A Novel Fuzzy-Neural Based Medical Diagnosis System

S. Moein, S. A. Monadjemi, and P. Moallem

Abstract—In this paper, application of artificial neural networks in typical disease diagnosis has been investigated. The real procedure of medical diagnosis which usually is employed by physicians was analyzed and converted to a machine implementable format. Then after selecting some symptoms of eight different diseases, a data set contains the information of a few hundreds cases was configured and applied to a MLP neural network. The results of the experiments and also the advantages of using a fuzzy approach were discussed as well. Outcomes suggest the role of effective symptoms selection and the advantages of data fuzzificaton on a neural networks-based automatic medical diagnosis system.

***Keywords*—**Artificial Neural Networks, Fuzzy Logic, Medical Diagnosis, Symptoms, Fuzzification.

I. INTRODUCTION

MEDICAL diagnosis always has been an art: we remember famous doctors as well as famous painters or composers throughout the history. Again, whom is called an artist? A person who can carry out something that others can not, and that is exactly what a good physician does during a medical diagnosis procedure. He (or she) employs his educations, experiences, and talent, to diagnose a disease. A diagnosis procedure usually starts with the patient complaints and the doctor learn more about the patient situation interactively during an interview, as well as by measuring some metrics such as blood pressure or the body temperature. The diagnosis is then determined by taking the whole available patients status into the account. Then depending on that, a suitable treatment is prescribed, and the whole process might be iterated. In each iteration, the diagnosis might be reconfigured, refined, or even rejected [1,2,8].

Whereas you need around five years to get your MSc or MA in other courses, you have to spend almost twice in a medical school to get your diploma. That simply suggests the complexity of the medical diagnosis. In each case diverse symptoms generated by diverse causes should be considered and added to the patient background. Epidemics also should be considered and the genetic factors too, and then a diagnosis can be materialized. After a while, a physician would be more experienced, but just gradually and in one branch of diseases. However, there are still some problems.

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A. Medical Diagnosis Problems

The major task of medical science is to prevent and diagnose the diseases. Here our focus is the second task, which as mentioned before, is not a direct and simple task at all. In 2001, Brause highlighted that almost all the physicians are confronted during their formation by the task of learning to diagnose [4]. Here, they have to solve the problem of deducing certain diseases or formulating a treatment based on more or less specified observations and knowledge [7]. Below some certain difficulties of medical diagnosis that have to be taken into account are listed:

- 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 [9].
- The quality of diagnosis is totally depends on the physician talent as well as his/her experiences.
- Emotional problems and fatigue degrade the doctor’s performance.
- The training procedure of doctors, in particular specialists, is a lengthily and expensive one. So even in developed countries we may feel the lack of MDs.
- Medical science is one of the most rapidly growing and changing fields of science. New results disqualify the older treats, new cures and new drugs are introduced day by day. Even unknown diseases turn up every now and then. So a physician should always try hard to keep his/herself up to date [4,7,9].

Regarding problems above, and also many others, the question would be how computers can help in medical diagnosis. Since decades ago, computers have been employed widely in the medical sector. From local and global patient and medicine databases to emergency networks, or as digital archives, computers have served well in the medical sector.

Meanwhile, in the case of medical diagnosis, regarding the complexity of the task, it has not been realistic yet to expect a fully automatic, computer-based, medical diagnosis system. However, recent advances in the field of intelligent systems are going to materialize a wider usage of computers, armed with AI techniques, in that application. A computer system never gets tired or bored, can be updated easily in a matter of seconds, and is rather cheap and can be easily distributed. Again, a good percentage of visitors of a clinic are not sick or at least their problem is not serious, if an intelligent diagnosis system can refine that percentage, it will set the doctors free to focus on nuclear and more serious cases.

B. Former Studies

WISER (Wireless Information System for Emergency Responders) is a system designed to assist first responders in hazardous material incidents. Developed by the National Library of Medicine, WISER provides a wide range of information on hazardous substances, including substance identification support, physical characteristics, human health information, and containment and suppression guidance. The WISER system concept is designed to work in a standalone or connected mode. The end user device is preloaded with the most critical information. At the scene, a wireless network sends new information between handhelds and routes requests for more information. If a wireless connection is not available, the handheld device still has full functionality with access to the critical local data available on the device. WISER also sends and receives information over the wide area wireless network, receiving new information from different health networks and administrations as well as other authorized resources. WISER can operate on mobile devices such as PDAs, providing the first responders with critical information in the palm of their hands [10].

Comprehensive decision support, including assistance in identification of an unknown substance and, once the substance is identified, providing guidance on immediate actions necessary to save lives and protect the environment [10].

Also, there are some other tools that can be helpful in medical diagnosis. MedWeaver is one of them, that we give a short explanation about it. MedWeaver is a unique Web-based facilitator, integrating powerful differential diagnosis tools with diverse information resources to generate personalized answers for healthcare professionals. Through the differential diagnosis and disease lookup modes, clinicians are guided to the focused content they need. The result is better decision-making. Studies show that clinical judgment combined with the use of differential diagnosis tools increases diagnostic quality and accuracy. MedWeaver employs DXplain, a computer-based decision support system developed by Octo Barnett [11].

In this study we aim to investigate the application of artificial neural networks in medical diagnosis and propose a simple and applied method for that. This paper is organized as follows: In Section II the proposed method will be introduced. Next in Section III the experiments will be discussed and the paper would be concluded in Section IV.

II. The Proposed Method

The first stage of this study was decoding the real and typical doctor-based diagnosis procedure by interviewing some experts. A few physicians assisted us to provide the diagnostic flow diagrams of some illnesses, and a list of symptoms that are known to be essential in each case. Fig. 1 shows two of the diagnosis flow diagrams obtained. Those diagrams were all double checked by another expert before the selecting of symptoms which was carried out next.

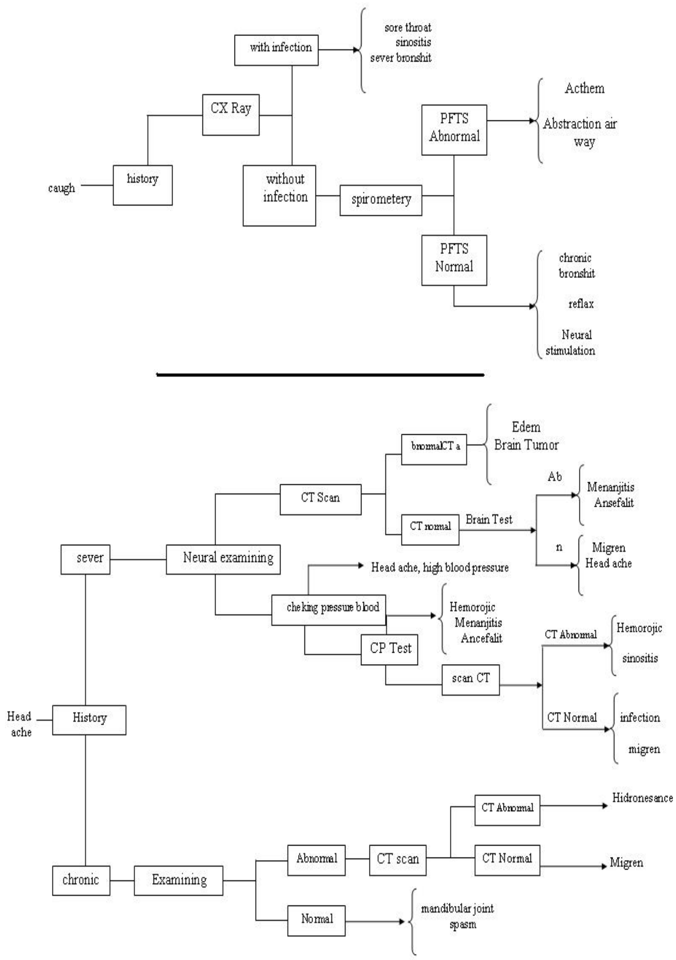


Fig. 1 Medical diagnosis procedure, two instances

Table I illustrates the symptoms selected in its columns respectively. Good amounts of work were carried out to convert an implicit diagnosis procedure to an explicit flow diagram for each disease, and then to extract an effective set of symptoms for each illness and their attributes.

Next we measured the selected features for many visitors of a particular clinic during two months, and configured our patients dataset of a few hundreds reliable records. The dataset contains eleven features (symptoms), and nine classes of disease. The first eight classes were assigned to eight particular illnesses, whereas the ninth one allocated to the healthy/normal persons.

A. Artificial Neural Networks (ANN)

Inspired from the animals' neural system, since their introduction in early 50's, ANNs show high performance in variety of applications, e.g. data analysis, pattern recognition, prediction, and so on. The main characteristics of an ANN are [5,12]:

- Black box structure,
- Simple computing nodes (neurons), with several connections,
- A unique structure to perform different tasks, using a learning by example, or training, scheme,
- Flexibility against noise,
- Interpolation.

ANNs are highly accurate and robust classifiers, the attribute that makes them appropriate for medical diagnosis. We tried a multilayer perceptron (MLP) neural network and applied an ordinary back propagation GDR training algorithms on that. As software simulator we used MATLAB package and the NETLAB toolbox. Fig. 2 illustrates a patch of developed MATLAB codes. Details and topology of the ANN used would be described later.

B. Dataset

Choosing acceptable, valid, and real data is vital, because system has to deal with the patient's health and even life. A dataset based on continuous range of numbers is the other issue. Table I shows a part of the used dataset. This dataset provided eleven symptoms of eight different diseases and a group of normal healthy people. The complete dataset contains the measured features of 160 patients.

The used data were normalized too by dividing each column to its maximum absolute value respectively. There is a problem about such a dataset that should be addressed carefully. Since the medical data are mostly in binary true/false form, a typical GDR training algorithm may face some zero-production problem. The problem was solved by adding a 0.1 bias term to zero inputs.

Table II shows the list of illnesses and their assigned labels.

C. The ANN and Training Scheme

We opted a three layer feed forward perceptron to keep the structure of the network as simple as possible. Instead, we focused on the number of hidden nodes and the number of training iterations (epochs) our variable parameters. The effect of changing each parameter on the classifier performance was tested separately. The rule of feature fuzzification on the diagnosis accuracy was also investigated. Table III shows a patch of trained weights of our ANN.

TABLE I
THE MAIN DATASET

ECG	CT scan	MRI	Head status	CBC	head ache	blood pressure	LP	Disease
-0.9	0.5	0.1	-0.9	0.1	0.1	0.6	0.1	1
-0.9	-0.9	0.1	-0.9	0.1	0.1	0.6	0.1	2
-0.9	0.1	0.1	-0.9	0.1	0.1	0.6	0.1	3
-0.9	0.1	0.5	0.5	0.1	0.1	0.6	0.1	4
-0.9	0.1	-0.9	0.5	0.1	0.1	0.6	0.1	5
0.1	0.1	0.1	0.1	0.5	0.1	0.6	0.1	6
0.1	0.1	0.1	0.1	-0.9	0.1	0.6	0.1	7
0.1	0.1	0.1	0.1	0.5	0.1	0.6	0.1	8
0.1	0.1	0.1	0.1	0.1	0.1	0.6	0.1	6
0.1	0.1	0.1	0.1	0.1	0.1	0.6	0.1	9
0.1	-0.9	0.1	0.1	0.1	0.5	0.65	0.1	4
0.1	0.5	0.5	0.1	0.1	0.9	0.8	0.9	5
0.5	-0.9	0.1	0.1	0.1	0.5	0.6	0.5	2
0.1	0.5	0.5	0.1	0.1	0.5	0.6	0.5	6
0.1	0.5	-0.9	0.1	0.1	0.1	0.8	0.1	5

```
[x, t, nin, nout, ndata] = datread('book1.txt') ;
xtr = x(1:80) ;
xtst = x(81:99,:) ;
ttr = t(1:80,) ;
ttst = t(81:99,:) ;
% Set up network parameters.
net = mlp(11, 60, 1, 'linear');

% Set up vector of options for the optimiser.
options = zeros(1,18);
options(1) = 1;       % This provides display of error
values.
options(9) = 1;       % Check the gradient calculations.
options(14) = 500;      % Number of training cycles.
```

Fig. 2 A section of MATLAB codes (A modified NETLAB procedure)

III. Experiments and Discussion

A. Experiments

Due to the lack of cases in our dataset and to increase the validity and generality of the results, a k-folding scheme with k=5 was applied. In this method, the training procedure is repeated *k* times, each time with 80% of the samples in the dataset as training and left 20% for testing. The 20% testing section is non-overlapping. All the reported results are obtained by averaging the outcomes of those five separate tests.

We started with continuous (non-fuzzy) features. The best diagnosis performance achieved was 88.5% correct classification with 30 nodes in the hidden layer and after passing 1500 training epoch. Fig. 3 shows one of the results of this stage.

TABLE II
DISEASES NAMES AND THEIR LABELS

Assigned label	Disease name
1	Sinusitis
2	Tumor
3	Ear ache
4	Heart disorder
5	Meningitis
6	Blood cancer
7	Blood disorder
8	Chest cancer
9	Normal

TABLE III
TRAINED ANN'S WEIGHT SET AFTER A FEW EPOCHS

-0.8189	0.721827	0.509804	1	0.992009	1.051009
-0.8189	0.721827	-1	0.847231	0.85546	1.944729
-0.8189	0.721827	0.078431	0.702678	0.705556	2.979522
-0.8189	0.721827	0.078431	0.566341	0.50655	4.458722
-0.8189	0.721827	0.078431	0.438221	0.50655	4.458722
0.480315	-0.37596	0.078431	0.318316	0.243588	6.660834
0.480315	-0.37596	0.078431	0.206628	0.199882	7.062859
0.480315	-0.37596	0.078431	0.103156	0.243588	6.660834
0.480315	-0.37596	0.078431	0.318316	0.096567	8.066487
0.480315	-0.37596	0.078431	0.0079	0.096567	8.066487
0.480315	-0.37596	-1	0.566341	0.567397	3.992018
0.480315	-0.37596	0.509804	0.438221	0.430529	5.062152
1	-1	-1	0.847231	0.846392	2.005646
0.480315	-0.37596	0.509804	0.318316	0.321516	5.972394
0.480315	-0.37596	0.509804	0.438221	0.430529	5.062152

Next we used a membership-based fuzzification scheme on our dataset to convert it to a fuzzified set of symptoms [2,3]. A linear membership function was selected for each symptom again after an interview with physicians. Normally three to five linguistic variables were assigned to each symptom, then the classification tests were repeated. Fig. 4 illustrates the fuzzy toolbox used and the fuzzy membership functions assigned to two of symptoms.

This time the maximum performance was 97.5% correct diagnosis which is a considerable accuracy. That performance was achieved by a 15-nodes ANN and just after 500 training iterations. Fig. 5 illustrates the outcomes of this test.

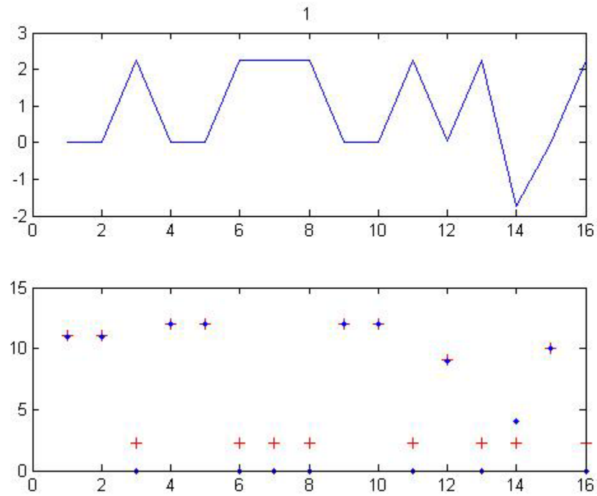
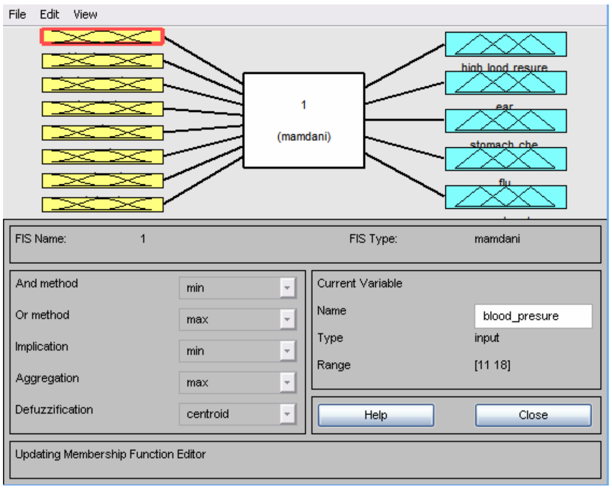


Fig. 3 The diagnosis result using the continuous dataset. Above: the output error, Below: the assigned labels/diseases. Number of hidden nodes was 30 and training was stopped after 150 epochs

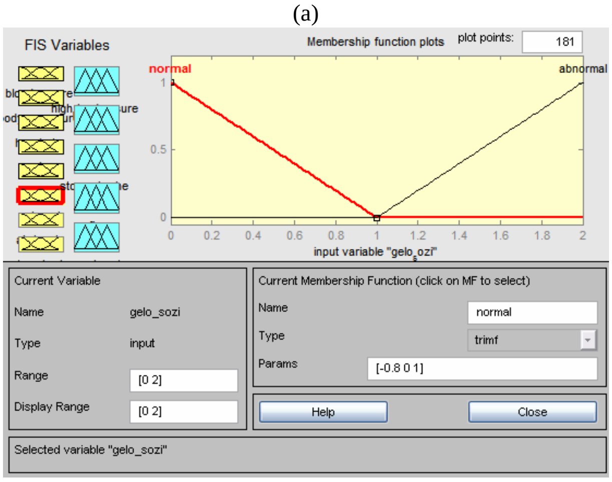
IV. CONCLUSION

In this paper we tried to offer a hybrid fuzzy-neural automatic system for medical diagnosis, but without concerning about how to calculate the best membership function for each fuzzy data. Actually, neural networks solved this problem for us and by employing a precisely designed and trained network we can diagnose diseases accurately. We showed that the advanced system which used a fuzzified dataset is more precise than the ordinary system with continuous range of symptoms data. Also a series of optimizations on the MLP classifier structure and training epochs increased the system performance. The best performance of 97.5% correct diagnosis was achieved using fuzzified symptoms and an optimized ANN with 15 hidden nodes and after 500 training epochs.

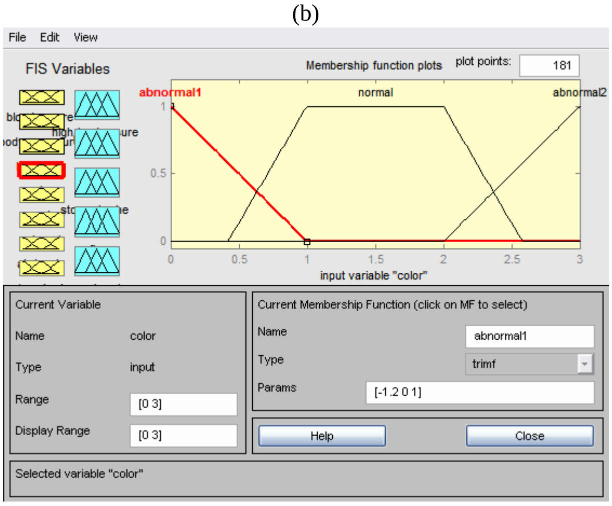
As the future work orientation, one may concentrate on the problem of advanced training algorithm for neural networks, or an automatic symptoms selection system. The hazard prediction system to predicate the possible future health problems of a given visitor regarding his current situation might be of interest too.



(a)



(b)



(c)

Fig. 4 The fuzzy toolbox (a), and the fuzzy membership functions of two symptoms (b and c)

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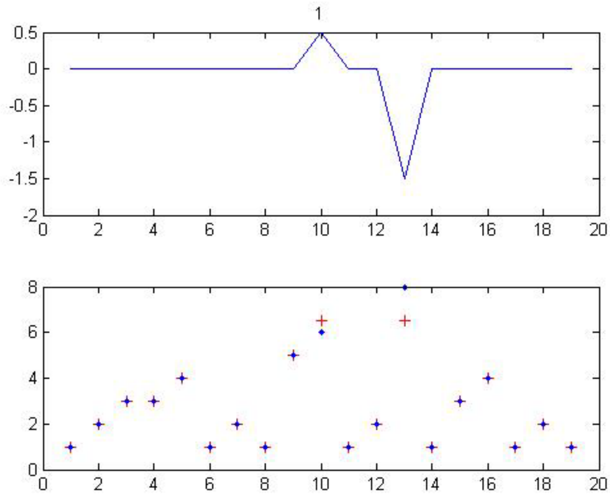

Fig. 5 The diagnosis result using the fuzzified dataset. Above: the output error, Below: the assigned labels/diseases. Number of hidden nodes was 15 and training was stopped after 500 epochs

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