



Neural Networks Oblige Diagnosis of the Ischemic CVA's by MRI

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

In present time the technological & computing evolution are promoted for new opportunities that will help to improve the standard of life between the new medical accomplishments, in particular and the standard of diagnostic evaluations. MRI is one of the imaging equipment for the diagnosis which has become more beneficial for technological development, because of this and due to the standard of a diagnosis manufacturer, that is one of the most engaging apparatus in the clinical application. The attentiveness in that pathology & in the general the encephalon picture analysis as the preventive diagnosis. The present research paper suggests the evaluation of the ability of ANN for the automatic identification of an ICVA by tissue images density obtained by MRI. In this examination the diagnosis and their medical reports were used to train the ANN classifier which extracted features from the given images. In this stage the ANN significantly contributes to the ICVA of MRI diagnosis aid, so since the test occurrence automatic identification of ischemic lesions that has been performed with the accuracy results that will be false positive and false negative.

Keywords: Artificial neural networks (ANN); diagnosis; identification; ischemic cerebral vascular accident (ICVA); magnetic resonance imaging (MRI).

1. INTRODUCTION

Magnetic resonance (MR) image is introduced by clinical medicine and that has assumed an unparalleled main role of importance classifying brain image magnetic resonance imaging (MRI) is an important technique which is used in studying the human brain [1]. MRI provides soft tissue and anatomy improved the quality of brain treatment and diagnosis. Magnetic resonance is a non-invasive technique. Computer technology plays an important role in the medical field and it will be pervasive and widespread in medical areas and those different areas like heart diseases, gastroenterology, and brain tumor and cancer research [2]. Full automatic for abnormal and normal brains that suffer brain problems, hence the MRI is obtained, which plays an important role in the field of medical science and clinical studies [3].

Medical imagology technology that has significantly improved their production due to an evolution of the computational assets, authorize deals with the more amount of manufacture images [4]. MRI is a technique which provides the images from the inside of the human body with anatomic information and capabilities of generating the virtual actual images of the human body by the image processing workflow in different planes of images can be obtained in 4 Dimensional and 3 Dimensional images [5]. This application materializes as a significance of increasing the quantity of data that allows the image reconstruction with the improving space resolution, small acquisition time & finally with low radiation petition to a patient [6]. The consequence of a large growing of anatomic data in the particular growing number of pictures per single examination [7]. Then time spent by a radiologist examining every image in the detail was extended. So this must lead to the delay for intervals of the clinical delivery report with the clinical expenses [8,9].

Considering pathologies like ICVA, untimely diagnosis will be anticipated aiming at the disease's consequences minimization. The ICVA is the 3rd cause of death in developed countries & according to the information from the cardiology society of Portuguese [10]. The 1st line of cerebrovascular disease that helps to identify the hemorrhages characterized by the higher density (white) picture and occupying the round area spaced or infarct characterized by lower density (dark) picture & occupying the vascular territory of some swelling [11,12].

ANNs must be applied in the wide variation of computational issues in pattern recognition, recognition & decision. Then considering the usually, a Radiologist analyzing the removal density of the tissue & its size, shape & location to manufacture the report, a ANN must be a viable solution to help the diagnosis procedure [13]. Moreover, the growing number of the ICVA implies the diagnosis in a useful time that minimizes morbidity or unifies the patient's death. The lessen number of the Radiologists correlated with the growing number of the individual investigations, each established by different images, may donate to a detained final report. The Radiologists will analyze the picture & produce the finishing clinical reports. These actualities establish the stimulation to create the present computationally intelligent applications, capable of abet the radiologist in an analysis of the MRI scan images & in future, authorize a preparatory trigger of the pathologic occurrences, when the absence of an expert radiologist [14,15]. There have been a handful of researches that help to determine the classification of Neural Networks Oblige Diagnosis of the Ischemic CVA by MRI image by using different algorithms. In previous research papers they used different algorithms which gave different output by using different techniques.

Luis Ribeiro, and colleagues discussed about neural networks assisted diagnosis of ischemic CVA through CT scan in which they used the computerized topography (CT) scan with the neural networks to find the ischemic cerebral vascular lesions diagnosis in the human body. In this research paper they suggested evaluating the capacity of the artificial neural networks (ANNs) for an automatic identification of the ICVAs by which means of the tissue density pictures acquired by the CT [16]. A Cranioencephalic CT'S exams & their separate medical reports that were used to train the ANN categorization by the means of attributes extracted by caready the first line of dino from the pictures. significantly contribute an ICVAs of CT diagnostic aid, since the among all test cases that automatic image & occupying is a recognizing of ischemic lesions that has been accomplished with no false positive & few false negatives [17].

M.G. Ruano and colleagues disclosed about the Radial Basis Function Classifier for the Automatic Diagnosis of Cerebral Vascular Accidents in which they use the CT for cerebral accidents vascular in diagnosis. In this paper the

author discussed a Radial Basis Function Neural Network (RBFNN) depending on the diagnosis systems for the automatic recognition of Cerebral Vascular Accident (CVA) between analysis of the Computer Tomography images is presented. The design of the neural networks classifier [18]. Moreover, considering all domains of lesion observation from the brain the tissues, their features space commonly contains asymmetry/symmetry information with respected to the ideal of mid-sagittal lines [19]. Another problem is how they handling multiple dispute impartialities in the designing process, such that maximization of the both specificity & sensitivity, the enforcing must be generalization. That deals with the challenges of a Multi Objective Genetic Algorithm (MOGA) depending on the approach used to establish the structure of the classifying, its corresponding frameworks and input attributes subject to multiple impartial, so their corresponding priorities and restrictions [15].

In previous paper author proposed some methodology but due to some reasons they don't find the accurate parameters through those methodologies. So to overcome this problem classifying the other methodology in this paper which helps to find the nearby parameters of neural networks.

What is the need of Neural Networks to Oblige Diagnosis of the Ischemic CVA by MRI?

In the present research paper using the neural networks with MRI scanner oblige Diagnosis of the Ischemic CVA that will

provide the techniques which help to find the diagnosis.

2. METHODOLOGY

Past research showed that despite CBT's well-established effectiveness in treating OCD, it remains significantly under-utilized. It was found that individuals who initiated treatment did not complete all the sessions or did not receive an adequate number of sessions. The stigma associated with OCD prevents many people from seeking treatment. Patients are sometimes not aware that CBT is an option for treatment. In many cases, depression, bipolar disorder or other co-occurring psychiatric disorders may impede treatment with CBT.

2.1 Design

The main aim of this research is to apply the ANN of the RBF type that detects the ICVA in the images encephalon acquired by the MRI scan. In the present study the group of 30 encephalon images with ICVA diagnosis used. So every exam is composed of the 2 ranges. In which one is covering the remaining brain and other is posterior fossa (respectively 10/10mm and 15/15mm cuts) [11].

2.2 Radial Basis Function of Neural Networks

A RBFNN must be used for this work classifier of a MRI encephalon image given the capacities for known pattern classification shown in Fig. 1.

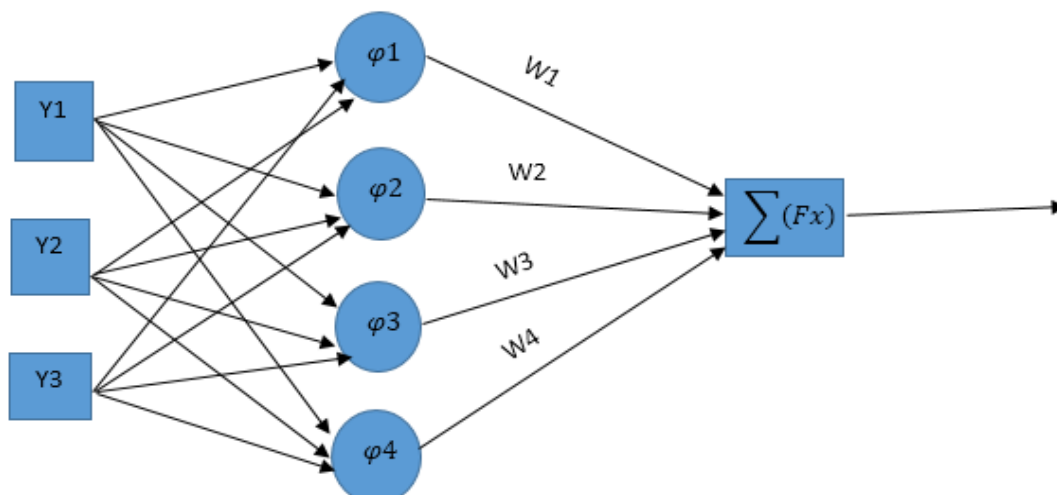


Fig. 1. The topology of Radial Basis Function Neural Networks in which the node y1,y2 and y3 goes to the every node of ϕ_1, ϕ_2, ϕ_3 and ϕ_4 gives output through the weighted w_1, w_2, w_3 and w_4 and show the neural image of diagnosis

2.3 Sample

It will contain 3 functional distinct layers and input layers used for sensory units of sets. The 2nd hidden layers of the sufficient dimension and see problem in hand which must apply the nonlinear transformation for the input space generating and usually high dimension and also units of hidden space and last layer that applies on the linear transformation from hidden space units of the output space. That given outputs by where,

$$[f(x) = \alpha + \sum_{i=1}^n w_i \phi_i(x, c_i, \sigma_i)] \text{-----} (1)$$

N = Numbers of Neurons
 ω_0 = Bias Term
 ω_i = Weight for linear output combiner

The function layer usually in Gaussian function:

$$[\phi(x, c_i, \sigma_i) = e^{-\frac{x-c_i}{2\sigma_i^2}}] \text{-----} (2)$$

The training methods engage containing 2 steps:

- 1) The unsupervised procedure which is known as OAKM algorithm optimal adaptive k means clustering that is used for the initial compute center locations and determine initial spreads.
- 2) The supervised procedure then engaged the Livener Maquardt algorithm. For further optimization non-linear attributes of the given networks.

In every training iteration output gives linear weight that is computed the least squares solution. Then methods reflect the linear or nonlinear topology of neural networks of RBF. The conclusion criterion used for stopping the training process that is mostly used in the nonlinear optimization issues. It will depend on 1 attribute related to the correct number figure in unprejudiced function & also use gradient & attributes vectors evaluate convergences of the attributes values when every stopping situation met the training phase is ended & attributes of the networks must be stored in latter usage [11,20].

2.4 Instrument

Cerebrovascular accident (CVA): (CVA) is the medical term for a stroke. A stroke is when blood flow to a part of your brain is stopped either by a blockage or the rupture of a blood vessel.

Artificial Neural Networks: Artificial neural networks, usually simply called neural networks, are computing systems vaguely inspired by the biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain.

MRI: Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body. MRI scanners use strong magnetic fields, magnetic field gradients, and radio waves to generate images of the organs in the body.

2.5 Data Collection

The picture employed that all were acquired by the means of MRI equipment that respecting all the protocols for encephalon (10/10-15/15mm) and archived in the format of DICOM. In the lab it will be converted into portable network graphics the format is 258 tones grey and respecting the actual image (514 514) size. The HUV values will be for every series, for every series will be respected and the process of neural networks analysis. Every point of interest that automatically removes white parts communicates to the bone and other regions not classified. The several small regions manually labelled as ischemic at 1 and normal at 0. For every pixel image that chosen region and feature set was extracted. In this containing the x, y, r for the pixels [17,12]. Let I represent the image matrix. The notation I stands for the intensity of the pixel in column x and row y. Consider the sub-matrix, consisting of the pixels square centred in point $I_{x,y}$ and having $(2xr)+1$ pixels on each edge.

$$P(x, y, r) = \begin{bmatrix} I_{x-r,y-r} & \cdots & I_{x+r,y-r} \\ \vdots & \ddots & \vdots \\ I_{x-r,y+r} & \cdots & I_{x+r,y+r} \end{bmatrix} \text{-----} (3)$$

They chose reflecting image statistics & related to context the pixels that interest in the presence of the model that have position and sharp edges within the images. Altogether the features from possible information set suitable for train RBFNN pixels classifier shown in Table 1.

2.6 Data Analysis

The overbar designates the average value 2 to communicate the median values & classifier the

standard deviation of the given argument. The computing characteristic points mendacious within a mask considered. From the given set of 30 examine randomly from the collected data of patient P02, P04 shown in Figs. 2 and 3. The P04 donated within 15 points for the training sets while 4 points were taken from P04 shown in Table 2.

3. RESULTS

At the starting stage neural networks were trained that have only 3 features (f2, f4, f8) as the inputs r1&r were made equal to the 20. So the different tribunal were accomplish varying the neurons number. The network's performance obtained training & set of tested data. So the performance will be checked between the error measured and desired classified & also networks output. So submitted a classifier & results that will analyze & compare the report of the radiologist. The process will be repeated in the recursive way till no neighbor's pixels were reported as the pathological. So the complete process must be repeated by adding or removing the features in the network's input & varying the no. of neurons for every input configuration. Then after the no. of trials outputs were significantly improving after the neurons NN having.

$$x = [f1, f2, f3, f4, f5, f6, f7, f8, f9]$$

After containing the patient P04 and P02 images it will show the single output of the total classifier in Fig. 4.

Then the output images will be marked with several colors' which depend on NN output for every tested pixel. The following color used to regard the networks outputs [21,3].

- [0.3, 0.6] = Pathology absence (yellow).
- [0.76, 1.4] = Pathology (red).
- [0.6, 0.76] = Positive marginal (Yellow).
- [0, 2, 0.4] = Clear pathology absence (blue).

4. DISCUSSION

The ANN located in the ICVA receives that presence when it is present in the given images. So the small errors which presented by ANN produced that related to the circumscription that affected an area that extended the lesion border when it was closer to the sulcs. In the examination of the patients which report indicated the normality so the networks confirmed results that will not show any kind of errors and they will not show any false negative. So in this research paper reports works should be in progress and further investigation will be conducted before using this methodology applied on the diagnosing tool of aiding. The tools and number of features that employ a termination

Table 1. This table show the all possible inputs [11]

Feature	Values
f1	$I(x,y)$
f2	$\text{Min}(P(x,y))$
f3	$P(x,y)$
f4	$\text{Max}(P(x,y))$
f5	$P(x,y)$
f6	$\sigma(P(x,y))$
f7	I
f8	$f3 - f7$
f9	$f1 - f7$
f10	$\sum = Lh(x + 1, y, rl) - Lh(x, y, rl)$
f11	$\sum = Lv(x, y + 1, rl) - Lv(x, y, rl)$
f12	x

Table 2. This table shows the RBFNN point that used to train [11]

	IMAGE 02		IMAGE 04		IMAGE 05		TOTAL
	Positive	Negative	Positive	Negative	Positive	Negative	
P02	3	5	2	2	3	-	15
P04	-	-	-	-	2	2	4

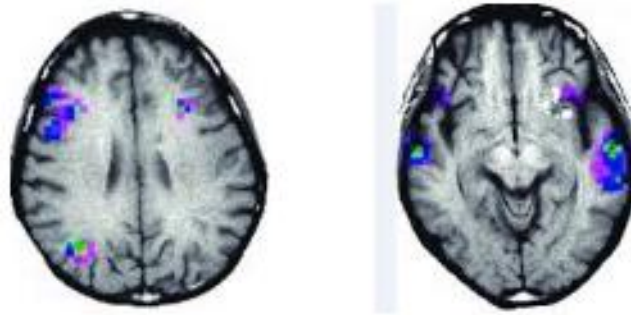


Fig. 2. Showing the image for the patient P04 and right image output classifier and left image masked image

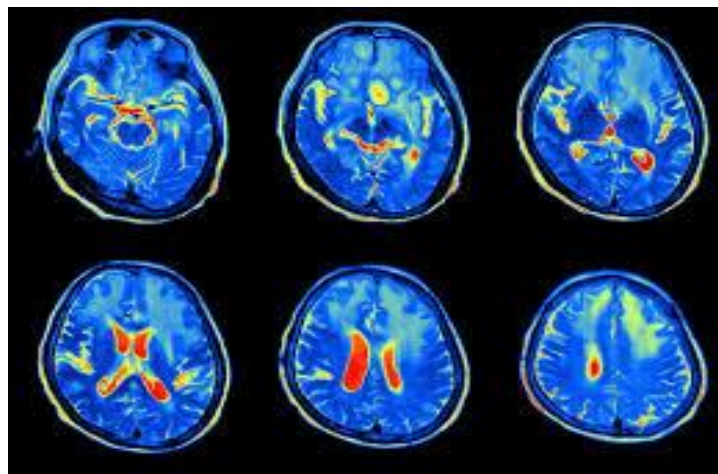


Fig. 3. Showing the image for the patient P02 showing the top and bottom image

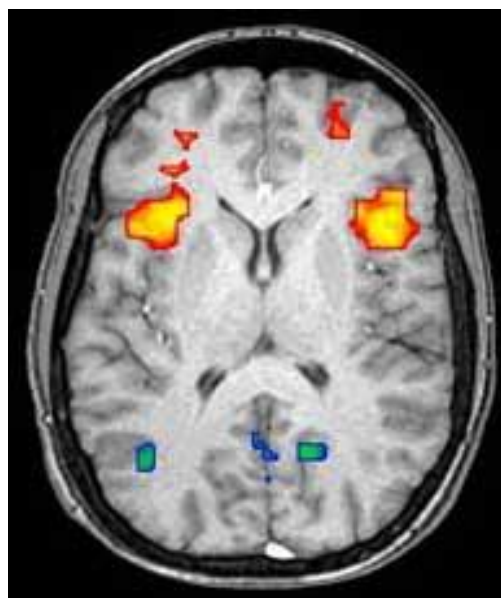


Fig. 4. This image shows the single output of the total classifier

criterion and classifier topology employed for further study. So all these issues must be addressed by using the combination of derivative based and genetic algorithms. The data

information will be used for the testing and training. They will allow the extraction of the performance of statistics which do not make any sense with small amounts of data. Due to the neural networks that benefits for the area of medical image diagnosis for the growing number of pictures produced by the exam for a given performance of the radiologists with & without the different CAD every patient that minimizes the time to report and therefore the systems for a mammography & providing the faster treatment.

In the images where points were taken to the training set, were very good as expected. The NN located the ischemic areas and marked them has described in medical report. It can be seen that the NN delimits the ischemic injury, marking the border of the injury (in yellow) with satisfactory accuracy. In Fig. 2 the image for the patient P04 and right image output classifier and left image masked image.

On the set of images showed in Fig. 3, regarding patient P02, the NN established a classification that matches the report of the Radiologist. The images are typical of an aging process from encephalon, characterized by the exuberance of the ridges, hypertrophic ventricles and an increase of the cephaloraquidian liquid. The NN located the ICVAs, without errors in the neighbourhood of the ventricles. Obsessive-Compulsive Disorder (OCD) is a commonly occurring, lifetime disorder characterized by recurring thoughts (obsessions) and behaviors (compulsions) which are overpowering and capable of causing serious disruptions in life's daily routines. The most common treatments for OCD are medication, psychotherapy – including Exposure and Response Prevention (EX/RP), a type of cognitive behavioral therapy (CBT) – or a combination of both. Although highly effective, CBT may not yield the desired result for all OCD patients. Moreover, treatment can span several weeks/months and entail substantial costs. A scale-based system was used to assign scores to the severity of OCD symptoms among participants pre- and post-treatment, with lower scores representing lower-severity or lower-frequency symptoms. Machine learning, a form of artificial intelligence (AI), was leveraged to analyze the fMRI scan data and the symptom severity scores to predict CBT response rates.

5. CONCLUSION

In this research paper suggesting the application of the RBF neural networks for the recognition of

diagnosis. ICVA will play an important role in contribution in the field of medical diagnosis that will be used as a support tool for radiologists in his regular life. That will minimize the elaboration report for the time emergent examinations and exploit the patient with the earlier treatment. In the results neural networks classifiers were in obedience with all medical reports that every image is tested. Once the ANN is trained then classifiers will be tested with the data that is never seen through the networks. In this stage the ANN significantly contributes to the ICVA of MRI diagnosis aid, so since the test occurrence automatic identification of ischemic lesions that has been performed with the accuracy results that will be false positive and false negative.

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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