FUZZY NEURAL NETWORK METHODOLOGY APPLIED TO MEDICAL DIAGNOSIS

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Abstract

This paper presents a technique for building expert systems which combines the fuzzy-set approach with artificial neural network structures. This technique can effectively deal with two types of medical knowledge: a nonfuzzy one and a fuzzy one which usually contribute to the process of medical diagnosis. Nonfuzzy numerical data is obtained from medical tests. Fuzzy linguistic rules describing the diagnosis process are provided by human expert. The proposed method has been successfully applied in veterinary medicine as a support system in the diagnosis of canine liver diseases.

1. Introduction

Medical expert systems have relied heavily upon the use of expert opinions and textbook information to form rules or protocols for making decisions, see e.g. [3]. Expert opinions usually take the form of qualitative knowledge and very frequently can be represented as a family of linguistic conditional rules of the type: IF "symptoms" THEN "diagnoses". The "symptoms" often have the form of linguistic statements, like "cholesterol is significantly increased" or "blood pressure is normal". The "diagnoses" can have the form of possibility distributions over some set of diseases, indicating that - for given "symptoms" - disease x is highly possible while disease y is less possible and disease z shouldn't be taken into account. Unfortunately, sometimes a variability between experts in a given domain exists which decreases the quality of the systems obtained.

On the other hand, an increasing number of hospital data base systems have been installed which collect on-line the results of many medical tests. This kind of data represents quantitative medical knowledge. A study of this data collected over time and the incorporation of the knowledge acquired would significantly enhance the quality of medical expert systems.

In a paper [9] considering the current state of medical expert systems, the authors suggest that the time has come to enhance programs which were based on a study of the problem-solving behaviour of clinicians, with knowledge obtained from numerically based methods. They also recognize the difficulty of this approach when they state that "an extensive research effort is required before all these techniques can be incorporated into a single program".

The purpose of this paper is to present a new technique for the construction of medical expert systems. This technique combines neural network structures [7] with some elements

of the theory of fuzzy sets [10]. The proposed technique can effectively cope with two types of medical knowledge: linguistic conditional IF-THEN rules which are expressed by a human expert and numerical data which are collected as a result of medical tests. That is, both mentioned types of medical knowledge can be formalized and incorporated into the expert system. Moreover, both the qualitative and quantitative data can also be processed by the expert system when decision making processes are performed. Some other applications of neural networks to the design of expert systems for medical diagnosis can be found in [1, 5].

The structure combining neural networks and fuzzy sets is called a fuzzy neural network. First, its learning phase is presented during which the network builds a formal representation for the available medical knowledge from a given domain.Then, the inference phase of the network is described. In this phase the network functions as a decision making system. In turn, the application of the proposed methodology in a veterinary medical field, where it has been used as a support system in the diagnosis of the canine liver diseases, is presented.

2. Fuzzy neuro-computational scheme for medical knowledge representation

The general procedure for the construction of an expert system which is based on fuzzy neural networks has the following stages:

a) the choice of the expert system structure in terms of its inputs and outputs and the definition of the primary fuzzy sets for inputs,

b) the derivation of the linguistic conditional rules representing a human expert's knowledge in a given medical domain as well as collecting available numerical medical data supporting the diagnosis process,

c) the development of a fuzzy neural-network-based scheme which - during the process of learning - builds a formal representation for the available qualitative and quantitative medical knowledge,

d) the assessment of the expert system quality against learning data and, if available, test data.

In a general case, the expert system has n inputs $x_1 \in X_1, x_2 \in X_2, ..., x_n \in X_n$ and one output y. Each input x_i represents one medical parameter which takes values from the set X_i. Output set $Y = \{y_1, y_2, ..., y_m\}$ is a set of potential diseases. The collections of the primary fuzzy sets represent the aggregations for the masses of numerical data from inputs. These aggregations or clusters are verbally described by means of linguistic labels and form the level at which learning and inference processes are then carried out. Primary fuzzy sets also establish the perception level for the classical neural network which is a part of the proposed fuzzy neural network. The collections of the primary fuzzy sets can be defined in a twofold way. If the qualitative medical knowledge (usually given by the domain human-expert) prevails in the overall description of the system then the primary fuzzy sets can also be defined by the human expert. For instance, many medical parameters can often be characterized by three basic verbal labels: "normal", "descreased", and "increased". These labels, in a natural way, can be formally represented by three fuzzy sets whose membership functions can be readily sketched by a human expert. In turn, these sets can be used as a collection of primary fuzzy sets. If three verbal labels (three fuzzy sets) do not create a sufficiently adequate representation of a given medical parameter, then one has to introduce a respectively higher number of them. On the other hand, if the quantitative medical data prevails in the system description then the primary fuzzy sets can either be defined by a human expert or generated by a formal algorithm of fuzzy clustering [2]. We assume that

for each input x_i a collection $A_{i1}, A_{i2}, ..., A_{in_i} \in F(X_i)$ of n_i primary fuzzy sets is defined. $F(X_i)$ denotes a family of all fuzzy sets defined on X_i.

The second stage of the construction of a fuzzy neural-network-based expert system consists in the derivation and formal representation of available qualitative and quantitative medical knowledge in a given domain. The qualitative knowledge is usually a set of K linguistic rules representing a human expert's knowledge. The rules have the form:

$$...ALSO$$

$$IF \ \ x_1 \ is \ A'_{1k} \ AND \ x_2 \ is \ A'_{2k} \ AND \ ... \ AND \ x_n \ is \ A'_{nk} \ \ THEN \ \ B'_k \qquad (1)$$

$$ALSO...$$

$$k = 1, 2, ..., K,$$

where A'_{ik} are the linguistic labels such as "increased", "normal", etc. and B'_k is a corresponding possibility distribution defined over the set Y of potential diseases. Linguistic labels A'_{ik} are formally represented by fuzzy sets which - for simplicity - are also called A'_{ik}; $A'_{ik} \in F(X_i), i = 1, 2, ..., n$. Analogously, the possibility distribution B'_k is represented by fuzzy set $B'_k \in F(Y)$. The possibility distribution assigns to each disease y_j from the set Y, a number from the interval $[0, 1]$, indicating how possible is occurrence of a disease y_j given the "symptoms" represented by input data in (1). Number 0 assigned to disease y_j means that y_j, according to an expert, can not occur. Number 1 - means that y_j certainly occurs. Regarding the earlier discussion of the primary fuzzy sets, one can notice that the input fuzzy sets A'_{ik} can also be used as the primary fuzzy sets.

The available quantitative medical data can also be presented in a rule-like form (we have L rules):

$$...ALSO$$

$$IF \ \ x_1 \ is \ x_{1l} \ AND \ x_2 \ is \ x_{2l} \ AND \ ... \ AND \ x_n \ is \ x_{nl} \ \ THEN \ \ B_l \qquad (2)$$

$$ALSO...$$

$$l = 1, 2, ..., L,$$

where x_{il} is a numerical value of medical parameter x_i and B_l is a corresponding possibility distribution as in (1). In order to unify the formal representation of rules (2) and (1), numerical values x_{il} of (2) are described by degenerate fuzzy sets $\tilde{x}_{il}$ called fuzzy singletons whose membership functions are of the form:

$$\mu_{\tilde{x}_{il}} = \left\{ \begin{array}{ll} 1, & \text{for } x_i = x_{il}, \\ 0, & \text{for } x_i \neq x_{il}. \end{array} \right. \qquad (3)$$

It is also possible that certain rules may contain both qualitative and quantitative data, that is some inputs of a given rule are described by linguistic terms (represented by fuzzy sets) and the other inputs are described by numbers (represented by fuzzy singletons) taken from medical tests.

The third stage of the proposed methodology for the expert system construction consists in the development of a fuzzy neural network which - through the learning process - builds an internal formal representation for both qualitative (linguistic, fuzzy) and quantitative (numerical) medical knowledge described by (1) and (2). Fig. 1 presents a structure of the proposed fuzzy neural network in the learning phase. Symbols A'_i, i=1,2,...,n denote fuzzy sets A'_{ik} from (1) or fuzzy singletons $\tilde{x}_{il}$ for (2). Analogously, B' denotes a corresponding fuzzy set B'_k from (1) or fuzzy set B_l from (2). Since the collections of primary fuzzy sets establish the perception level for the classical neural network of Fig. 1, it means that both
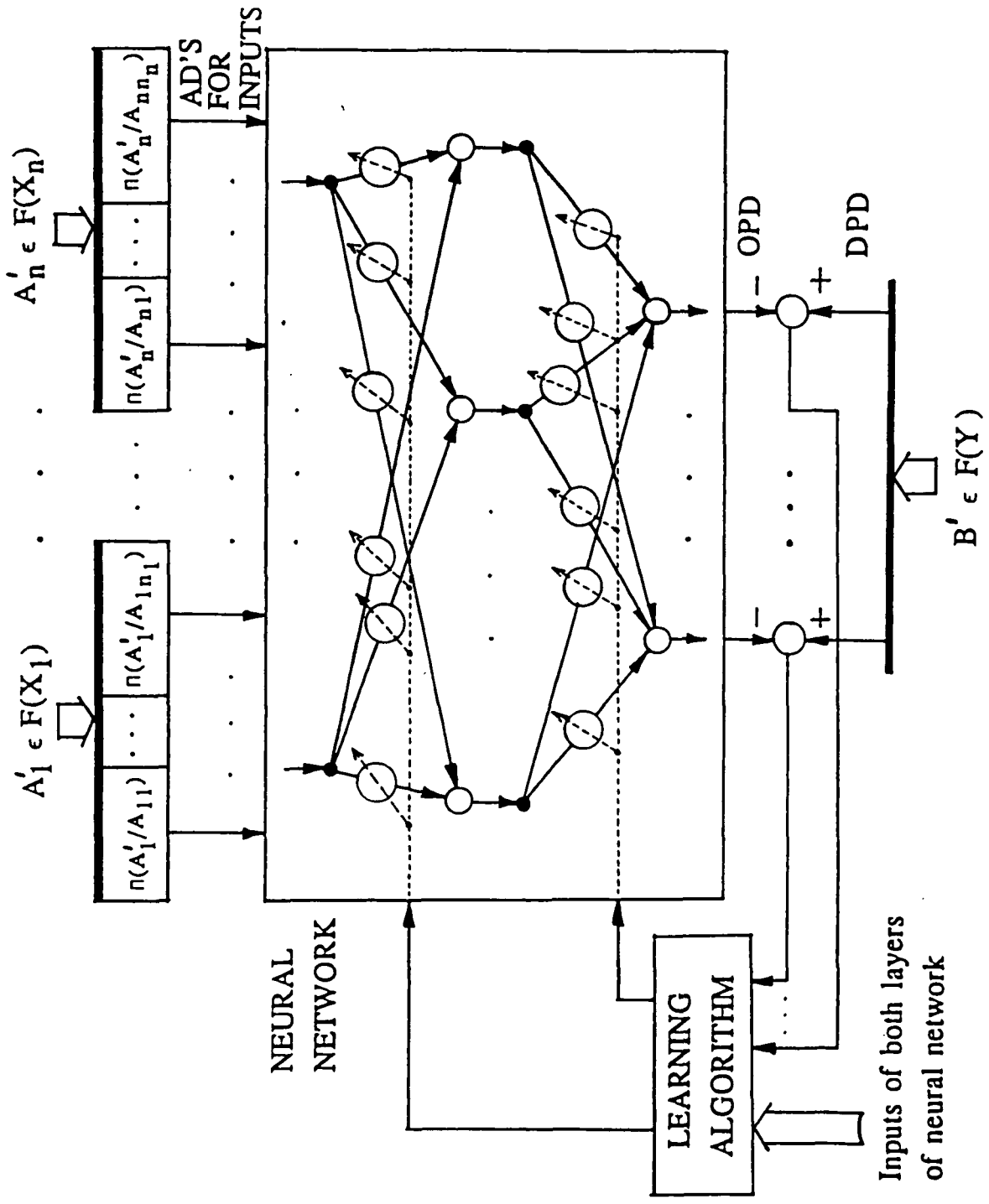
Figure 1: Structure of the fuzzy neural network in the learning phase

nonfuzzy and fuzzy data which are to be processed by the fuzzy neural network, first must be "transferred" to that perception level. The representations of the input transferred data are called activation degrees of primary fuzzy sets for particular inputs (AD's for inputs, for short - see Fig. 1). The AD's are calculated using the notion of a possibility measure [11] that is for input x_i the AD of a given primary fuzzy set A_{ij} induced by input fuzzy set A'_i is expressed by:

$$\Pi(A_i'/A_{ij}) = \sup_{x_i \in X_i} \{min[\mu_{A_i'}(x_i), \mu_{A_{ij}}(x_i)]\} \tag{4}$$

In a special case of nonfuzzy numerical data $x_i^0 \in X_i$, fuzzy set A_i' is reduced to a fuzzy singleton $\tilde{x}_i^0$ and then the expression (4) has the following form:

$$\Pi(\tilde{x}_i^0/A_{ij}) = \mu_{A_{ij}}(x_i^0). \tag{5}$$

The AD's for inputs are then processed by the classical neural network (see Fig. 1), which generates at its outputs an output possibility distribution (OPD - for short). OPD's are in turn compared with corresponding desired possibility distributions (DPD's - for short) coming from the rules (1) and (2). The differences between the DPD's and OPD's are then processed by the learning algorithm which adjusts the neural network weights in such a way as to minimize these differences. As for the classical neural network of Fig. 1, we use a two-layer perceptron [7] because of its universal properties [7,6]. The new back-propagation learning algorithm [8] will be used as a training technique for this network. The overall cost function which is being minimized during the learning process has the form:

$$Q_1 = \frac{1}{mP} \sum_{p=1}^{P} \sum_{j=1}^{m} (v_j^p - d_j^p)^2, \tag{6}$$

where: v_j^p are the OPD's ($j = 1, 2, ..., m$) generated by the neural network for the p-th sample of training data; there are K samples of training data of the type (1) and L samples of training data of the type (2), thus P=K+L,
d_j^p are the corresponding DPD's coming from the p-th sample of training data.

The network is trained by initially selecting small random weights and then presenting all available training data repeatedly until the weights converge and the quality index is reduced to an acceptable value - see [7,8] for the details.

3. Inference scheme

After the learning process is performed and the optimal values for the weights are stored, modifying slightly the scheme of Fig. 1, the structure of a fuzzy neuro-computational inference engine can be obtained. It is presented in Fig. 2. Symbols A_i^0, $i = 1, 2, ..., n$ represent the input data ("symptoms") describing the condition of a new patient. If this data results from laboratory tests, it has a numerical form and is represented by a fuzzy singleton - cf(3). Input data may also result from the assessment made by the physician. In this case, very often they have the form of linguistic terms which are represented by fuzzy sets.

The structure of Fig.2 processes the input data and generates the corresponding possibility distribution PD over the set Y of diseases. PD indicates, given the input data, the possibility of occurrence of each disease from the set Y.

The assessment of the expert system quality remains yet to be done. Initially, this assessment should be done with regard to the training data. The cost function Q_1 represented by (6) is also the quality index describing the accuracy of the mapping of the training data by the formal fuzzy-neural-network-based system. The other quality index is the averaged error between the possibility distributions generated by the system and the desired possibility distributions taken from the training data:
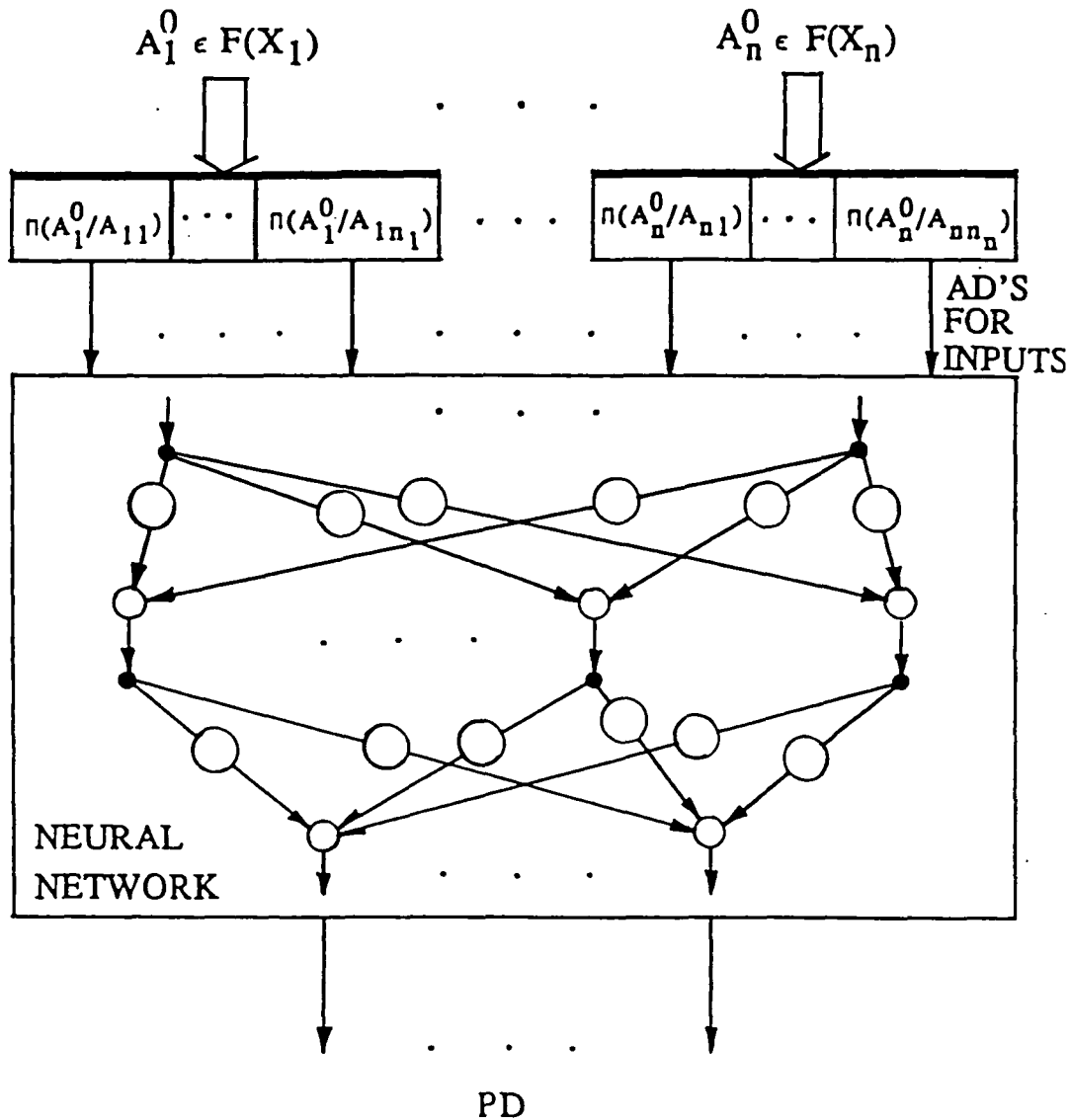
$$A_1^0 \in F(X_1) \qquad\qquad A_n^0 \in F(X_n)$$

$$\pi(A_1^0/A_{11}) \cdots \pi(A_1^0/A_{1n_1}) \quad \cdots \quad \pi(A_n^0/A_{n1}) \cdots \pi(A_n^0/A_{nn_n})$$

AD'S
FOR
INPUTS

NEURAL
NETWORK

PD

Figure 2: Structure of the fuzzy neural network in the inference phase

$$Q_2 = \frac{1}{mP} \sum_{p=1}^{P} \sum_{j=1}^{m} |v_j^p - d_j^p|, \tag{7}$$

and the variance corresponding to Q_2. v_j^p and d_j^p in (7) are the same as in (6). The expert system quality can also be assessed against test data if it is available. In this case, an analogous index to Q_2 and the variance corresponding to it can be used.

4. Application to veterinary medical diagnosis

Now the entire methodology leading to the development of the expert system based on a fuzzy neural network will be illustrated for a domain from the veterinary medical field, that is the diagnosis of liver diseases in small animals and in particular canine liver diseases, cf[4]. Clinicians can accurately diagnose whether or not liver disease is present in about 75 %

of all cases. They can only predict in about 15 % cases the specific type of liver disease. The diagnostic process involves physical examination and laboratory tests; often either a biopsy or a necropsy is performed. The cost of doing laboratory tests is about 20 times cheaper than that of performing a biopsy or necropsy. The latter ones provide more valuable information but, on the other hand, there are some risks in performing biopsy [4]. The aim of this paper is to build an expert system which uses mainly laboratory data and, in a limited range, also verbal rules formulated by a human expert, to determine specific types of liver disease. The expert system will produce a possibility distribution over the set of liver diseases indicating the possibility of occurrence of each of those diseases for a given set of input data.

According to the general procedure for the construction of such an expert system, first, we have to determine its structure in terms of inputs and outputs. Overall, there are 40 medical (biochemical and hematologic) parameters used in the liver disease diagnosis. After a detailed analysis of the correlations between particular parameters finally a subset of 15 biochemical and hematologic parameters has been chosen - see [4] for details. These parameters are listed in Appendix A; they are used as the inputs of our system. The output of the system is a set of 14 liver diseases; they are listed in Appendix B. For each input a set of 3 primary fuzzy sets has been defined using a fuzzy clustering technique [2]. As for the classical neural network of Fig. 1, a two-layer perceptron has been used. It has 15x3=45 inputs and 14 outputs. After some experimentation, 30 nodes in a hidden layer have been set. As a result of the training process, cost function Q_1 (6) - after 1500 iterations - has been reduced to 0.0004 - see Fig. 3. Switching to the inference phase - see Fig. 2 - the assessment of the expert system against training data resulted in the averaged error Q_2 equal to 0.0088 and the corresponding variance equal to 0.0003. For the training data, the system never produces a response which is essentially contradictory to the desired one. An example of the assessment of the system against training data is presented in Fig. 4. There were also available two sets of test data, not used during the training process. For them we obtained, respectively, Q_2 equal to 0.0357, variance equal to 0.0100, and Q_2 equal to 0.0506, variance equal to 0.0134. They show a high level of correctness of the expert system responses.

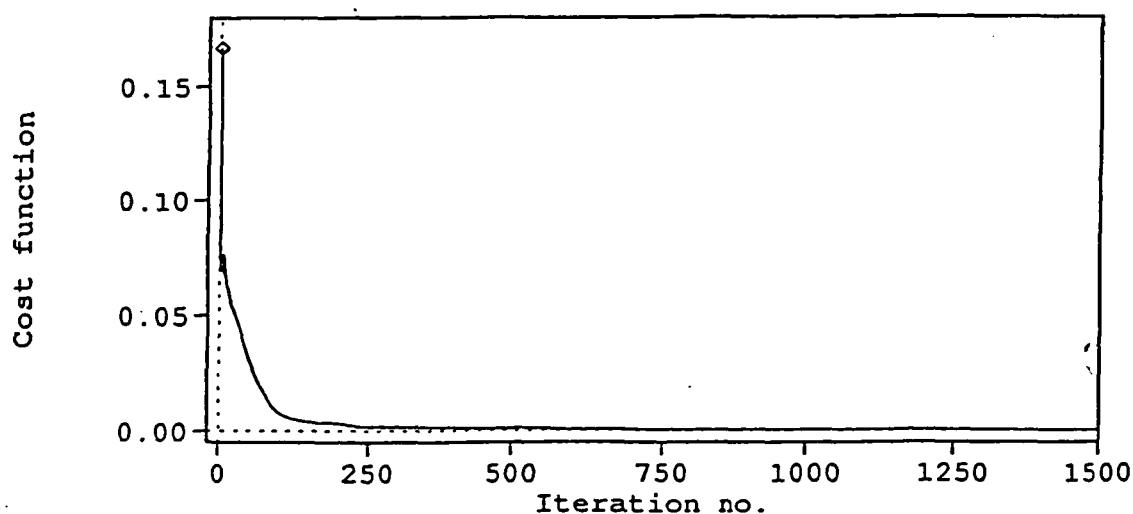Fig. 5 shows an examplary response of the expert system in the inference phase.

Figure 3: Cost function Q_1 versus number of iterations plot

TEST OF THE EXPERT SYSTEM AGAINST LEARNING DATA

Learning data set No.: 2

(p.d. means the possibility distribution over the set of diseases),
dotted line - desired p.d. (obtained from the learning data),
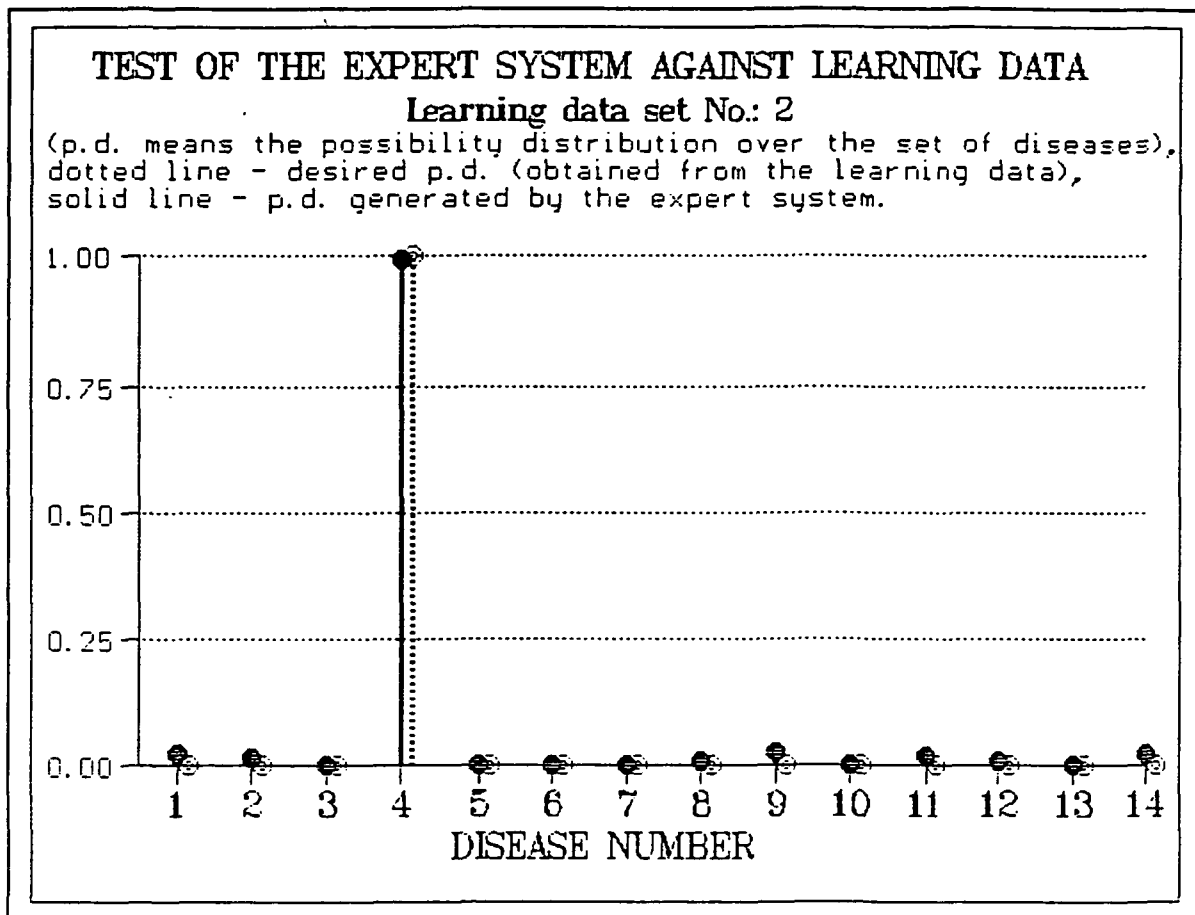solid line - p.d. generated by the expert system.

Figure 4: Assessment of the expert system against learning data - an example

5. Conclusions

In this paper we have introduced a method for building expert systems which can effectively deal with two main types of medical knowledge: a) a nonfuzzy one (numerical data from medical tests) and b) a fuzzy one (linguistic rules provided by a human expert). The proposed technique combines the fuzzy-set approach with neural network structures, which are characterized by high learning and adaptive capabilities. The proposed method has been successfully applied in the veterinary medical field as a support system in the diagnosis of canine liver diseases.

References

1. W.G. Baxt, "Use of an artificial neural network for data analysis in clinical decision-making: the diagnosis of coronary occlusion". Neural Computation, 2, pp. 480-489, 1990.

2. J.C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", Plenum Press, New York, 1981.

3. B. Buchanan and E. Shortcliffe, "Rule-Based Expert Systems: The MYCIN Experiment of the Stanford Heuristic Programming Project", Addison-Wesley, 1986.
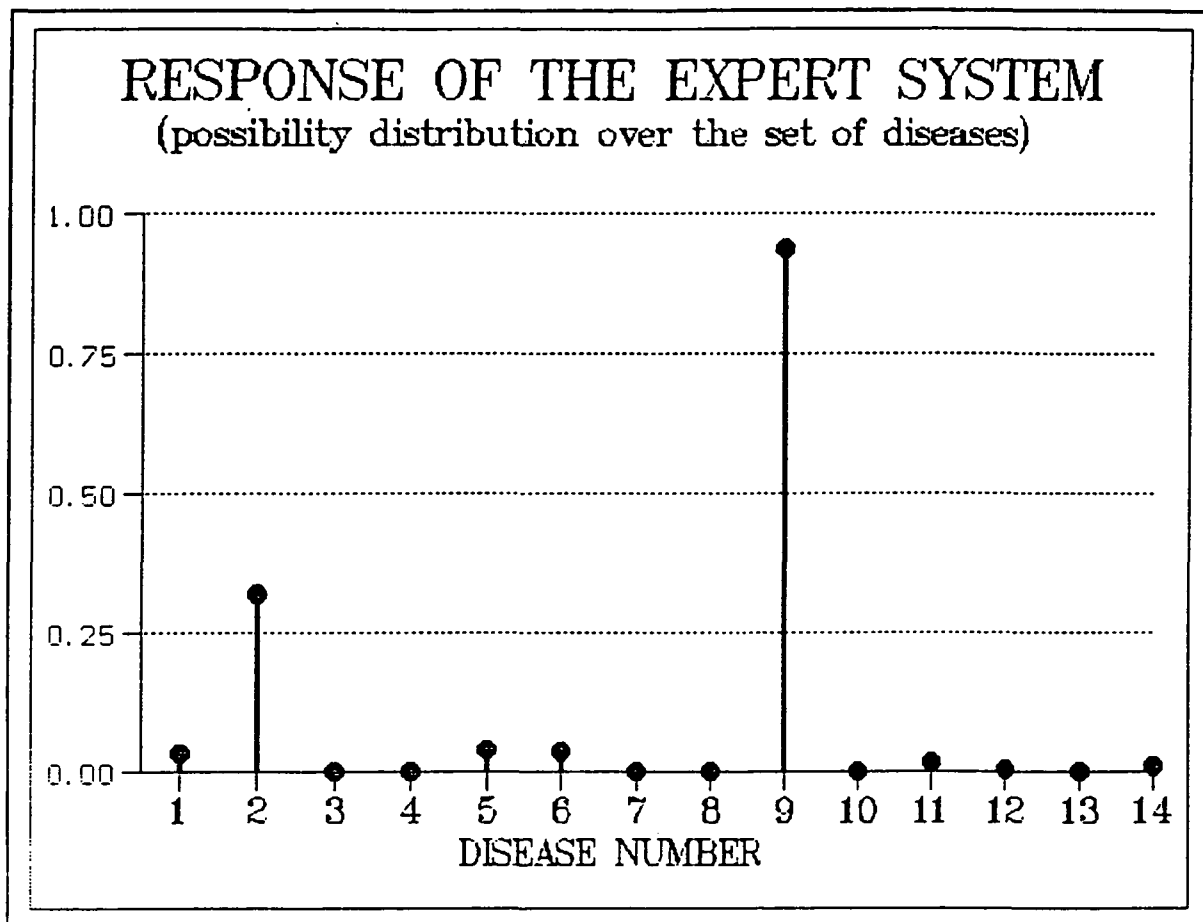
RESPONSE OF THE EXPERT SYSTEM
(possibility distribution over the set of diseases)

Figure 5: Examplary response of the expert system

4. M. Deutsch-McLeish, P. Yao and T. Stirtzinger, "A study on the use of belief functions for medical expert systems", Journal of Applied Statistics, vol. 18, no. 1, pp. 155-174, 1991.

5. S.I. Gallant, "Connectionist Expert Systems", Comm. of the ACM, 31(2), pp. 152-169, 1988.

6. K.Hornik, M. Stinchcombe, H. White, "Multilayer feedforward networks are universal approximators", Neural Networks, vol. 2, no. 5, pp. 359-366, 1989.

7. R.P. Lippmann, "An introduction to computing with neural nets", IEEE ASSP Magazine, pp. 4-22. April 1987.

8. D.E. Rumelhart et al., "Learning internal representations by error propagation", in: "Parallel Distributed Processing: Explorations in the Microstructure of Cognition", Vol. 1: "Foundations", D.E. Rumelhart and J.L. McClelland (Eds), MIT Press, Cambridge, MA, 1986.

9. W. Schwartz, R. Patil and P. Szolovits, "Sounding board, artificial intelligence in medicine", New England Journal of Medicine, vol. 16, no. 11, pp. 685-688, 1987.

10. L.A. Zadeh, "Fuzzy sets", Information and Control, vol. 8, pp. 338-353, 1965.

11. L.A. Zadeh, "Fuzzy sets as a basis for a theory of possibility". Fuzzy Sets and Systems, vol. 1, pp. 3-28, 1978.

Appendix A. Medical parameters which are the inputs of the expert system

Biochemical parameters		Hematologic parameters	
AALB	Albumin	HHCT	Hematocrit
AALKP	Alkaline phosphatase	HIMMAT	Immature leucocytes
AALT	Alanine aminotransferase	HLYMPH	Lymphocytes
AAST	Aspartate aminotransferase	HMCV	Mean corpuscular volume
ACBILI	Conjugated bilirubin	HRETIC	Reticulocytes
AGLUC	Glucose	HRBC	Red blood cells
ATPROT	Total protein	HSEGS	Neutrophil segmentations
AUREA	UREA		

Appendix B. Set of liver diseases - the output of the expert system

1	=	Primary and Metastatic Tumors	2	=	Hepatocellular Necrosis
3	=	Hepatic Congestion	4	=	Hepatic Failure
5	=	Hepatomegaly	6	=	Hepatic Fibrosis and Cirrhosis
7	=	Infectious Hepatocellular Necrosis	8	=	Traumatic Injury Hepatic
9	=	Hepatic Atrophy and Hypoplasia	10	=	Hepatic Fatty Infiltration
11	=	Steroid Hepatopathy	12	=	Hepatocellular Dissociation
13	=	Hepatic Encephalopathy	14	=	Hepatic Torsion