A Study on the Artificial Intelligence Supports in Medical Applications

Manoj Chopra[1]

[1]Department of Computer Science
Bonnie Foi College, Bhopal
manoj_19143@rediffmail.com

Abstract: ***Medical decision making demands an increasing ability to understand and structure the critical information on the Medical field. As the Medical evolves into a networked force, decision makers should select and filter information across the Medical field in a timely and efficient manner. Human capability in analyzing all the data is not sufficient because the modern Medical field is characterized by dramatic movements, unexpected evolutions, chaotic behavior and non-linear situations. The Artificial Intelligence (AI) ingredient permits to explore a greater range of options, enabling the staff to analyze more possible options in the same amount of time, together with a deeper analysis of these options.***

Keywords: Artificial Intelligence, Neural Networks, Fuzzy Logic, Genetic Algorithms, Course of Action

1. Introduction

Medical decision should consider information about a huge range of assets and capabilities that may perform complex tasks of multiple types: collection of intelligence, movements, direct/ indirect Operations, infrastructure, and transports. The Medical and the science of computers has always been incredibly closely tied. Famous names in AI, such as Alan Turing, were scientists that were heavily involved in the Medical. Turing, recognized as one of founders of both contemporary computer science and artificial intelligence, helped create a machine (called Bombe, based on previous work done by Polish mathematicians) to break any portion of the German Enigma code.

As computing power increased and pragmatic programming languages were developed, more complicated algorithms and simulations could be realized. For instance, computers were soon utilized to the Medical equipment that would be affected by various parameters. The simulations grew powerful enough that the results of many of these were really good. Artificial Intelligence applications in the West started to become extensively researched when the Japanese announced in 1981 that they were going to build a 5th Generation computer, capable of logic deduction and other such capabilities.

Inevitably, the 5th Generation project failed, due to the inherent problems that AI is faced with. Nevertheless, research still continued around the globe to integrate more 'intelligent' computer systems into the Medical field. Emphatic generals foresaw Medical by hordes of entirely autonomous buggies and aerial vehicles, robots that would have multiple goals and whose mission may last for months, driving deep into Human Body. The problems in developing such systems are obvious - the lack of functional machine vision systems has lead to problems with object avoidance, friend/foe recognition, target acquisition and much more. Problems also occur trying to get the robot to adapt to its surroundings, the terrain, and other environmental aspects.

Nowadays, developers seem to be concentrating on smaller goals, such as voice recognition systems, expert systems and advisory systems. The main Medical value of such projects is to reduce the Workload on a Doctor. Modern Doctors work in incredibly complex electronic environments - receiving information not only from their own equipments, but from many others. All this must be organized in a highly accessible way. Through voice-recognition, systems could be checked, modified and altered without the doctors. Expert/advisory systems could predict what the Doctors would want in a given scenario and decrease the complexity of a given task automatically. Aside from research in this area, various paradigms in AI have been successfully applied in the Medical field. For example, using an EA (evolutionary algorithm) to evolve algorithms to detect targets given radar/FLIR data, or neural networks differentiating between mines and rocks given sonar data in a submarine. I will look into these two examples in depth below.

2. A review of the possibilities to introduce AI algorithms in Medical applications

AI based Medical decision behavior models can be classified into the following groups: models based on neural networks (NN), fuzzy logic (FL), genetic algorithms (GA) and expert systems (ES).

2.1 Neural Network Application

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. Neural network technology performs "intelligent" tasks similar to those performed by the human brain. It acquires knowledge through learning and then stores that knowledge within inter-neuron connection strengths known as synaptic weights. Neural Networks can be applied to a wide variety of problems, from breast cancer detection to classification of satellite imagery. Below, we've included numerous examples of how NeuroSolutions and other NeuroDimension products can be used to apply neural network technology to real-world applications. The major problem in medical field is to diagnose disease. Human being always make mistake and because of their limitation, diagnosis would give the major issue of human expertise. One of the most important problems of medical diagnosis, in general, is the subjectivity of the specialist. It can be noted, in particular in pattern recognition activities, that the experience of the professional is closely related to the final diagnosis. This is due to the fact that the result does not depend on a systematized solution but on the interpretation of the patient's signal (Lanzarini and Giusti, 1999).

Brause(2001) highlighted that almost all the physicians are confronted during their formation by the task of learning to diagnose. Here, they have to solve the problem of deducing certain diseases or formulating a treatment based on more or less specified observations and knowledge. For this task, certain basic difficulties have to be taken into account.

The basis for a valid diagnosis, a sufficient number of experienced cases, is reached only in the middle of a physician's career and is therefore not yet present at the end of the academic formation. This is especially true for rare or new diseases where also experienced physicians are in the same situation as newcomers. Principally, humans do not resemble statistic computers but pattern recognition systems. Humans can recognize patterns or objects very easily but fail when probabilities have to be assigned to observations. Brause(2001) also give an example of a study in the year 1971 showed these basic facts in the medical area. This study had shown that human have many limitations in diagnosis. The results of this experiment were as follows:

- Best human diagnosis (most experienced physician): 79.7%
- Computer with expert data base: 82.2%
- Computer with 600 patient data: 91.1%

From this result we can see that humans can not ad hoc analyze complex data without errors.

2.2 Neural Network Capabilities

This paper ware discussed how Neural Network approach can diagnose disease using patient medical data such as breast cancer, heart failure, medical images, acidosis diseases, and lung cancer

2.2.1 Diagnose Breast Cancer

Breast cancer is the second largest cause of cancer deaths among women. The automatic diagnosis of breast cancer is an important, real-world medical problem. A major class of problems in medical science involves the diagnosis of disease, based upon various tests performed upon the patient. When several tests are involved, the ultimate diagnosis may be difficult to obtain, even for a medical expert. This has given rise, over the past few decades, to computerized diagnostic tools, intended to aid the physician in making sense out of the confusion of data (Kiyan and Yildirim, 2003).

Neural network have been applied to breast cancer diagnosis. (Kiyan and Yildirim, 2003) employed Radial Basis Function, General Regression Neural Network and Probabilistic Neural Network in order to get the suitable result. From overall results, it is seen that the most suitable neural network model for classifying Wisconsin Breast Cancer data is General Regression Neural Network. This work also indicates that statistical neural networks can be effectively used for breast cancer diagnosis to help oncologists.

2.2.2 Diagnose heart failure

Making prognosis for patients with congestive heart failure is difficult due to the complex nature of this multisystem disease. No single criterion helps to identify patients at risk, and a combination of several prognostic parameters is recommended (Cowburn et al., 1998). Neural networks are associative selflearning techniques with the ability to identify multidimensional relationships and perform pattern recognition in non-linear domains. Atieza et al., (2003) identified that classification is the best result for this cases.

2.2.3 Diagnose by Medical Images

Neural networks are extremely useful, since not only are they capable of recognizing patterns with the aid of the expert, but also of generalizing the information contained in the input data, thus showing relations which are a priori complex. (Laura and Armando, 1999) combined the processing of digital image and neural network to carry out the required recognition and classification. As a result, the solution to the problem can be divided in two parts: the segmentation of different elements, and their subsequent classification. In this case good results good results have been obtained thanks to the definition of a new clustering algorithm based on e re-definition of the input image. As for the classification stage, different solutions using neural networks have been compared, the results obtained being correct, with an error smaller than 10%.

Neural Networks are used in pattern recognition because of their ability to learn and to store knowledge. Because of their 'parallel' nature can achieve, Neural network can achieve very high computation rates which is vital in application like telemedicine (Siganos, 1995).

2.2.4 Diagnose Acidosis Diseases

Ultsch et al. (1995) used the capability of neural network to diagnose acidosis diseases by using knowledge based system in their hybrid system. The data set consists of 11 attributes originating from the blood analysis. Several classification methods according to (Deichsel and

Trampisch, 1985) were used to explain these data. The Neural Network together with the UMatrix method was able to classify the data into the subcategories healthy, lacacidemia, metabolical acidosis, respiratory acidosis and one patient with cerebral deficiency. They used rule generation module to extracted rules out of the Neural Network, which were described by 4 or 5 attributes resembling more closely the decisions made by medical experts (Ultsch and Li, 1993).

2.2.5 Diagnose Lung Cancer

Lung cancer is another diseases that commonly known as a deadly disease in the world. Many patients suffer from this disease. Early detection of this disease is very important to prevent this disease. Expertise have to measures for early stage lung cancer diagnosis mainly includes those utilizing X-ray chest films, CT, MRI, isotope, bronchoscopy, andneedle biopsies. According to Zhou et al. (2001) at present, the specimens of needle biopsies are usually analyzed by experienced pathologists. Since senior pathologists are rare, reliable pathological diagnosis is not always available.

Zhou et al. (2001) named his an automatic pathological diagnosis procedure named Neural Ensemble based Detection (NED). It is proposed and realized in an early stage Lung Cancer Diagnosis System (LCDS). NED utilizes an artificial neural network ensemble to identify cancer cells in the images of the specimens of needle biopsies obtained from the bodies of the subjects to be diagnosed. A fast adaptive neural network classifier has been used to identify the lung cancer cell. Zhou et al. (2001) stated that a fast adaptive neural classifier that performs one-pass incremental learning with fast speed and high accuracy and does not require the user manually set up the number of hidden units.

2.3 Fuzzy Logic

FL is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

A comparative analysis of the candidate AI techniques

Regarding the learning capacity of various AI techniques ES, FL, NN, GA can be ordered from low to high. ES and FL as suggested by Zadeh are not capable of learning anything. NN and GA have learning capability, although on average, pure GA usually need a longer learning time (Russo, 1998), but when a priori knowledge is concerned, the order is inverted. GA need no a prior knowledge; NN need very little; FL and ES need quite detailed knowledge of the problem to be solved. NNs are capable of learning and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm. NNs are capable of learning from examples, but what is learned is not easy for humans to understand. Complexity and interactions between the hidden nodes of a NN make it unattainable to understand how a decision is made. The outputs have to be trusted blindly, and this is what does not endear the NN to decision makers. GAs is affected much less than NNs by the problem of local optima and has far less likelihood than a NN of finding a local optimum rather than a global one; this is likely to correspond to a less significant learning error. Their learning speed is generally slower and they are computationally intensive requiring much processing power. ES are more flexible to modification than neural or genetic based systems because rules can be adjusted over time, and when the system doesn't perform properly but it is impossible to build in the absence of experts and a priori knowledge. In comparison with FL, more rules are needed in expert systems to cover possible outcomes. Subjective FL's linguistic representation is very close to human reasoning. It is much less complex in terms of computational effort. Unlike in ES, overlap or ambiguity between rules can be managed in FL. It is not capable of learning and it is impossible to use when experts are not available. The objective FL (Takagi, Sugeno, 1985), inherits all the advantages of subjective fuzzy logic, but not the less desirable features. It possesses good learning capacity and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm. The system generates a fuzzy knowledge base, which has a comprehensible representation. Therefore, one can easily understand how a decision is made. It is independent of experts and it has a low degree of computational complexity. The optimization of a fuzzy model requires some effort in order to arrive at the optimal mix of membership functions and the number of fuzzy rules. Lack of available tools that optimize these functions is the main bottleneck.

2.4 Generic Algorithms

Genetic Algorithms (GAs) are non-linear adaptive optimization methods that mimic natural evolution processes via non-exhaustive searches among randomly generated solutions. Genetic Algorithms are highly operative for searching through large or complex data structures seeking the optimal solution for decision, classification, optimization and simulation.
Genetic algorithms are based on the ideas of natural selection and genetics. Non-figurative representations also called ‘chromosomes’ or ‘genotype’ of candidate solutions and ‘individuals’ or ‘phenotypes’ are subject to Genetic Algorithm optimization problems. To simplify the idea, a Genetic Algorithm search space is comprised of genes corresponding with letters, chromosomes equal to words and the genotype with a word family.

Genetic Algorithms mimic “the survival of the fittest” of individuals dominating over the weaker ones over successive generations which is analogous with the behavior of DNA chromosomes within a population of individuals. Genetic algorithms are dependent on existing data (population) to identify patterns. They in principle operate in the following steps:

- Encoding problems in a string and generating an initial population
- Calculation of the fitness value for each representation (chromosome) via genetic operation
- Iterations of reproduction including stochastic selection of parents to reproduce, application of the genetic algorithm (mutation, crossover) to the parents and evaluation of the children's fitness value to insert them into the population to replace weaker individuals of the present one.

Genetic Algorithms are explored in medical applications to characterize patterns and results. For example, optimizing image analysis such as, assessing classes of cells in blood cell microscope images or for facilitating magnetic resonance tomography (MRT) treatment planning and 3D visualization of image data. Genetic algorithms developed for mammography were adapted for mining patient's having abdominal aortic aneurysms by analyzing abdominal computed tomography (CT) scan reports for common patterns and features of successful and unsuccessful surgeries. Genetic algorithms can be used for optimizing pharmaceutical products. Recently, it was shown that Genetic Algorithms were able to identify additional anti-bacterial peptides with a high activity during a study.

Finally, it was shown that Genetic Algorithms enhance the precision of artificial neural networks (ANNs) such as for hip-bone fracture prediction or for optimizing efficient search strategies of ANNs to predict and discriminate pneumonia within a training group. This suggests that combining Genetic Algorithms and artificial neural networks to form genetic algorithm neural networks (GANNs) is an important approach for improving the analysis of medical data.

2.5 Expert Systems

Expert systems (ES) use a knowledge base including a set of rules and an inference mechanism that provides computer reasoning through inductive, deductive, or hybrid inductive- deductive reasoning. Knowledge base rules usually are undertaken through interview with traders. Rules in such knowledge-based systems are represented in the form of computer readable sentences. Checking for consistency and validity of rules is essential for a knowledge-based system, which is complex and difficult in the financial field, even when it is a system with only a dozen rules.

Lee, Jo (1999) developed an expert system based on candlestick analysis to determine the timing of action. In candlestick analysis there are several patterns which can imply future battlefield movements. Various such patterns were used to construct the knowledge base. Several aspects, such as recognition of patterns, formulization of pattern definition, rule generation based on the patterns, performance evaluation of the rules, should be considered, which requires much effort.

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4. The use of DSS - CoA in operation planning

CoA design is based on the understanding of the situation assessment, work analysis, resources status assessment. According on the time available, the decision staff should develop different CoAs that answer to some critical questions (when, who, what, where, why and how), each of them suitable, feasible, acceptable, exclusive, complete. The analysis of these CoAs could be based on the fact that the staff has to deal with huge volume of information in a very short time period DSS would be helpful in any step of the operation planning process.

DSS-CoA should be based on a detailed investigation of how the staff perform CoAs evaluation, analysis, selection. Since the evaluations of the CoAs according to the different criteria might include uncertainty, ambiguity, fuzziness, subjectivity, is necessary to minimize the risk component introduced during the evaluation process. A graphical and intuitive tool could balance the relative importance of the set of criteria. A stability interval analysis tool could be the answer to the increase of the awareness of the decision-maker about the role of relative importance coefficients.

The design, development, implementation of DSS- CoA is based on formal models of a CoA designed in special processes of knowledge acquisition. The event model uses operational information required by the evaluation and analysis tools and contextual information. Even if the event model would have been a lot simpler without this contextual information, this information is critical in the CoAs generation process. DSS should be integrated to the organization workflow, and should be designed in a way to facilitate the acceptance and the transition. DSS should interact with other information, planning and decision systems.

DSS-CoAs selection support the following functions: description of the event, development/description of possible CoAs, identification of criteria to be used in the evaluation process, evaluation of the CoAs according to the selected criteria, analysis and comparison of these CoAs, and post-execution analysis that are performed sequentially or simultaneously. Decision staff is in charge of describing the events and the capability to support this function should allow the creation of new events, the upgrade of the description of an existing event, the retrieval of old events to trigger the CoAs development or the selection processes. The event description should be based on a framework that include information related to situation review, assumptions about the enemy, enemy forces and CoAs, planning guidance, other consideration aspects, theatre of operation features, and own forces capabilities. This information is essential to fully understand the problem, essential for a better assessment of the situation. CoAs facility should include the creation of a new CoA, the update of existing ones, and the verification of CoA feasibility. In this case a model that include information related to action items that describe the actions to be performed by the resources (what, who, how, when) should be used to represent a CoA. As soon as the CoAs description is completed, the planning officer needs a communication channel to trigger the evaluation and selection processes.

The automated evaluation of each CoA is made according to each criterion. Heuristics may be used or subjective assessment may be directly provided by the users. A selection facility must allow automated CoAs comparison and the decision-maker considers different criteria when comparing CoAs. This facility should then, according to different types of situations, propose different criteria to be considered in the evaluation process, and predefined weights and thresholds accordingly. Even if the proposed criteria should be considered, the decision-maker should have the possibility to select those he considers most appropriate for the actual situation. This should be performed in an interactive way. When the criteria are selected, the CoA comparison should be done automatically, using Multiple Criteria Decision Analysis (MCDA) procedure, and different types of results must be presented to the decision-maker. A graph may represent the ranking of the CoAs. It is essential that information about the quality of each CoA should be presented since this graph only indicates only the rank of CoAs. Among the analyses that can be provided to help a decision maker, there is a dominance check which verifies if a CoA is better than all other CoAs on all the criteria, no matter the value assigned to the different thresholds. A weight stability analysis offer to the decision-maker information on the sensitivity of the criteria when weights changes. A what-if analysis on the model parameters or on the CoAs evaluations allows the decision-maker to foresee the effects of the actual settings on the prioritization of the CoAs. This enables the user to either select any CoA while providing justifications, or ask for more satisfactory CoAs and information.

A post-analysis facility should allow the reconsideration of the relevance of the choice made while the event is completed. Once a CoA has been selected and executed, the team of Doctors could then re-evaluate if its decision was the best one or not, and why. This precious knowledge should be archived for reference to future operations. This knowledge will be used to learn from experience.

Finally, the functional facilities must allow the management of the criteria, and the default parameters used within the different decision analysis procedures. This facility must support an analyst in creating new criteria, updating existing ones and associating criteria with generic instances of events. Also, this facility should enable him to set default values for different parameters. Since the processes of defining events and CoAs, evaluating and comparing CoAs, and selecting the most appropriate one are realized through a team effort, it is important to be able to assign different facilities to different people by defining user's profiles event editor, responsible to describe an event; CoA editor, responsible to define and describe appropriate CoAs for a specific event; Team of Doctors is to select the most appropriate CoAs; analyst for managing the criteria and to set the parameters according to the preferences of the decision-maker; system administrator, responsible to define who can have access to the system to do what. DSS-CoA must have a facility to manage the user's profile, and maintain the databases on event, CoA and criteria and this ingredient could be used by a system administrator to create new users, assign privileges, and update user's profile.

5. Conclusions

The AI ingredient in Medical decision making offers a strong support capable to create natural sketch-based interfaces that domain experts can use with low training. The users expressed the desire for a single integrated framework that captures CoA sketches and statements simultaneously and capable to provide a unified map-based interface to do both tasks. The interest is to design a framework capable to express CoA sketches equipped with visual understanding. DSS-CoA offers the inspiration to define a set of facilities appropriate for any DSS developed for the evaluation and selection of CoAs: event management facility; CoA management facility; CoA evaluation facility; CoA comparison, analysis and selection facility; Post-analysis facility; criteria management facility; system administration facility. DSS-CoA users should be aware about the limitations and the level of trust and an explanation facility providing result explanations adapted to the user (background, experience, knowledge, preference) and the context (time available) are important in Medical decision training.

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Author Profile

Manoj Chopra received the Master Degree in M.Sc. (Computer Science) from Makhan Lal University 2008 and M.Phil. in Computer Science form Vinayaka Mission Universityin 2009. He stayed in various Colleges of computer and communication. He has 6 year of teaching experience. He is now with Bonnie Foi Group of Research and Education Society, Bhopal (M.P.).