñar una buena detección de cardiomegalia. Finalmente, se mejoran los resultados de clasificación del método difuso propuesto utilizando una red neuronal función de base radial (RBF) en términos de precisión, sensibilidad y especificidad.

Palabras clave: Cardiomegalia; clasificador difuso; red neuronal Función de Base Radial; radiografías de tórax.

1. Introduction

Radiography helps medical staff to provide the most accurate diagnosis possible, which enables insight into the human body. In radiology, radiographies of the chest are the most common and they are used to diagnose conditions affecting the chest cavity, contents and nearby structures. [1,2].

The interpretation of chest radiographs is notoriously difficult, due to the intensity, the brightness, or the contrast which is not appropriate to provide a good delineation of anatomical structures and other regions of interest. For these reasons computer-aided diagnosis for chest radiography is becoming increasingly important to assist and automate specific radiological tasks [1-5].

Some applications of computer analysis of the chest radiographies are reported in the literature: estimation the total volume of the lung and pulmonary nodule detection, estimation of the cardiothoracic ratio *CTR* detection of cardiomegaly, pneumothorax detection, estimation of pneumoconiosis severity, interstitial disease detection, and detection of abnormalities found in mass screening for tuberculosis [1].

Cardiomegaly is a symptom of cardiac insufficiency. The number of people suffering cardiac insufficiency increases every year. In the USA there are about 260,000 deaths caused by cardiac insufficiency every year [6]. In Mexico, there are about 750,000 patients affected by cardiac insufficiency and the number of cases increases 10% per year [7]. More newer alternative methods of diagnosis are been developed [4,5,8-11], so that non experts in cardiology can make a reliable diagnosis and start a preventive treatment for patients who suffer cardiac insufficiency, until they are able to treat this condition with a cardiologist.

Segmentation of the heart from chest radiographic images has been studied by several researchers, usually with the aim of detecting cardiomegaly (enlargement of the heart) [6,9-11]. Methods exist that employ local thresholding, region growing, edge detection, ridge detection, morphological operations, fitting of geometrical models or functions about the heart shape, dynamic programming, and the use of rule-based schemes [1,4,5,8-11]. On the other hand, several attempts have been made to classify each pixel in the image into an anatomical class, such as heart, mediastinum, diaphragm, lung or background. Neural networks or Markov random field modeling are used as classifiers of a variety of local features including intensity, location, and texture measures [1].

In this paper we present a robust fuzzy classifier to decide if a chest radiographic image has cardiomegaly or not. The proposed fuzzy algorithm is the focus of the paper and it is very robust in finding the correct feature values that are important to measure the heart enlargement in chest images to detect cardiomegaly. This algorithm corrects the false characteristic values obtained during the basic segmentation stage where Sobel edge detection and mathematical morphology algorithms are used. Recently, we demonstrated the robust properties of a similar fuzzy feature extraction algorithm used to detect Acute Lymphoblastic Leukemia [12]. For this reason, we decide to use in this paper the results of a basic segmentation stage to demonstrate that the proposed fuzzy classifier could potentially provide a robust solution and reliable diagnosis of cardiomegaly. Finally, we improve the classification results of the proposed fuzzy classifier method using the criteria of the New York Heart Association (NYHA) and the American College of Cardiology - American Heart Association (ACC-AHA) [13] on a Radial Basis Function (RBF) neural network [14].

2. Methodology

2.1. Cardiac insufficiency

A cardiac insufficiency is defined as a clinical syndrome, in which anomalies in the heart structure (i.e. abnormal growth of the heart) cause the malfunction and incapacity of this organ to expel or refill blood at the rate needed by other organs to work [4-6]. Cardiac insufficiency can be defined in terms of its symptoms which are: dysponea, weakness, cyanosis, swelling, palpitation etc. These symptoms are the result of the pumping function of the heart [6].

Cardiomegaly is a symptom of cardiac insufficiency and it refers to the abnormal growth of the heart. This condition is caused by the excessive work of the heart that has to perform a properly function, just like a muscle; the heart increases its size and strength when it is forced continuously. Cardiomegaly can be identified by measuring of the cardiothoracic ratio *CTR* [4-6],

$$CTR = (R + L)/T \tag{1}$$

where R and L are the longest distances from the central vertical line (middle line of the chest) to the right and left heart boundaries, respectively, and T is the longest horizontal distance from the left to the right boundary of lung (see Fig. 1). The cardiothoracic ratio shows the relationship between the size of the heart and the size of the chest, if *CTR* is greater than 0.5, it indicates cardiomegaly in most of cases [4,6].

In order to assess the level of cardiac insufficiency or heart failure (HF), two classifications are commonly employed. One is based on symptoms and exercise capacity according to the New York Heart Association (NYHA) functional classification and American College of Cardiology - American Heart Association (ACC-AHA) classification describes the HF in stages based on structural changes and symptoms [13].

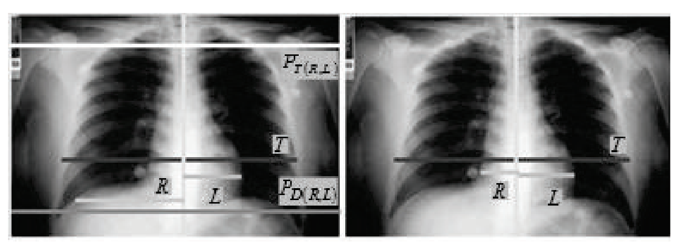
We can distinguish four classes of the NYHA classification (the severity is based on the symptoms and the physical activity), which are as follows:

Class I. No limitation of physical activity. Ordinary physical activity does not cause undue fatigue, palpitation, or dyspnoea.

Class II. Slight limitation of physical activity. Comfortable at rest, but ordinary physical activity results in fatigue, palpitation, or dyspnoea.

Class III. Marked limitation of physical activity. Comfortable at rest, but less than ordinary activity results in fatigue, palpitation, or dyspnoea.

Class IV. Unable to carry on any physical activity without discomfort. Symptoms at rest. If any physical activity is undertaken, discomfort is increased.



a) b)

Figure 1. Measurement of heart size, a) incorrect measurement, and b) correct measurement.
Source: The Authors

The ACC-AHA working group introduced four stages of HF (the stages of heart failure are based on structure and damage to heart muscle):

Stage A. At high risk for developing heart failure. No identified structural or functional abnormality; no signs or symptoms.

Stage B. Developed structural heart disease that is strongly associated with the development of heart failure, but without signs or symptoms.

Stage C. Symptomatic heart failure associated with underlying structural heart disease.

Stage D. Advanced structural heart disease and marked symptoms of heart failure at rest despite maximal medical therapy.

2.2. Proposed method

Lung boundaries identification in a chest radiograph is a necessary step to detect abnormalities such as interstitial disease, pneumothorax, cardiomegaly, and pulmonary nodules [5-8]. The features that are important in the chest images to detect cardiomegaly in terms of *CTR* are: the chest size by finding the parameter T, the middle line localization of chest (vertebral column) to compute the distances L and R, and the heart size is obtained from the sum of L and R (see Eq. (1) and Fig. 1(b)).

We also compute the distance between the middle line and the clavicles, this is used to validate if a chest radiograph is well taken, or on the contrary another radiograph should be taken (i.e., if the relative orientation of body changes with respect to the direction of the x-ray beams this can cause that a normal heart can have an apparently abnormal cardiac shadow in the resulting image making the calculated *CTR* measure incorrect). Fig. 2 presents the distances found between the middle line and the clavicles where to validate the radiography, the difference between the measurements of the right and left side of the middle line should be of $\pm 8\%$. This value is obtained to analyzing different radiography images from our database according to the medical staff.

Some problems are found in obtaining the maximum size of the heart because there is some ambiguity with respect to the measurement if this is part of the heart, the trachea or the diaphragm (see Fig. 1a to see an incorrect measurement). To solve this problem the implementation of a fuzzy system is proposed [15-18].

The fuzzy membership functions used to compute the fuzzy membership values are used for each side (right R and left L boundaries) of the heart about the middle line to describe if a pixel in the radiography is part of the chest using a data base of 11 images as follows,

$$P_{T(R,L)} = \begin{cases} 1, & p \le \left(\bar{p}_{T(R,L)} - \sigma_{T(R,L)}\right) \\ 1 - \dfrac{p + \bar{p}_{T(R,L)} - \sigma_{T(R,L)}}{2\sigma_{T(R,L)}}, & \left(\bar{p}_{T(R,L)} - \sigma_{T(R,L)}\right) < p < \left(\bar{p}_{T(R,L)} + \sigma_{T(R,L)}\right) \\ 0, & otherwise \end{cases} \tag{2}$$

where $\sigma_{D(R,L)}$ is the standard deviation of a starting pixel of the diaphragm, $\sigma_{T(R,L)}$ is the standard deviation of an ending pixel of the trachea, $\bar{p}_{D(R,L)}$ is the average of a starting

$$P_{H(R,L)} = \begin{cases} 1, & \left(\bar{p}_{T(R,L)} + \sigma_{T(R,L)}\right) \le p \le \left(\bar{p}_{D(R,L)} - \sigma_{D(R,L)}\right) \\ 1 - \dfrac{p + \bar{p}_{D(R,L)} - \sigma_{D(R,L)}}{2\sigma_{D(R,L)}}, & \left(\bar{p}_{D(R,L)} - \sigma_{D(R,L)}\right) < p < \left(\bar{p}_{D(R,L)} + \sigma_{D(R,L)}\right) \\ \dfrac{p + \bar{p}_{T(R,L)} - \sigma_{T(R,L)}}{2\sigma_{T(R,L)}}, & \left(\bar{p}_{T(R,L)} - \sigma_{T(R,L)}\right) < p < \left(\bar{p}_{T(R,L)} + \sigma_{T(R,L)}\right) \\ 0, & otherwise \end{cases} \tag{3}$$

$$P_{D(R,L)} = \begin{cases} 1, & p \ge \left(\bar{p}_{D(R,L)} + \sigma_{D(R,L)}\right) \\ \dfrac{p - \bar{p}_{D(R,L)} + \sigma_{D(R,L)}}{2\sigma_{D(R,L)}}, & \left(\bar{p}_{D(R,L)} - \sigma_{D(R,L)}\right) < p < \left(\bar{p}_{D(R,L)} + \sigma_{D(R,L)}\right) \\ 0, & otherwise \end{cases} \tag{4}$$

pixel of the diaphragm, $\bar{p}_{T(R,L)}$ is the average of an ending pixel of the trachea, $P_{T(R,L)}$, $P_{H(R,L)}$, and $P_{D(R,L)}$ are the membership values of trachea, heart, and diaphragm, respectively. These parameters are computed for each side (right R and left L boundaries) of the heart about the middle line, and p is the horizontal measure from the boundaries of the R and L distances about the middle line.

To provide more robustness to the proposed method, the membership function *Similar* (Eq. (5)) is used to evaluate if the longest distance R and L found are correct measurements or not (i.e., if the measurement is part of the heart or part of another area such as the diaphragm or trachea). The

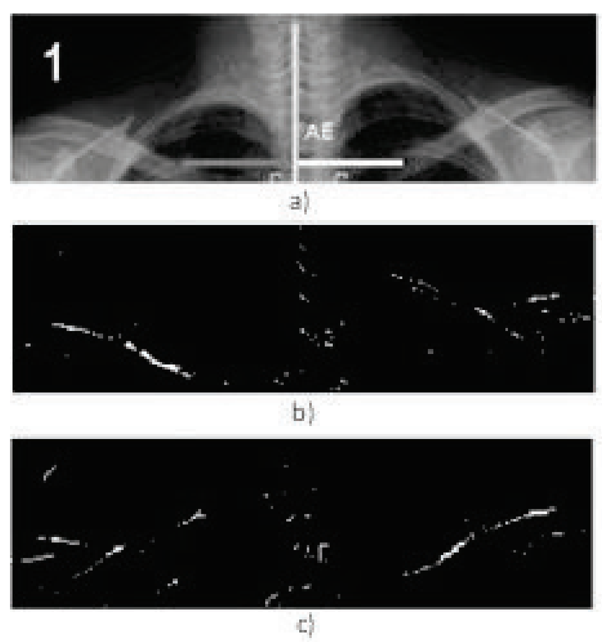


Figure 2. Validation of chest radiography, a) Distances found from the middle line to clavicles, b) Erosion to find the right clavicle, and c) Erosion to find the left clavicle.
Source: The Authors

membership fuzzy value *Similar* indicates if this is strongly related or not to the heart area. Moreover, this fuzzy value will help to discover if there is an abrupt growth of the measurements, meaning that the measurements go through the heart area to the diaphragm area.

$$Similar = \begin{cases} -\frac{a_{(R,L)}}{10} + 1, & 0 \leq a_{(R,L)} \leq 10 \\ 0, & otherwise \end{cases} \quad (5)$$

where a is the pixel difference between the longest found distance measurement and the longest distance in the heart area where the membership value is equal to 1 computed for each side (right R and left L boundaries) of the heart about the middle line.

Using the *Similar* and $P_{H(R,L)}$ membership functions values, the algorithm is able to decide if the longest distance is a measure of the heart or not. The designed fuzzy rule makes the decision as follows:

$$\text{IF } p \text{ IS } heart \text{ OR } a \text{ IS } Similar \text{ THEN } b \text{ IS } correct \quad (6)$$

where OR connective is the fuzzy union representation $(y = a + b - a \cdot b)$ and b is a membership value of the *correct* fuzzy set computed as,

$$correct = \begin{cases} 1, & b \geq 0.8 \\ 0, & otherwise \end{cases} \quad (7)$$

where $b \geq 0.8$ was experimentally chosen to provide the robustness needed to improve the accuracy of the heart size measurement.

Algebraic form of fuzzy rule (6) is as follows:

$$b = \left(0.2P_{H(R,L)} + Similar\right) - \left(0.2P_{H(R,L)} \cdot Similar\right) \quad (8)$$

where the *heart* membership value $P_{H(R,L)}$ is multiplied by 0.2 to decrease the effect it has on the decision, 0.2 value is found to empirically agree to the best detection results.

The membership function (7) of the *correct* fuzzy set indicates the membership level of the measurement obtained from the fuzzy rule to determine the heart size in an accurate form, if the membership value obtained is 0, it indicates that a new measurement should be taken, and the algorithm has to evaluate if the new measurement taken has a membership value of 1 to determine if the measure belongs to the heart. Problems encountered in the feature extraction of the heart size are solved using (7) and the results are shown in Fig. 1, where the measurement obtained without implementing a fuzzy method (see Fig. 1(a)) for measuring of the right side of the heart is incorrect because it does not belong to the heart. After applying the fuzzy method (see Fig. 1(b)) the system found the correct measurement of the right heart size.

3. Results

3.1. Segmentation results

Several chest image radiographies are obtained from a Mexican medical data base (200 images) to train and test the proposed algorithm. The stages of proposed method are given as follows:

a) *Preprocessing*. Chest radiographies display a wide dynamic range of X-ray intensities. In unprocessed images it is often hard to obtain data from the mediastinum because the contrast in the lung fields is limited. A solution to this kind of problem in image processing is the use of local histogram equalization methods [1]. Histogram equalization adjustment is used to enhance contrast of the processed radiographic image [19,20]; which achieved similar contrast in all images and agreed to the best result obtained with the segmentation algorithm. Fig. 3(a)-3(b) presents an original chest image and the processed image using the histogram equalization method where one can see that this image is enhanced.

b) Segmentation. Mathematical morphology algorithms are used to skeletize the pre-processed images [19]. Fig. 3(c)-(d) illustrates these processes in order to find the middle line of the chest, erosion is made with a rectangular structural element of 5xm pixel size, where m is the vertical size of the image. The resulting image is shown in Fig. 3(e). A similar process is used to compute the distance between the middle line and the clavicles to validate if a chest radiograph is well taken before finding the middle line of the chest. In this case, erosion is performed with a rectangular structural element of 2x3 pixel size, Fig. 2(b)-(c) shows the results of this erosion in both clavicles. Also, in the pre-processed image, thresholding is needed before Sobel edge detection (Fig. 3(f)) to highlight the heart in the pre-processed image and to eliminate the ribs to obtain the heart boundaries (parameters R and L defined previously) of Fig. 3(g)-(h).

c) Feature extraction. From the segmentation results we are able to find the middle line of the chest, the heart size (R and L distances), and the chest size (T distance). The middle line of the chest is computed by finding the middle line of the white block of Fig. 3(e) to obtain the black line of the image of Fig. 3(i). When this line is found we can obtain the longest R and L distances (using an array containing different measures of R and L distances) by counting the distance that exists between the middle line and the right and left boundaries of heart using Fig. 3(g)-(h). We also compute the distance between the middle line and clavicles applying a similar procedure using the images of Fig. 2(b)-(c). The chest size is now found as the longest distance between the right and left chest boundaries. Measurements of the middle line and the chest size are achieved successfully. Fig. 3(i) shows these measurements.

d) Fuzzy rules. We need to validate the longest R and L distances by using the fuzzy membership functions shown in equations (2) to (4) to evaluate whether these distances are significant measurements or not. Fig. 1(a) depicts a non significant measurement where this distance includes a part of the diaphragm, to avoid this problem we apply the following steps:

1) Find the longest value of R and L distances and the pixel pertinence (whether it is or not a part of the heart) of the distance values from the array that contains the measures

of *R* and *L* distances.

2) Evaluate the *R* and *L* distances using the *correct* fuzzy set. If *correct*=0, the measurement is incorrect and the algorithm evaluates the following distance taken from the distance array up to find a distance and a pixel that corresponds to a result of *correct*=1. It indicates that the measurement represents the longest distance between the middle line and the heart boundaries (*R* and *L* distances).

a. *Classification.* The *CTR* is computed using the *T* and the correct (*R*, *L*) measurements found by the proposed fuzzy method, with these results we obtain the performance of proposed method using the condition *CTR* > 0.5, this indicates that the chest radiograph image has cardiomegaly, otherwise, it does not.

3.2. *Fuzzy classifier results*

The performance of the proposed fuzzy method is evaluated in terms of medical purposes, we compute the sensitivity and specificity [4,8,9,11,12]. *Sensitivity* is the probability that a medical test delivers a positive result when a group of patients with certain illness is under study, and *specificity* is the probability that a medical test delivers a negative result when a group of patients under study do not have certain illness, both sensitivity *Sn* and specificity *Sp* are represented as:

$$Sn = TP/(TP + FN) \tag{9}$$

$$Sp = TN/(TN + FP) \tag{10}$$

where *TP* is the number of true positive that are correct, *FN* is the number of false negatives, that is, the negative results that are not correct, *TN* is the number of negative results that are correct and *FP* is the number of false positives, that is, the positive results that are not correct.

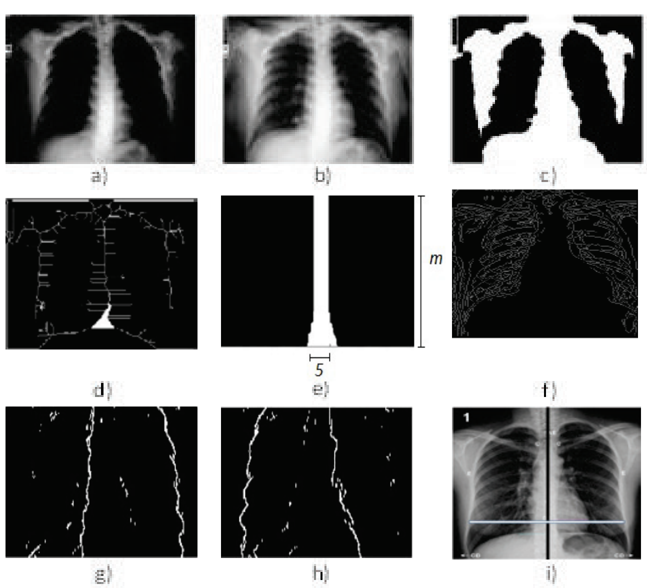


Figure 3. Experimental results, a) Original chest image, b) Processed image with histogram equalization method, c) Processed image with morphological operators, d) Skeletization of the image, e) Erosion to find the middle line, f) Edge detection, g) Right border of heart, h) Left border of heart, and i) Measurement of middle line and chest size.
Source: The Authors

Table 1 shows some numerical values results obtained from the measure of cardiothoracic ratio using a simple comparative method without fuzzy logic and the proposed fuzzy method. The variable *CTRT* shows the true (manual) measure obtained from the chest radiography, *Tt* indicates the true classification value, *CTRC* and *CTRF* indicates the measure values obtained with the comparative and proposed fuzzy method, respectively, in terms of correct (*c*) and wrong (*w*) classifications, and in terms of medical purposes. The procedure of comparative method is performed using a fixed region in the image and assuming that it is a heart region, and obtaining the maximum distance as if this was the correct measurement of the heart size. The fuzzy method is implemented using the whole image and it is evaluated whether the longest distance found is the correct measurement of the heart. Analyzing the results of Table 1, the proposed fuzzy method is able to provide a good *CTR* classification and to fix the measured errors produced during the segmentation stage outperforming the results of comparative method.

Table 2 shows the sensitivity and specificity values obtained from the proposed fuzzy method and the comparative method without fuzzy logic (COMP) in the determination of cardiomegaly. We can observe that the specificity of the proposed method outperforms the comparative method. In the case of sensitivity, the comparative method has better performance in comparison with the proposed fuzzy method.

3.3. *Neuro-fuzzy classifier results*

Table 1.
Comparative classification results in terms of cardiothoracic ratio where *class* is the classification.

Chest images						
#	*CTRT*	*Tt*	*CTRC*	*class*	*CTRF*	*class*
1	0.450	false	1.000	*w - FP*	0.427	*c - TN*
2	0.396	false	0.418	*c - TN*	0.379	*c - TN*
3	0.402	false	0.644	*w - FP*	0.396	*c - TN*
4	0.350	false	0.353	*c - TN*	0.336	*c - TN*
5	0.432	false	1.000	*w - FP*	0.396	*c - TN*
6	0.444	false	0.447	*c - TN*	0.408	*c - TN*
7	0.571	true	0.760	*c - TP*	0.558	*c - TP*
8	0.584	true	0.885	*c - TP*	0.595	*c - TP*
9	0.350	false	0.352	*c - TN*	0.349	*c - TN*
10	0.372	false	0.536	*w - FP*	0.383	*c - TN*
11	0.391	false	0.625	*w - FP*	0.380	*c - TN*
12	0.552	true	0.648	*c - TP*	0.530	*c - TP*
13	0.357	false	0.578	*w - FP*	0.414	*c - TN*
14	0.402	false	0.618	*w - FP*	0.411	*c - TN*
15	0.450	false	0.684	*w –FP*	0.455	*c - TN*
16	0.540	true	0.537	*c - TP*	0.510	*c - TP*
17	0.719	true	0.724	*c - TP*	0.724	*c - TP*
18	0.510	true	0.931	*c - TP*	0.474	*w -FN*
19	0.843	true	0.912	*c - TP*	0.833	*c - TP*
20	0.729	true	0.903	*c - TP*	0.743	*c - TP*
21	0.509	true	0.509	*c - TP*	0.489	*w -FN*
22	0.523	true	0.525	*c - TP*	0.506	*c - TP*
23	0.675	true	0.676	*c - TP*	0.676	*c - TP*
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
80	0.530	true	0.529	*c - TP*	0.547	*c - TP*

Source: The Authors

Table 2.
Experimental results in the determination of *CTR* to detect cardiomegaly where σ is the standard deviation and ε es el error.

Method	*Sn* (%)	*Sp* (%)	ε (%)	σ
COMP	100.00	33.33	33.33	0.1713
Fuzzy	93.85	100.00	6.35	0.0212

Source: Authors

Table 3.
Experimental results in the detection of cardiomegaly using an RBF neural network.

Method	*Sn* (%)	*Sp* (%)	ε (%)
FRBF NYHA	96.17	100.00	5.88
FRBF ACC-AHA	98.79	96.38	4.62

Source: The Authors

To improve the results of the proposed fuzzy method (see Table 2), we use two different Radial Basis Function (RBF) neural networks [12] where the inputs of the first network are given by the clinical data of patients given under the New York Heart Association (NYHA) classification based on the functional incapacity degree of patient (i.e. physical activity) and the second classification with the American College of Cardiology-American Heart Association (ACC-AHA) based on a pre-diagnostic of patient (i.e. structural abnormality) [6,13]. Additionally, the parameters found in the fuzzy logic algorithm are added as inputs in the RBF networks.

Table 3 shows that the proposed fuzzy logic-neural networks (Fuzzy-RBF NYHA and Fuzzy-RBF ACC-AHA) improve the results of accuracy, sensitivity, and specificity values of the proposed fuzzy logic based method (see Table 2).

4. Discussions

There are several similar researches on cardiomegaly detection in the literature [4,8,9,11], we compared our approach with some of them. It has been proved that a correct segmentation of the lung fields is enough to compute the *CTR* indicative of cardiomegaly, since parts of the boundaries of the lung fields coincide with the heart contour [1]. For this reason we take the lung segmentation results of two methods to compare our proposal in terms of accuracy, sensitivity, and specificity. In paper [8] the authors present a knowledge-based approach to segmentation and analysis of the lung boundaries in chest X-rays. The image edges are matched to an anatomical model of the lung boundary using parametric features to find the *CTR*, this system shows a sensitivity of 88% and a specificity of 95% [8]. Another technique presents a novel segmentation method that extracts cardiac and thoracic boundaries with respect to the regions of interest from radiography images providing robustness in noisy environments like chest radiographies. In this technique, the accuracy of segmentation is 98.53% with standard deviation of 0.52, and the sensitivity and specificity are measured as 93.37% and 98.21%, respectively [4].

Other methods after finding the lung segmentation compute the *CTR*. An accuracy of 94.9% is obtained in a method based on gray-level histogram analysis and an edge detection technique with feature analysis [9]. A method based on image filtering with convolution masks, segmentation with thresholding and edge detection achieves an accuracy of 90.5% with a sensitivity of 83.3% and a specificity of 93.3% [11].

Our proposed fuzzy approach provides an accuracy of 93.65% of correct detection (see the error of Table 2) and 93.85% and 100.00% of sensitivity and specificity, respectively. From this comparative we can see that the performance of the proposed fuzzy method provides the best results in terms of accuracy, sensitivity, and specificity in comparison with other methods in most of cases. An advantage of the proposed approach is that it uses classical morphology operations to segment the lungs providing low computational complexity and the proposed fuzzy method is robust to find the correct measures of *CTR* providing fast computation because the fuzzy rules use elementary arithmetic operations and have a good performance in the detection of cardiomegaly.

Finally, the proposed fuzzy logic-neural networks (FRBF NYHA and FRBF ACC-AHA) improve the results of the proposed fuzzy logic based method (see Table 2) and outperform other ones published in recently literature [4,8,9,11] by balancing the tradeoff between accuracy, sensitivity, and specificity.

5. Conclusions

The proposed fuzzy and fuzzy – RBF neural networks are able to detect cardiac insufficiency in terms of cardiomegaly. The proposed methods have demonstrated better classification of chest parameters and detection of cardiomegaly in comparison with the traditional method and others published in literature in terms of accuracy, sensitivity, and specificity. Analyzing chest radiographies by means of use of fuzzy logic and RBF neural networks are possible and can be used as an alternative diagnosis test using the proposed algorithms.

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