Hybrid model based on Decision Trees and Fuzzy Cognitive Maps for Medical Decision Support System

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Abstract—**For medical decision making processes (diagnosing, classification, etc.) all decisions must be made effectively and reliably. Conceptual decision making models with the potential of learning capabilities are more appropriate and suitable for performing such hard tasks. Decision trees are a well known technique, which has been applied in many medical systems to support decisions based on a set of instances. On the other hand, the soft computing technique of Fuzzy Cognitive Maps (FCMs) is an effective decision making technique, which provides high performance with a conceptual representation of gathered knowledge and existing experience. FCMs have been used for medical decision making with emphasis in radiotherapy and classification tasks for bladder tumour grading. This paper proposes and presents an hybrid model derived from the combination and the synergistic application of the above mentioned techniques. The proposed Decision Tree-Fuzzy Cognitive Map model has enhanced operation and effectiveness based on both methods giving better accuracy results in medical decision tasks.**

Keywords— **Fuzzy cognitive maps, decision trees, ID3 algorithm, decision making, tumour characterization**

I. INTRODUCTION

Decision trees have mainly applied in medical systems to support decisions based on a set of instances. They usually are combined with other statistical learning methods to enhance their classification accuracies [1,2]. Several attempts have been proposed to hybridise Decision Trees with other machine learning techniques. There been proposed methods to combine DTs with NNs [3-6], Bayesian networks with DTs [7-9], as well as fuzzy logic theory with DTs proposing the Fuzzy Decision Trees [10-12].

Fuzzy cognitive maps approach is an advanced modeling method, combining characteristics of both neural networks and fuzzy logic theories and it has been used to develop advanced medical decision support systems. The utilization of existing knowledge and experience on the operation, control and supervision of complex systems is the core of this modeling technique. Experts design FCMs by transforming their knowledge in a dynamic cognitive map [13]. FCMs have already been used to model behavioral systems in many different scientific areas. For example, in medical domain, FCMs have been proposed as a generic model for medical decision making in the radiotherapy process and for bladder tumor grading in classification tasks [14,15].

When the Decision Tree is constructed, it is easy to convert the tree into a set of rules by deriving a rule for each path in the tree that starts at the root of the tree and ends at the leaf node. These decision rules have the form of If-Then rules and we propose to use them to modify the weight settings and values of the FCM model. Thus an enhanced FCM model will be developed, which will be trained through the unsupervised NHL algorithm, do that to ensure indicating the decision [16].

This paper is structured: section II presents the background of decision trees and fuzzy cognitive maps. Section III combines these techniques proposing a new hybrid model for succeeding decision making with the emphasis on existing and possible future applications in medicine. Section IV concludes the paper outlining some future directions.

II. DECISION TREES AND FUZZY COGNITIVE MAPS: MAIN ASPECTS

A. Brief description of Decision Trees

Decision trees is a method used to make decisions based on a set of instances. There are two types of nodes in a decision tree: decision nodes and leaves. Leaves are the terminal nodes of the tree and they specify the ultimate decision of the tree. Decision nodes involve testing a particular attribute. Usually, the test at a decision node compares an attribute value with a constant. Ultimately, to classify an unlabeled instance, the case is routed down the tree according to the values of the attributes tested in successive decision nodes and when a leaf is reached, the instance is classified according to the probability distribution over all classification possibilities [17,18].

The decision tree is typically constructed by means of a ‘‘divide-and-conquer’’ approach. At first an attribute is selected, which is placed at the root node of the tree. This root node splits up and divides the dataset into different subsets, one for every value of the root node. Each value is specified by a branch. Then, the construction of the tree becomes a recursive problem, because the process can be repeated for every branch of the tree. It should be noted that only those instances that actually reach the branch are used for the construction of the tree. Different algorithms can be adopted (C4.5, CHAID, CART) to determine which attribute to split on given a set of examples with different classes [19,20].

The CHAID algorithm starts at a root tree node, it divide it into child tree nodes until leaf tree nodes terminate branching. The splits are determined using the chi-squared test. When the decision tree is constructed, it is easy to convert the tree into a set of rules by deriving a rule for each path in the tree that starts at the root and ends at the leaf node. Decision rules are often represented in decision table formalism. A decision table represents an exhaustive set of mutual exclusive expressions that link conditions to particular actions, preferences or decisions. The decision table formalism guarantees that the choice heuristics are exclusive, consistent and complete [20].

Despite their popularity, it was shown for some application domains that the model structure of decision trees can sometimes be instable. This means that when carrying out multiple tests, mostly the same variables enter the decision tree but the order in which they enter the tree is different. The reason for this is known as ‘‘variable masking’’, i.e., if one variable is highly correlated with another, then a small change in the sample data (given several tests) may shift the split in the tree from one variable to another.

Decision Tree Induction is another method from the field of machine learning. Comparisons with other techniques such as Neural Networks have been done [21,22], but it has been shown that the accuracy of the techniques is similar. Why then use decision trees? Two main reasons explain the popularity of DTI:

- DTI produces understandable tree-structures which elucidate the reasoning of the method (many other techniques lack this and are harder to interpret)
- DTI can be used to produce a disjunction of hypotheses for a problem.

In a decision tree, the “depth” of the tree only determines the maximum number of conditions, which is used in decision rules. This is a maximum and non-fixed number. For this reason, the idea to integrate DTs with the above mentioned FCMs into a new decision tool was conceived.

B. Fuzzy Cognitive Maps background

The graphical illustration of the FCM is a signed directed graph with feedback, consisting of concepts and weighted interconnections among concepts. Concepts are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist among concepts (Fig.1). In general, each concept stands for states, variables, events, goals, values of the system which is modeled as an FCM [13]. Each concept is characterized by a number A_i, which represents each value and it results from the transformation of the real value of the system’s actions in the range [0, 1]. All the weighted interconnection values belong to the range [-1, 1]. With the graphical representation of the behavioral model of the system, it becomes clear which concept influences other concepts and in which degree.

The most essential part in modeling a system through a FCM model is the determination of the concepts that best describe the system, the direction and the grade of causality between concepts. Causality is an important part in the FCM design, because it indicated whether a change in one variable causes change in another. Another important element in FCM design is the determination of which concept influences other concept and in what degree [23].

The causal knowledge of the dynamic behavior of the system is stored in the structure of the map and in the interconnections that summarizes the correlation between cause and effect. The value of each node is influenced by the values of the connected nodes with the corresponding causal weights and by its previous value.

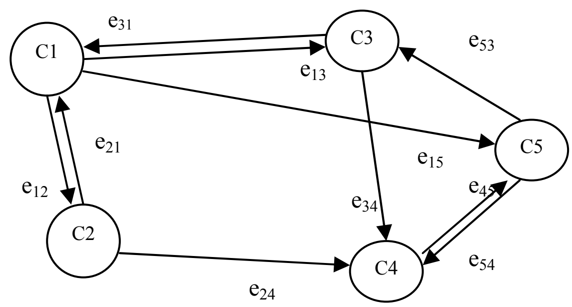

Fig.1 A simple Fuzzy Cognitive Map

Thus, the value A_i of each concept C_i is calculated by applying the following calculation rule:

$$A_i^{(k+1)} = f\Big(A_i^{(k-1)} + \sum_{\substack{j \neq i \\ j=1}}^{N} e_{ij} \cdot A_j^{(k-1)}\Big) \qquad (1)$$

where $A_i^{(k)}$ is the value of node C_i at time *k*, $A_j^{(k-1)}$ is the value of node C_j at time *k-1*, e_{ij} is the weight of the interconnection between node C_i and node C_j and f is the sigmoid threshold function.

Learning techniques for fine-tuning FCM causal links are used to increase the efficiency and robustness of FCMs, by selecting and modifying the initial FCM weights as they have been determined by experts. Two unsupervised learning algorithms, the Active Hebbian Learning and the Nonlinear Hebbian Learning have been recently proposed to train FCM grading tool for assessing medical diagnosis [16, 24].

It is a very important task to combine the advantages of decision tree induction in terns of understanding and simplicity with the advantages of FCMs in terms of modelling and simulation. The derived hybrid model can be more efficient of each one of them and useful to assist medical decision making.

III. HYBRID MODEL FOR MEDICAL DECISION MAKING

The main contribution of the proposed method is the combination of two computational techniques, the decision tree induction method (created by any decision tree algorithm, for example ID3) with the FCM approach. There are proposed two approaches for constructing hybrid model for medical decision making depending on the kind of the available data.

In the first approach, if a large number of input data exists, a decision tree can be induced from the available data. Then a fuzzy rule base is derived which is used together with experts' knowledge to construct the FCM model. The derived FCM model is subsequently trained using an unsupervised learning algorithm to achieve improved decision accuracy. For this work, the C4.5 algorithm has been chosen to develop the decision tree. And then, the NHL algorithm is chosen as a suitable training algorithm for unsupervised FCM training.

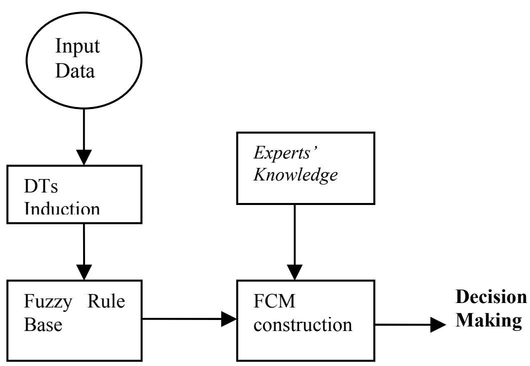

Fig. 2: Constructing Decision Trees from input data and then determining Fuzzy Cognitive Maps

In the second approach, where qualitative and quantitative data are initially available, the hybrid DT-FCM is proposed where its structure is briefly outlined in figure 2. The quantitative data are used to induce a decision tree and the qualitative data (through experts' knowledge) are used to construct the FCM model. Then, the FCM's flexibility is enhanced by the fuzzification of the strict decision tests, which are derived from the IF-THEN rules that are used to assign weights direction and values in the FCM. Finally, the updated FCM model with the new weight setting is trained using the unsupervised NHL algorithm to ensure reaching a decision.

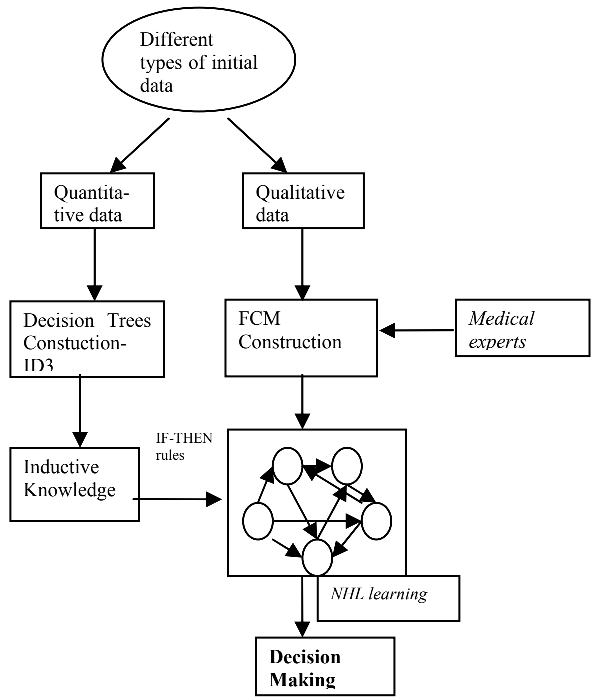

Fig. 3: The decision making system based on Decision Trees and Fuzzy Cognitive Maps

This methodology can be applied in two stages, depending on the type of the initial input data: at first step, the quantitative data are used, the decision tree generators are explored and an inductive learning algorithm produce the fuzzy rules which then are used for the FCM model construction; at second stage, the available experts' knowledge (qualitative data) is used for the construction of the FCM model. Then the unsupervised NHL algorithm is used to train the FCM model and to calculate the target output concept responsible for the decision line. When there are both quantitative and qualitative data, the initial data are divided and each data type is used to construct the DTs and the FCMs separately. Next the fuzzy rules induced from the inductive learning procedure are introduced in the FCM model to enhance its structure and finally, through the training process, the overall hybrid model reaches a proper decision.

The proposed modelling technique for medical decision has three major advantages. First, the rules derived from the decision trees have a simple and direct interpretation and they are introduced in the initial FCM model to update its operation and structure. Second, the procedure, which introduces the decision tree rules into an FCM also specifies the weight assignment through new cause-effect relationships among the FCM concepts. Third, the proposed technique fares better than the best decision tree inductive learning technique and the FCM decision tool.

IV. Conclusions

In this research work, two computational intelligence techniques, the statistical learning technique of decision tress and the soft computing technique of FCMs were synergistically combined in order to maintain the main advantages of both techniques. The new hybrid system, having the main characteristics of both techniques, enhances its operation and reliability. A new framework of Fuzzy Cognitive Map utilizing Decision Trees is proposed that updates the traditional Fuzzy Cognitive Map and has better performance specifications. The inclusion of decision tree generators in the structure of the FCM is examined and it is expected that the performance of the new DT-FCM system could be better to deal with different kind of input data eliminating numerical errors.

In future, our research work will be directed towards the implementation of the hybrid system in classification tasks proving its efficiency.

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