REAL TIME COMPUTER AIDED DIAGNOSIS OF INTERNAL ILLNESS

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Abstract: The advancement in computer technology has encouraged the researchers to develop software for assisting doctors in making decision without consulting the specialists directly. The aim of this software is to help the doctors to diagnose the diseases real-time in a simple way or to prevent them diagnosing the illness wrongly. According to this purpose, this program analyzes the patients' complaints and their lab-tests by a computer and that computer program helps the doctors to diagnose every internal-medicine. Also this study helps the people who aren't specialized on one topic, who are practitioner or doctors who are tired because of the over time period.

INTRODUCTION

The steady expansion of medical knowledge has made it more difficult for the physician to remain abreast of medicine outside a narrow field. Consultation with a specialist is a solution when the clinical problem lies beyond the physician's competence, but frequently expert opinion is either unavailable or not available in a timely fashion. Attempts have been made to develop computer programs that can serve as consultants [1-2]. By the 1970s it became clear that conventional tools such as flow charts, pattern matching and Bayes' theorem were unable to deal with most complex clinical problems. Researchers then began to study the expert physician to obtain detailed insights into the basic nature of clinical problem solving [3-6]. The results derived from such studies have subsequently formed the basis for computational models of the cognitive phenomena, and these models have further been converted into so-called artificial intelligence programs [7]. Many of the early efforts to apply artificial intelligence methods to real problems, including medical reasoning; have primarily used rule-based systems [4-8]. But most serious clinical problems are so broad and complex that straightforward attempts to chain together larger sets of rules encounter major difficulties. Problems arise principally from the fact that rule-based programs do not embody a model of disease or clinical reasoning. In the absence of such models, the addition of new rules leads to unanticipated interactions between rules and thus to serious degradation of program performance [7]. Given the difficulties encountered with rule-based systems, more recent efforts to use artificial intelligence in medicine have focused on programs organized around models of disease. Efforts to develop such programs have led to substantial progress in our understanding of clinical expertise, in the

translation of such expertise into cognitive models, and in the conversion of various models into promising experimental programs. The physician's ability to sharply limit the number of hypotheses under active consideration at any one time is a key element in expert performance [8-12]. Computer programs that use the strategies of experts can accomplish this same goal and devote the bulk of their computational resources to the sophisticated evaluation of a small number of hypotheses. Controlling the proliferation of hypotheses is only the first step in creating effective artificial intelligence programs. To deal with the circumstance in which one disease influences the clinical presentation of another, the program must also have the capacity to reason from cause to effect. Moreover, the required pathophysiologic knowledge must be organized in a hierarchical fashion so that the information becomes more detailed as one progress to deeper levels of the knowledge base. Quantitative information, or rough qualitative estimates, must also be added to the causal links if the program is to separate the contribution of each of several disorders to a complex clinical situation. Proposed study presents a real time diagnosis of the diseases for the doctors and to prevent the doctors to diagnose an illness wrongly when they are overtime period. According to this aim a computer program has been written that evaluates the patient's complaints and the results of the lab tests and it is about all the possible internal medicine that can be diagnosed at the human beings and also the computer program is quick and real timed. In addition, this program helps the doctors who aren't specialized and who are get tired from the overtime periods to diagnose the illness in a short time correctly and this program helps to remove all the risks of the illnesses that can be overlooked.

METHODOLOGY

Any program designed to serve as a consultant to the physician must contain certain basic features. It must have a store of medical knowledge expressed as descriptions of possible diseases. Depending on the breadth of the clinical domain, the number of hypotheses in the database can range from a few to many thousands. In the simplest conceivable representation of such knowledge, each disease hypothesis identifies all of the features that can occur in the particular disorder. In addition, the program must be able to match what is known about the patient with its store of information. According to this aim, a specialized program using Artificial Neural Network (ANN) has been projected in this study. The

structure of ANN algorithm consists of a Multi Laver Perceptron (MLP), which is used error of the Back Propagation training algorithm. This Back Propagation algorithm has a supervisor learning rule. So, we used Generalized Delta Rule Learning in this study. For this reason firstly ANN has been educated by using the real educating data that are taken from the patients which are about the internal medicine. It can be seen in Figure-1; the data that used at educating are the complaints of the patient, the analysis of the patient's blood and urine. The complaint findings of the patient have been evaluated as 'existent' or 'not existence' and at the educating data, 'existent' is located in logic-1 (normalized 0, 9) and 'not existence's located in logic-0 (normalized 0, 1). The blood and urine test result's data have been used as a reference data at the educating data as being divided to 1000 to normalize the reference data at the 'Artificial Neural Network' entrance. For example; the reference data of hemoglobin are min: 14 max: 18. In our program's training system hemoglobin's reference data are normalized as min: 0.014 max: 0.018. The program was educated like this. The urine test's results which are positive (+) or negative (-) are shown as negative 0.1, positive 0.9 at our educating data. Our program not only the patient's complaint's data but also the normal(not ill, healthy) people's complaint's and lab analysis are considered for educating and testing of ANN. Figure-2 shows the form of the program. As you can understand from the Figure-2, normal and different illnesses findings' educating data are used firstly. The ANN implementation involves using a three layer perceptron by educating error of the back propagation.

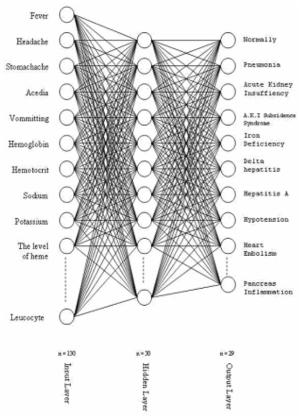


Figure-1: Used MLP structure

Figure-2 shows the end of training process in program. As it was understood from the figure, the training iteration number and the error results are shown at the screen. The program form Figure-4 describe the first testing process of the normal datum groups' results after the pogramme was educated .At the testing process ,the first line consists the normal data (who aren't ill's data) fort his reason the normal button is yellow and logic 1.After that the data of the different illnesses has been tested by educating process. As it can be seen Figure-3, the testing data result for a patient who has Hepatitis-C. As the Figure-3 shows the patient is Hepatitis-C. The used test data belong to a real Hepatitis-C patient so it means that the program can diagnose Hepatitis-C %98. If it is necessary, it is possible to make the same program fort he different groups of illnesses.

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Figure-2: The form of end of program

CONCLUSIONS

Most approaches to computer-assisted diagnosis have, until the past few years, been based on one of three strategiesflow charts [1, 2, and 4], statistical pattern-matching, or probability theory [5-7]. All three techniques have been successfully applied to narrow medical domains, but each has serious drawbacks when applied to broad areas of clinical medicine. Flow charts quickly become unmanageably large. Further, they are unable to deal with uncertainty, a key element in most serious diagnostic problems. Or that each clinical finding occurs independently of all others [13-14]. In theory, these problems could be avoided by establishing a database of probabilities that copes with all possible interactions [15]. Programs using ANN techniques have several major advantages over programs using more traditional methods [16-18]. This program has a greater capacity to quickly narrow the number of diagnostic possibilities, and has very high recognition accuracy. The program's software that we used Pascal and it is a kind of program of Delphi which has a visual programming language. The reason of using the visual programming is to know that the user of this program will be a government health official not a computer engineer. In the future, this study is able to help the doctors to evaluate the lab tests in a short time and according to lab tests diagnose the illness quickly. As a result there is no way to overlook any of the details. At the same time in the crowded hospitals it will make patients pleased because they won't have to wait long for the lab test's results. This preliminary work is a preworking and it can be developed with my counselor for not only the internal medicine but also the other illnesses.

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Figure-3: A test result of an illness group

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