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ORIGINAL ARTICLE **OPEN ACCESS**

Design of A Fuzzy Expert System And A Multi-Layer Neural Network System For Diagnosis Of Hypertension

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ABSTRACT
The hypertension is one of the most dangerous diseases that seriously threat the health of people and communities in the worldwide. This kind of disease often leads to fatal outcomes such as heart attack, stroke and renal failure. One of the most dangerous aspects of the hypertension is that you may not know that you have it. In fact, nearly one-third of people who have high blood pressure don't know it. The only way to know if your blood pressure is high is through the regular checkups. Therefore, an intelligent and accurate system in order to diagnosis this disease is needed. In this study, we've used two methods for the diagnosis of the hypertension. Firstly, a Fuzzy Expert system (FEs) is introduced for the diagnosis of the hypertension in adults. The input parameters include Systolic Blood Pressure (SBP) and Body Mass Index (BMI). Secondly, the multilayer neural network (MNN) with 5 inputs, 5 hidden layers and 1 output is employed for the diagnosis of the hypertension. The inputs include SBP, smoking, age, weight and BMI. Finally the results of two systems (FEs and MNN) are compared individually.
Keywords: *fuzzy expert system, hypertension, risk factor, multilayer neural network*

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INTRODUCTION

Nowadays different techniques of artificial intelligence technologies such as expert systems and neural network systems are largely used in medical areas. As we know, the control of the hypertension is considered as systolic blood pressure>140 mmHg and diastolic blood pressure>90 mmHg [1]. Thus, the use of an expert system that provides information to the user about the factors and dangers of high blood pressure is very important.

In this study, we firstly introduce a fuzzy expert system with three membership functions: Low, Medium and High. The inference engine used in this study is the "Mamdani" inference engine. Then, a multilayer neural network is employed with 5 inputs, 5 hidden layers and 1 output for training purposes and the diagnosis of the hypertension. In the following, in section 2, the related works are examined; in section 3, the fuzzy expert system is introduced. In section 4, the neural network system and its characteristics are defined. The materials and method are described in section 5.The proposed method (Fuzzy Expert system and Multilayer neural network) and the simulation results are studied in section 6.

Related works

The force exerted by the contraction of heart to provide the adequate and continuous blood flow within the blood vessels is called the blood pressure andthe hypertension is defined as an increase in bloodpressure [1]. The hypertension is a frequent, chronic, age-related disorder, which often entails debilitating cardiovascular andrenal complications [2]. Shrivastava *et al.* [3] have presented a fuzzy expert system with age, BMI and heart rate as input variables. Each variable has been represented as very precise fuzzy sets in order to improve the performance of the fuzzy system. Das *et al.* [4] have made a comparison between Fuzzy and neuro-fuzzy system for the purpose of hypertension diagnosis. The data used in their study includes four input parameters such as age, blood pressure, heart rate and BMI. The paper has also compared Levenberg-Marquardt (LM), Gradient descent (GD) and Bayesian Regulation (BR) back propagation algorithm. They concluded that the Neuro-Fuzzy System with LM training algorithm has the best results among the compared systems.

Abdullah *et al*. [5] have developed a Fuzzy Expert system with 8 fuzzy rules for the diagnosis of hypertension using age, BMI, and heart rate as input factors. The output is in the form of Low, Medium and High. Their results show that the Fuzzy Expert System is an easy and cheap method for the problem of diagnosing the risk of hypertension. Djam *et al*. [6] have developed a web-based Fuzzy Expert System for the public to diagnose the hypertension risk. Systolic Blood Pressure, Diastolic Blood Pressure (DBP), age and BMI have been taken as input parameters. The output is in the form of Mild, Moderate and Severe risk. Their study explains the created system in detail using UML diagrams and screen shots of the web pages. Also, from the results obtained in their work it can be concluded that the created Fuzzy System can efficiently handle the real patient situations like a Medical Expert. Zhao *et al*. [7] tested a logistic regression model to examine the independent influence of changes in body mass index (BMI), health-related behaviors and social risk factors on changes in self-reported diagnosis of hypertension with using BMI, physical activity, smoking, alcohol, acute condition, memory status, gender, residence, education, marital status, and income parameters. Fukui *et al*. [8] investigated the risk factors for the development of diabetes mellitus, the hypertension, and the dyslipidemia simultaneously in a community-based observational cohort study with using sex, age, BMI, SBP, DBP, smoking, alcohol and exercise parameters. Tsioufis *et al*. [9] have determined the relationship between risk factors (insulin, leptin, homocysteine, and urinary albumin excretion) and circadian BP variations in essential hypertensive subjects. Polak *et al*. [10] haveemployed the artificial neural networks with six factors (smoking, age, weight, height, sex and High blood lipid) for high blood pressure.Due to the substantial plasticity of input data, ANNs have proven useful in the analysis of blood and urine samples of diabetic patients [11], Fernandez de Canete *et al*. [12], diagnosis of tuberculosis [13], Elveren and Yumuşak [14]), leukemia classification [15], analysis of complicated effusion samples [16], and image analysis of radiographs or even living tissue [17], Saghiri *et al*. [18]). Ture *et al*. [19]have made a comparison between decision tree approach, statistical algorithms and neural network approach for diagnosing hypertension by taking input factors from 694 subjects as age, sex, triglycerides, uric acid, cholesterol, BMI, lipoprotein, smoking habits and family history of hypertension [20]. The paper has divided the input data into four datasets comprising of diabetic, non-diabetic, hypertensive and non-hypertensive samples. They concluded that element back propagation network has the best for 3 datasets and cascade forward network proved the best for 1 of the datasets.

Expert systems

Expert systems are a branch of artificial intelligence that they were introduced at the first time by Artificial Intelligence (AI) association and were developed in the mid-1960s.The main idea is considered in expert systems on the basis of "the expert systems are kinds of artificial intelligence programs that they reach a level of expertise and expert in a particular field". Therefore, specific knowledge of an expert (human) is transmitted into a computer. Then this knowledge is stored in the computer and can be represented by the set of rules.If needed for specific advice, users can access to the existing knowledge. Computer using the inference reaches a specific result based on the knowledge stored. Expert systems represent a powerful and flexible tool to find solutions to various issues that often cannot be solved with traditional methods. The Diagnosis Expert System is a system based on the rule and web-oriented system for automatic detection of diseases. The main idea in these systems is based on using the internet to disseminate technical information and a few experienced doctors and specialist expertise for guidance. The general diagnosis model of the system can be seen in Figure 1 in which the steps 2 and 3 may be repeated in several times.

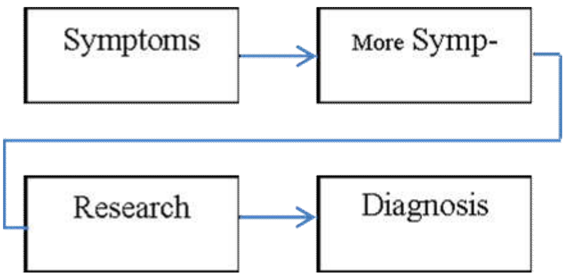

Figure.1. General model of diagnosis system.

Some reasons for using the medical expert system include:

- Doctors sometimes are incurred by mistake.
- Doctors cannot always adapt themselves with latest findings of medical information.
- In general cases, the use of automated decision is effective.
- Health care organizations wishing to increase the quality of care and reduce its costs.

3.1 Performance and implementation of expert systems

- Diagnostic expert systems to achieve accurate results and step by step, are imitated the reasoning of expert physician. Obviously, expert systems require a very large number of rules and facts in medical science about diseases and patient condition to be able to provide accurate results.
- To implement the system can be used symbolic techniques such as simple decision trees, statistical probabilistic methods, descriptive rule-based expert systems, genetic algorithms or even a combination of these techniques.
- The end user via a user interfaces to communicate with the system and has the possibility explanation and reaching the aim step by step with the inference engine of system. To achieve its goals and include the proposed treatment, the explanation facilities combine the inference engine and they consult and suggest the extra explanation. Finally, they'll be achieving the desired result.

Expert system structure

In an expert system, users are directed according to their wishes. Knowledge base is one of the most important components of expert system. An expert can provide new knowledge into the knowledge base.The modeling is done through the knowledge base in expert systems and the knowledgebase develops when new knowledge is imported. This means that software does not need to write again. Special rules are intended for the logical test. The structure "IF-Then" has been used to build the rules. The structure is defined as follows:

If (one or more conditions are met) then (outcomes)

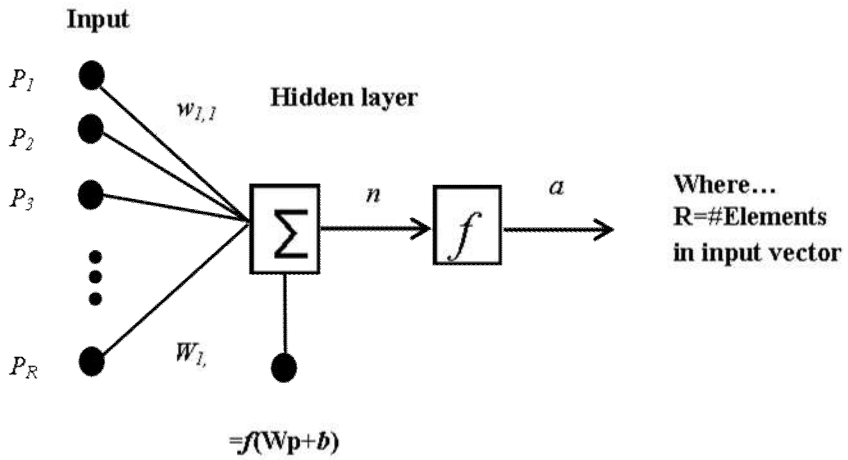

Figure. 2. A sample of general neuron.

But more than one condition may be used for creating a structure "If_ Then".According to situation this condition can be defined by phrases "And"or"Or".For example, the "And" will be used when two conditions were investigated and the desired results are that both these conditions are true. But if only one condition is true, the phrase "Or" is used.

Neural networks

Neural networks are composed of a series of layers of simple elements called neurons, that operate with together in parallel. A simple neuron with R inputs is shown in Figure 2. Each input vector is weighted by choosing appropriate weights (w)and the sum of weighted inputs and bias show the inputs of transfer function [37]. The general structure of artificial neural networks usually composed of the input layer, hidden layer and output layer. Input layer is a transport layer and provides data. The last layer or output layer contains the values predicted by the network and introduces the output of model. The hidden layer is composed of Processor neurons where is performed the data processing. The number of layers and number of neurons in each hidden layer will typically be determined by trial and error. The neurons in adjacent layers are fully connected.

One of the well-known models of neural networks is multi-layer perception model (MLP) that most commonly used. This model has an input layer, one or more hidden layer and an output layer. An artificial nerve assigns a weight to each input. Then the inputs are accumulated and they are used in a threshold function. After the training process, the neural networks can product the appropriate outputs for unseen inputs. The number of inputs, outputs, hidden layers and nodes are determined configuration of neural network. The appropriate number of nodes and layers are decided empirically, but the input properties of network should be determined exactly. The inputs and properties of network play an important role in decision-making.

Properties and differences between Fuzzy Expert Systems and Neural Networks

According to that neural networks have high computational, stability and the ability to learn, they are more common than expert systems. Unlike, expert systems act based on rules that exist in expert's information domain, the neural networks are formed based on connectionism and mathematical functions. They are imitated architecture and operation of human brain.

Expert systems are used in a sequential mode and their operation is based on the operation of mathematical logic. But neural networks, act based on parallel operation. Expert systems acquire knowledge from the outside environment normally and the expert, then this knowledge will be added to the knowledge base as coded. It should be noted that, neural network acquire the knowledge from the training raw data in a learning process and they use inductive reasoning for inference.

Considering that the knowledge is clear for expert systems, it is also easy evaluation and validation. But the knowledge for neural network is not clear, so it would be difficult for the user to understand and change it.So we can conclude expert systems for inference are user friendly. So expert systems in the user interface have the ability to provide explanations of the inference process, the acquisition of new knowledge at the time of diagnosis by an expert and used to reduce the complexity of heuristic searches. However, these systems have problems in acquiring knowledge and usually they don't have fault tolerance and noise data. But in neural network, knowledge engineering act based on data, so these systems accept noise data easier and more effective. Unfortunately, neural networks don't have Suitable user interface. However, neural network learning algorithms can be acquiring dependencies between features of objects in a noise data set. This property may be used in cases such as pattern recognition, Skillful reactions Knowledge discovery that don't represented by expert as declarative. This group of neural network techniques because they act automatically and without requiring expert, have more advantages than traditional knowledge engineering methods. According to the available evidence, the most neural network techniques are more suitable for discover implicit knowledge than traditional rule-based systems.

Neural networks

Hypertension is the most common disease and it markedly increases both morbidity and mortality from cardiovascular and many other diseases [27]. Hypertension is a major risk factor for coronary heart disease and stroke in many countries [28]. Hypertension remains a common etiologic factor for the development of heart failure [29].

Types of blood pressure

Different types of hypertension are observed when the disease is sub-categorized [2,30,31]. These types are shown in Table 1.

Table 1. Types of hypertension.

Types of hypertension	Systolic blood pressure (mmHg)	Diastolic blood pressure (mmHg)
Grade 1	≥ 140 and ≤ 159	≥ 90 and ≤ 99
Grade 2	≥ 160 and ≤ 179	≥ 100 and ≤ 109
Grade 3	≥ 180	≥ 110
Isolated systolic hypertension	≥ 140	≤ 90

Risk factors

Some of the primary risk factors for essential hypertension include the following[1]:

- Obesity
- Lack of exercise
- Smoking
- Consumption of salt
- Consumption of alcohol
- Stress level
- Age
- Sex
- Genetic factors

In this study we have used both SBP and BMI for fuzzy expert system and five risk factors such as SBP, smoking, age, weight and BMI for neural network system.

Another risk factor measures that have the potential to slightly diminish blood pressure are regular dynamic exercise (30–45 min for at least 4 days per week) and abstaining from smoking [2]. Blood vessels become less compliant with age, leading to increased peripheral vascular resistance and elevated BP [33]. Obesity was determined by BMI: normal weight (18.5–24.9 kg/m2), overweight (25–29.9 kg/m2), and obese (30 kg/m2 and more) [32].

Table 2. Table of proposed fuzzy expert system rules

SBP/BMI	Low	Medium	High
Low	Low	Low	Low
Medium	Medium	Medium	Medium
High	High	High	High

Databases

Databases used in this study for hypertension are shown below [1]:
[D1] Blood Pressure Dataset (DAT)
[D2] HARVEST (Hypertension and Ambulatory Recording Venetia Study) Dataset (TXT)
[D3] Behavioral Risk Factor Surveillance System (XPT)
[D1] [34] Dataset is a case study in data analysis at the 2003 Annual Meeting of the Statistical Society of Canada. Session organizer was Peggy Ng who is working at York University. The data file (ASCII file, comma delimited data file) contains 500 observations (subjects) and 501 variables. The 501 variables consist of one response variable (systolic blood pressure) and 500 predictors (17 clinical covariates and 483 genetic markers). 264 female and 236 male individuals with an age range of 18–64 years. 101 cases treated for hypertension and 399 untreated cases are present in this database.
[D2] [35] dataset is a trial designed to assess whether ambulatory monitoring adds something to office (clinical) blood pressure in predicting the development of fixed hypertension and of cardiovascular complications in patients with borderline to mild hypertension. The data give information on 1,100 subjects compiled by Dr Paolo Palatini, Professor of Clinical Medicine at the University of Padua, Italy. 306 female and 794 male individuals with an age range of 14–54 years. This database includes 129 individuals with and 971 individuals without hypertension.
[D3] [36] The Behavioral Risk Factor Surveillance System (BRFSS) is a collaborative project of the Centers for Disease Control and Prevention (CDC) and US states and territories. The BRFSS, administered and supported by CDC's Behavioral Surveillance Branch, is an ongoing data collection program designed to measure behavioral risk factors in the adult population (18 years of age or older) living in households.

6Proposed method and simulated results

In this study, we propose a fuzzy expert system for the diagnosis ofthe hypertension. The fuzzy expert system includes 2 inputs including BMI and SBP, 1 output, three membership function such as Low, Medium and High and Mamdani inference engine. Diagram related to two inputs are shown in

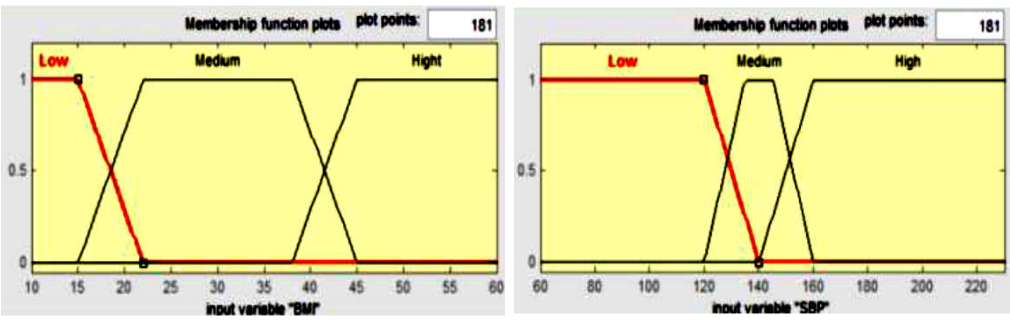

Figure. 3. Diagram related to two inputs of proposed fuzzy expert system: (a) BMI input (b) SBP input.

Figure 3.The rules used in this study are formed as If-Then. A sample of the rule:
If (SBP is Low) and (BMI is Low) then(Hypertension is Low)
The output diagram of the system and the rules are given in Figure 4. A multilayer neural network is used for diagnosis of hypertension. This network includes 5 inputs, 5 hidden layers and 1 output. The inputs of the network are included SBP, smoking, age, weight and BMI. The diagram of the proposed multilayer neural network system is shown in Figure 6. The inputs of the neural networks have been considered

70% for training, 15% for testing and 15% for the evaluation. The system operates by asking the inputs (SBP, smoking, BMI, age and weight) from users and considering the imported inputs. It then gives a value as an output. The resulting output is compared with the value of defined target and then the error value is determined. The surface diagram is shown in Figure 5. An example of the proposed neural networks system is also shown in Figure 7.

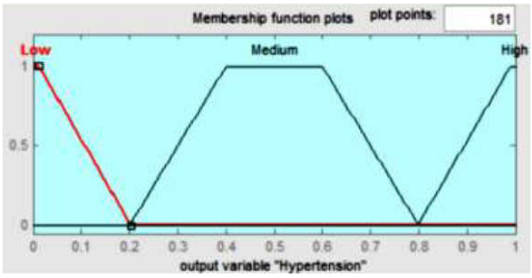

Figure. 4.output Diagram of proposed fuzzy expert system.

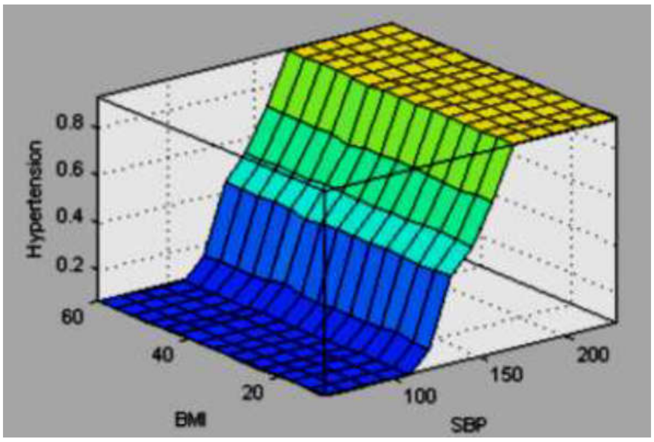

Figure. 5. Diagram to surface of fuzzy expert system.

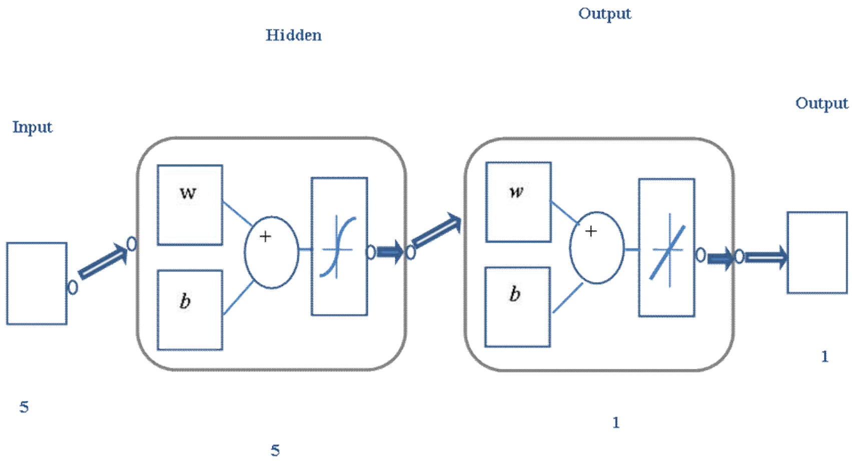

Figure. 6. Schema of the proposed multi-layer neural network system.

CONCLUSIONS

One of the most widely used diagnostic methods is Fuzzy Expert Systems. This type of systems actually implements the human intelligence and reasoning. In these systems, using a set of decision rules, tests, physical signs and laboratory analysis provide different suggest for diagnosing diseases. Often, it is very difficult to express the rules of the system, so converting difficult and complicated rules to clear and easy rules may be lead to the loss of primary data. The fuzzy expert system requires a good engineer that is defined medical domain. On the other hand, if new levels of knowledge and information are added, the tree structure will become more complex. Also, expert systems can be considered as a good and successful approach when they are developed for incompatible and independent diseases. In this study, we applied fuzzy expert system with two inputs such as BMI and SBP, and one output called Hypertension and three membership functions such a sLow, Medium, High and Mamdani inference engine. Then is used a multi-layer neural network with 5 inputs, 5 hidden layers and 1 output for the diagnosis of high blood pressure. The inputs of the network are SBP, smoking, age, weight and BMI.

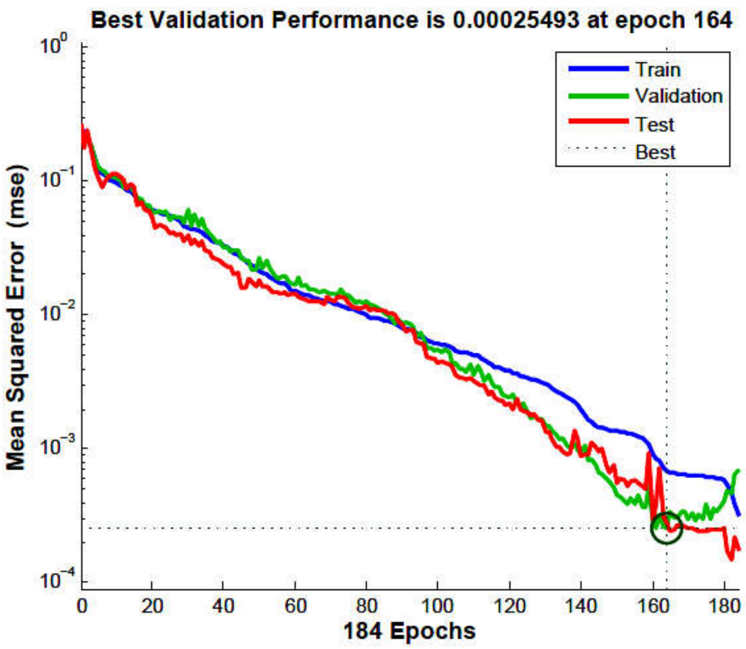

Figure. 6. An example of proposed neural network

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