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A framework for application of neuro-case-rule base hybridization in medical diagnosis

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ABSTRACT

Every approach to handling automation has its unique limitations. In the symbolic (rule base) approach, the brittleness of rules leads to the ineffectiveness of handling noisy data, but it derives its strengths in heuristic search. In the same vein, a case base reasoning paradigm is bedeviled with retrieval and adaptation problems. Neural Networks (NN) methodology suffers from intolerance of incremental insertion of new knowledge and limited explanation capability, but triumphs over other methods when it comes to adaptation using its generalization characteristics. Based on all these, a tight coupling of case base, rule base and neural networks methodologies is proposed for medical diagnosis. The case base provides the 'desired' outputs, which constitute an input to the neural networks. The results obtained from the trained neural networks assisted in formulating diagnostic rules, which form the rule base. Through the rule base, an inference engine that represents the hybrid is built. Data collected from three hospitals in Nigeria on hepatitis patients were used to test the functionality of the proposed system. The results obtained from the hybrid were compared with that obtained from the Multilayer Peceptron Neural Networks (MLPNN) training using NeuroSolutions 5.0 and found to covary strongly. The hybrid exhibits an explanation characteristic, a feature not found in neural networks.

1. Introduction

The task of carrying out an effective and efficient medical diagnosis is a complex one that involves a state space search of medical knowledge, which could become cumbersome when the variables involved are numerous. The human mind can effectively manage a combination of 7 ± 2 pieces of information consecutively [1]. Diagnostic decision support systems are designed to improve the diagnostic performance of physicians [2]. It is recognized that the most important task in achieving hospital efficiency is to optimize the diagnostic process in terms of the number and duration of patient examinations, with accompanying accuracy, sensitivity, and specificity [3].

A number of expert systems have attempted to address the subject of knowledge acquisition, representation, and utilization in medical diagnosis. However, the problem of managing imprecise knowledge still exists. The process of combining facts in the medical problem domain to obtain an optimal diagnostic result is still a complex problem in the field of medical knowledge engineering. As research in medical diagnosis deepened, emphasis shifted to the representation and utilization of unstructured, imprecise, and dynamic knowledge. Szolovits recognized [4] that uncertainty is the central and critical fact about medical reasoning. Uncertainty characterizes the sources of information available to medical expert systems. Such sources include the patient, physician, laboratory, technical methods of evaluation, and mathematical models that simulate the diagnostic process [5].

Researchers in medical expert systems in the past decade have attempted to find ways to manage uncertainty in medical diagnosis [4]. One of the earliest efforts in this direction attempted to develop heuristic methods for imposing structure on ill-structured components of medical diagnosis, resulting in the INTERNIST diagnostic program [6]. Evolutionary algorithms [3], case base reasoning [7], and hypertext-based [8] systems have been applied in the management of imprecise and unstructured medical knowledge. However, the utilization of neural networks and fuzzy logic became very popular in attempting to resolve the problems of imprecision and uncertainty (e.g. [9]). Neural network based models for medical diagnosis are proposed [10], while fuzzy models are discussed elsewhere [11]. The use of one paradigm appears unsatisfactory, as there is the need to have models that

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handle both fuzzy and crisp data. In Ref. [12], genetic algorithm is introduced to optimize the performance of the neuro-fuzzy system in a non-medical application.

We propose a tight coupling of case base, rule base and neural networks methodologies for medical diagnosis. Since medical knowledge consists of both objective and subjective knowledge, the objective knowledge can be represented in the form of rules while subjective knowledge, which is dynamic, can be modeled in terms of experience or guesses of different experts form the cases. In order to optimize performance both the objective and subjective knowledge are represented in what is termed as a neurocase-rule base system. This study proposes a three-component fusion hybrid soft technology that integrates the following components in the medical diagnostic process:

(a) case base reasoning,
(b) rule base reasoning, and
(c) neural network technology.

An integrated NeuroCaseRule base system train on BackPropagation Neural Network (BPNN), with the training data obtained from three hospitals that employ case base reasoning in their diagnoses has been developed. The BPNN aside from its primary role of ensuring generalization also assisted in performing input contribution measures in order to discard some irrelevant input decision variables. The relevant variables are then used in retraining to ensure accuracy. The results obtained assisted in extracting some rules in collaboration with a team of medical doctors (domain experts).

In Section 2, a review of the component technologies is presented, while the design of the system architecture is presented in Section 3. The functionality of the system is tested and reported in Section 4. In Section 5, the results obtained from the case study are discussed, while some conclusions are drawn in Section 6.

2. Review of component technologies

In this section, a brief review of the component technologies is carried out in order to identify their strengths, shortcomings, and synergies that exist with their fusion.

2.1. Case base reasoning (CBR)

The experience acquired in treating a patient either successfully or unsuccessfully is called a 'Case'. When such experiences (Cases) are recalled in order to reason and tackle a new problem such a method of diagnosis could be termed as a Case-based approach.

It is believed that similar problems have similar solutions as such similar solutions approaches could be used to solve them. Two major tasks are identified as follows:

(a) retrieval of similar cases, and
(b) adaptation or revision of the solution of former similar cases.

Retrieval is easy if there are few cases as a simple sequential search could be applied otherwise if there are more cases it will require faster non-sequential indexing or classification or nearest neighbor algorithm [13].

If there are no marked differences between a current case and a similar case, a simple transfer of the solution is enough or only few substitutions are made [14]. When there are marked differences, the case base approach suffers from adaptation problem. Presented in Fig. 1 is a typical case base reasoning cycle [15]. CBR relies on the contextual knowledge stored in the case base library. When the number of cases is small, it could be quite misleading using CBR to solve problems.

2.2. Rule base reasoning (RBR)

Rules are probably the most common form of knowledge representation and they are present in most Artificial Intelligence (AI) applications such as Expert Systems and Decision Support Systems. The problem solving ability of many rule base systems is based on state space search in which a state represents the progress towards finding a solution at a single instant in time. Rule base systems are relatively simple models that can be adapted to any number of problems. To create a rule base system for a given problem the following must be created:

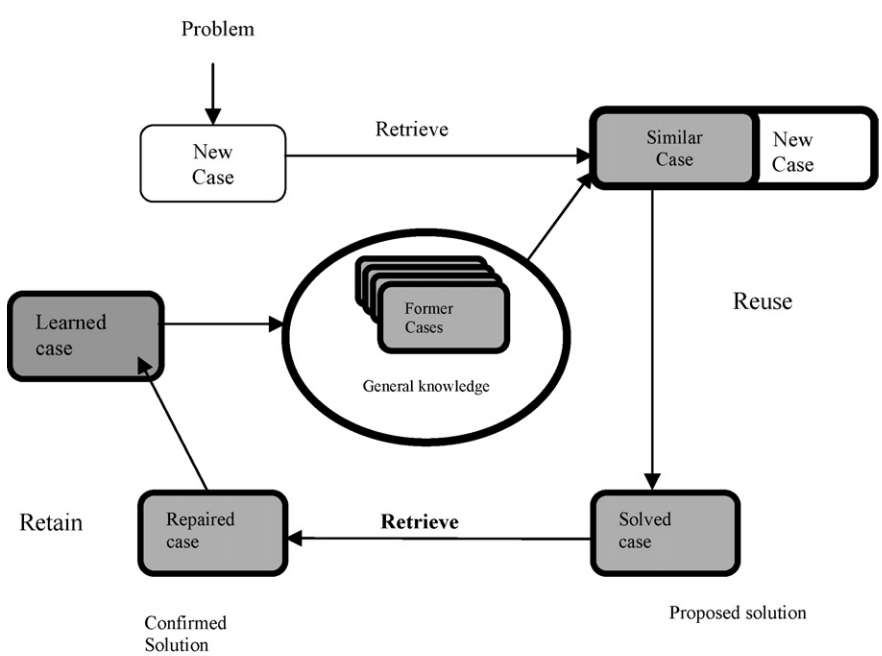

Fig. 1. Case base reasoning cycle developed by Aamodt.