CASE BASED REASONING VERSUS ARTIFICIAL NEURAL NETWORKS IN MEDICAL DIAGNOSIS

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Abstract

Embedding Machine Learning technology into Intelligent Diagnosis Systems adds a new potential to such systems and in particular to the imagiology ones. In our work, this is achieved using the data acquired from MEDsys [1][2][3], a computational environment that supports medical diagnosis systems that use an amalgam of knowledge discovery and data mining techniques, which use the potential of an extension to the language of Logic Programming, with the functionalities of a connectionist approach to problem solving using Artificial Neural Networks [4]. One's goal aims to conceive an alternative method to detect medical pathologies, as an alternative to the one in use in the actual medical diagnostic system; i.e., Case Based Reasoning versus Artificial Neural Networks. A comparative study of these two approaches to machine learning will be presented, taking into account its applicability in MEDsys.

Keywords: Decision Support Systems in Medicine, Artificial Neuronal Networks, Case Based Reasoning.

1. Introduction

Artificial Intelligence is the realm of *Medicine*, either in *diagnostic and educational systems*, in *expert laboratorial information systems*, or *machine learning systems* that may elaborate in new forms of knowledge. Indeed, contemporary *Medicine* has moved away from seeing disease in isolation, to understand that illness occurs at a complex system level; i.e., by seeing things at a meta level one come ever closer to understand what it really means to be diseased, and how that state may be reversed. *Artificial Intelligence* may support both the creation and the use of medical knowledge, namely in generating alerts or reminders; providing *diagnostic assistance*; judging on *therapy critiquing and planning*. That is the case when it looks for inconsistencies, errors and omissions in existing treatment *plans* or formulates a *treatment* based upon a patient specific condition and accepted treatment guidelines, using *agents and agent-based technology for information retrieval*. A case that is triggered when an agent knows the patients preferences and needs and uses the Internet to search and retrieve information; or in *image recognition and interpretation*, a case that is relevant, for example, in mass-screenings, when the system can flag potentially abnormal images for human attention. Indeed the majority of Computer Vision applications used in diagnostic reporting in Medical Imaging involve real time analysis and description of object behaviour from image sequences.

In the traditional clinical process, the physician elaborates on a pattern that matches the interpretation of the clinical data on a generic clinical model that emerges as a consequence of the education and experience of the expert. However, the reasoning process may be improved if the physician is able to:

- ask for an opinion;
- consult the evolution of the clinical past data and forecasts from it;
- visualize exams, clinical analysis and images; and
- ask for support to take a decision.

With the support of *Clinical Historic Databases*, agent technology may provide responses to those who give assistance to patients with a maximum of quality and medical evidence. Agents can help physicians at this level. This is the reason why we choose to elaborate on a comparative study of using Case Based Reasoning (CBR) versus Artificial Neural Networks (ANNs) in computer tomography based diagnosis under the umbrella of MEDsys.

2 – The MEDsys System

The use of Artificial Intelligence (AI) in Medicine is primarily concerned with the construction of AI programs that perform diagnosis and make therapy recommendations. Unlike medical applications based on other programming methods, such as the purely statistical and probabilistic ones, medical AI programs are based on symbolic models of diseases, and their relationship to patient factors and clinical manifestations. In Medicine such an approach can provide decision support, for example, to the radiologist conducting a form of dialogue with the technicians to query the knowledge base of a particular agent and test hypothesis. The strategy is to compare a modality independent model with the image via an intermediate symbolic feature space. The system is characterised by the use of explicit anatomical models for the visualisation of the anatomical structures identified in the image segmentation. The anatomical model makes a major component of the system, and is organised in terms of a semantic network. The inference engine handles the decision making praxis during the process of segmenting major anatomical landmarks. MEDsys is a decision support system to be used in image interpretation; it starts with an analysis of the most relevant features present in an image and produces a diagnostic. ANN's were used in getting such a diagnostic, and the results so far obtained surpass those of different experts doing the same job; i.e., the primary goal went to emulate the radiologist's expertise in the identification of malfunction regions through the use of a combination of pure symbolic systems and the use of computational pattern recognition techniques provided by the ANNs. One also aims to minimise the number of unnecessary medical interventions which might otherwise be necessary to make an accurate diagnosis. CT has some advantage over other imaging modalities, once it can provide images of tissue with a variety of contrast levels based on a simple adjustment of the window width and level of the image's raw data; i.e., it provides information that is not seen on film.

3 – A Case Study

One modality was used, the Axial Computed Tomography, under a GE prospeed equipment. The images were in raw data (DICOM) format, and 188 images were selected. The selected images refer to the section of the head that passes through the apex of the squamous part of the occipital bone and the frontal sinus.
The knowledge agent was configured as a multilayered feed forward ANN with one hidden layer, bias connections, the logistic activation function and RPROP training. 25% of the selected images were used as test cases.

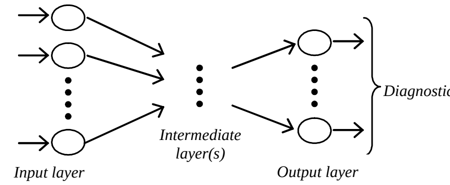

Figure 1 – The ANN topology

The input layer of the ANN is made of the normalized values for each image, plus the patient's sex and age. The output layer is made of its diagnosis (Figure 1).
The images, the patients gender and age were presented to two physicians that pronounced their own judgment according to what is depicted in Table 1 (notice that some of the images point to more than one pathology). It is interesting to notice that under the same circumstances and based on the same information, judgments of the two physicians only match on 78% of the cases (Table 2), which points to the necessity of further judgements, something that can be at the doorstep by using intelligent medical systems of the type MEDsys.

Table 1 - The physician's judgments.

	Cases	
Agree	147	78%
Partially agree	15	8%
Disagree	26	14%

Table 2 - The physician's match or agreement.

	Physician A		Physician B	
Normal	125	125	111	111
Atrophy	48		62	
Isquemic Lesions	12		24	
Hemorragy	6	73	7	101
Malign Tumour	3		3	
Normal Variants	4		5	

This process will be accomplished in terms of insights into *the most similar case*, *an interval of values and generalization of pathologies*, and *the generalization of pathologies with similarities*.

- **The most similar case.**

When one goes out in the search of an answer, it is usual to look in at the simplest form of CBR; i.e., starting from a first case, the process continues with the remaining ones in the search for the most similar case. The CBR life cycle in this situation may be stated as:

- The new case is set, in terms of the patient's data (i.e., the patient's medical records and the new data (i.e., image(s)));
- A comparison between this data on the one in the archive, for each case.

The similarity between cases is computed in terms of its attributes, following an evaluation function of the form [5]:

$$similarity - measure(case_i) = \sum_{j=1}^{n} w_j v(x_j)$$

where w_j and $v(x_j)$ denote, respectively, the weight of attribute x_j in the whole set of the case's attributes and an attribute's valuation taken from the interval [0,1] [6].

- **The interval of values and generalization of pathologies**

For all the cases in the case's memory and for each pathology, a set of parameters were selected [7][8], and their relevance to the diagnostic was evaluated [6][9]. This process is called of *pathology generalization*. The similarity measure is given, as before, in terms of the function:

$$similarity - measure(case_i) = \sum_{j=1}^{n} w_j v(x_j)$$

however, under this specific conditions, and in order to evaluate the contribution of each parameter to the diagnostic, their domains are set in advance.

- **The Generalization of pathologies with similarities**

It follows the same approach to problem solving presented in the previous sections, but the similarity measures are considered not in terms of individual cases taken from the cases' memory, but with relation to the *most general pathology case*. The pathology selected is the one that presents the highest similarities values with respect to all pathologies.

4 – System Architecture and Technologies.

The MEDsys *Agents* were mainly developed using the C programming language, *CGI* and *PERL* running uder the LINUX operating system. These modules set the via for the visualisation and exploration of original *DICOM* data from the imaging devices (e.g., *CT*, *MR*) (Figure 2). They provide the physician front-end to the system, either for image consultation using interactive image visualisation functions, namely graylevel windowing (Figure 3), or to obtain diagnostics (Figure 4).

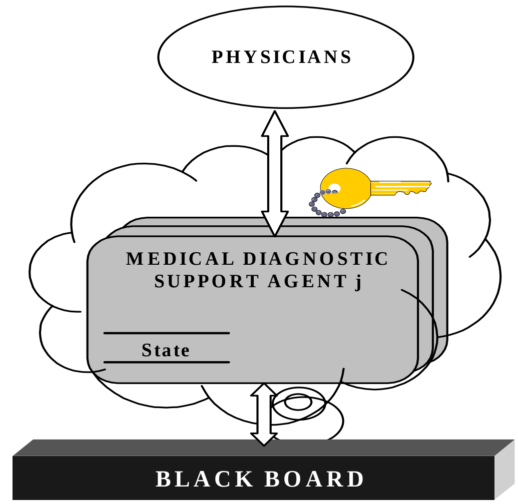

Figure 2- The Medical Diagnostic Support Agents

To implement the diagnostic procedures it was used an extension to the language logic programming [4] (Figures 5,6,7).

Figure 3 - The Diagnostic Support Agent – A Study request for Diagnostic Purposes.

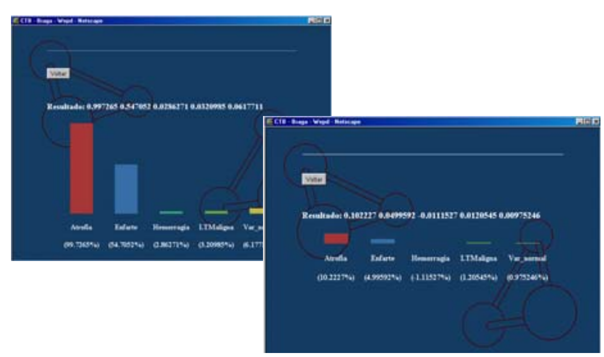

Figure 4 - The Diagnostic Support Agent – The diagnosis generated by the System.

Figure 5 - Data Acquisition

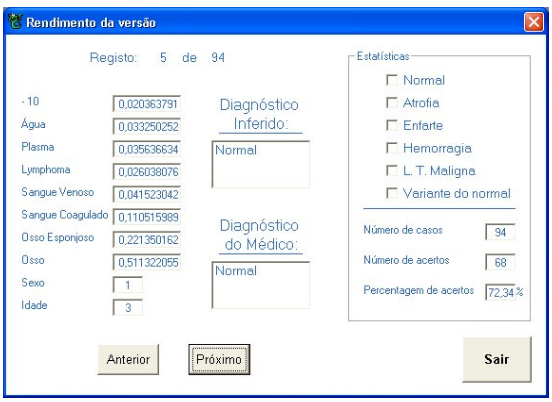

Figure 6 – Getting a Solution

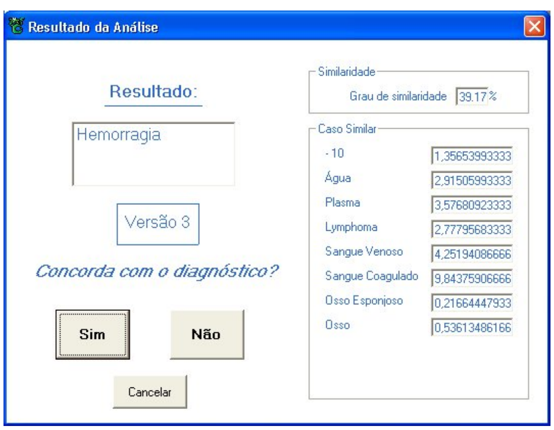

Figure 7 - Diagnostic Results

5 – Results analysis

In this work we had in mind to asses the possible inclusion of a CBR's based agent in MEDsys, being the problem addressed in terms of the *most similar case*, *Interval of values and Generalization of pathologies*, and *generalization of pathologies with similarities*. The results are given in Table 3. On the other hand, since there exists test cases, it is possible to look to the accuracy of each solution, in a pathology by pathology base, being in this case the results given in Table 4. Taking the results depicted by Tables 3 and 4, it is noted that the highest levels of accuracy happen when one's look at the pathologies individually, although the pattern may not be necessarily the same for all the pathologies. Therefore, it is possible to conclude that the CBR's approach has potential as a diagnosis tool.

Table 3 - Percentage of Accuracy between versions

Version	Accuracy
Most similar Case	72 %
Interval of values and Generalization of pathologies	65 %
Generalization of pathologies with similarities	58 %

Table 4 - Diagnosis accuracy between version and pathology.

Version	Normal	Atrophy	Isquemic	Hemorragy
Most similar Case	89	60	50	0
Interval of values and Generalization of pathologies	74	80	0	0
Generalization of pathologies with similarities	64	65	50	33

It is now possible to compare results obtained using ANN's and those gotten with the use of CBR, in order to consider the possibility of integrating CBR in MEDsys. The accuracy with ANN's is around 67% [3] (remember that with the same information, two different physicians agreed on 78% of the cases). From the tests referred to above, the first solution presents itself with a slightly better result (72%). When we try just to test if a medical image is "normal" or not, using ANN's we obtained results of 82% [1]. Once again the first solution gave the best results, with 89% of accurate outcomes.

Table 5 : Diagnostic accuracy by pathology (ANN's)

Atrophy	Isquemic lesion	Hemorragy
80%	92%	94%

We are now in a position to compare the ANN's and CBR's agent's performances. ANN's shows to be particularly suited for single pathology diagnostics (Table 5), although one's objective, since the beginning, was far away to produce a system to outperform that based on ANN's. The results also show that with a CBR based approach to problem solving, it is possible to produce feasible diagnostics (Tables 1 and 2).

6 – Conclusions

In order to obtain a solution to a particular problem, one looks at the case based repository, in order to find similarities between those cases and the case that is being object of close examination. This praxis allows us to assess the impact of using CBR procedures in the MEDsys, and it is believed that if more information had been made available, the results so far obtained would be more convincing [1]. It is also believed that we must come to a close integration of ANN's and CBR's technologies; they are not exclusive, but complementary.

9 - Acknowledgements

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