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Estimating risk levels for blood pressure and thyroid hormone using artificial intelligence methods

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***Abstract*—In this work, artificial intelligence methods are designed and adopted for evaluating various risk levels of thyroid hormone and blood pressure in humans. Fuzzy Logic (FL) method is firstly exploited to provide the risk levels. Additionally, a machine learning was proposed using the Adaptive Neuron-Fuzzy Inference System (ANFIS) to learn and assess the risk levels by fusing a multiple-layer Neural Network (NN) with the FL. The data are collected for standard risk levels from real medical centers. The results lead to well ANFIS design based on the FL, which can generate such interesting outcomes for predicting risk levels for thyroid hormone and blood pressure. Both proposed methods of the FL and ANFIS can be exploited for medical applications.**

***Keywords*—blood pressure; thyroid hormone; Artificial Intelligence; Fuzzy Logic; Adaptive Neuron-Fuzzy Inference System**

I. Introduction

THE thyroid hormone is produced to aid in controlling the body's metabolism. Since Thyroid Hormones (THs) have significant impacts on cardiovascular processes, it is possible that THs have a role in the development of hypertension. Your heart rate slows if you don't have enough thyroid hormone. Blood pressure increases in order to circulate blood throughout the body since it also reduces the elasticity of the arteries. Another potential effect of decreasing thyroid levels is elevated cholesterol levels, which contribute to clogged hardened arteries. Diabetes frequently raises the Low-Density Lipoprotein Cholesterol (LDLC), "bad" cholesterol levels, while lowering the High-Density Lipoprotein Cholesterol (HDLC), "good" cholesterol levels, in an individual's body. One of the most important factors in lowering a person's risk of heart disease is controlling cholesterol levels [1].

Diabetes can result from high cholesterol and vice versa. Because of it, it's crucial to use nutrition to manage disorders. If you have either high cholesterol or diabetes, or both, there are several foods you should stay away from. In addition, variables like heredity and weight, unhealthy food, and lifestyle choices are main contributors to elevated cholesterol levels. Excessive blood sugar and the risk of type 2 diabetes can both be caused by excessive cholesterol [1].

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In literature, interesting related studies to the topic and/or materials can be found. The analysis consists of Fuzzy Logic (FL) as well as hard clustering was employed for thyroid disease [2]. Both hard and fuzzy clustering techniques were evaluated on the thyroid illness data set to determine the ideal number of clusters. After the clustering results for all ways were displayed, the Sammon mapping method is used to produce a low-dimensional (often 2D or 3D) representation of a collection of points scattered over a high-dimensional pattern space [2]. According to [3], machine learning was exploited, which can be applied in the health system to classify thyroid disease. This study was conducted utilizing data from Iraqi citizens with the aim of classifying thyroid disorder into three categories: hyperthyroidism, hypothyroidism, and normal. Decision trees, naive Bayes, logistic regression, random forests, Support Vector Machines (SVM), k-nearest neighbors, Multilayer Perceptron (MLP), and linear discriminant analysis were all utilized to identify thyroid illness. In a population-based Tehran thyroid study of the relationship between thyroid function and blood pressure, several testing results were provided within the normal range [4]. Tehran Thyroid Study (TTS) data from 4756 participants without a history of thyroid illness were examined. There were still 4756 people, of whom 2634 (55.4%) were women and 2122 (44.6%) were men.

In [5], medical disease analysis utilized a model of feature extraction and Neuro-fuzzy with the Artificial Neural Network (ANN) technique for classification purposes. In [6], a FL study is conducted based on blood pressure values. Then, to accommodate the idea of partial truth, where the truth value might vary from entirely true to completely false, FL has been expanded. Blood pressure readings were used as inputs and a fuzzy algorithm was utilized in this work. At the conclusion, the values of the output are examined. A comprehensive study for the categorization of the FL technique and an evaluation of the literature on the diagnosis of infectious diseases are given in [7]. In [8], a sophisticated method for detecting thyroid issues was considered. Under the direction of a doctor, data from 116 patients were tested and 306 patient training records were obtained from Al-Jamhoree Hospital. The FL method and the ANN concept were used to conduct this investigation. This study's primary goal is to evaluate the potential and application of three suggested algorithms. FuzRBF-1, FuzRBF 2, and FuzRBF 3 are neural networks that can identify and diagnose thyroid disease. In connected health care, the deep Neuro-fuzzy risk technique is employed with a severity prediction by utilizing recommendation systems [9]. In [10], machine learning methods are exploited to analyze the performance of thyroid disease. The objective and the main contribution is to decide different risk levels for both blood pressure and thyroid hormone and the relationship between them. Many researchers have emphasized FL and its exploitation in a wide range of applications [11], [12], [13], [14], [15], [16], [17], [18], and [19].

An intelligent approach for Controlling a Steam Valve (CSV) was proposed in [20]], it is based on the adoption of the Adaptive Neuron-Fuzzy Inference System (ANFIS). Intelligent Steam Valve (ISV) is the name of the suggested technique. In order to gather the best CSV data, an FL is initially used in this study. The intended ISV is then provided by utilizing the ANFIS in conjunction with a multiple-layer NN and the FL. A Fast Bounding Box (FBB) technique, a sophisticated segmentation algorithm that employs the gene segmentation algorithm employed in the CT image separation procedure, was recommended in [21]. The noise-reduced picture is utilized to detect the number of motions and tumors, and the genetic algorithm is used to establish a threshold. Selected segmented picture characteristics were determined using the GLCM2 method. When dealing with the kind of lung, whether it is normal, intermediate, or pathological, the ANFIS is employed. In [22], experimental measurements of asphalt concrete's stiffness modulus characteristics were made for various exposure durations and temperatures. The Nijboer stiffness module was used to compute the stiffness modules. Asphalt core sample basic physical characteristics and bitumen content were used to determine the stiffness modules. The samples were subjected to temperatures of 17 ° (the reference temperature), 30 ° , 40 °, and 50 ° for 1.5, 3, 4.5, and 6 hours, respectively. These were before undergoing marshall stability tests on each sample. To forecast the stiffness modules of asphalt core samples, an alternative prediction model of Sugeno type based on the ANFIS was constructed utilizing the test findings. The work in [23] created a dynamic adaptive neuron-fuzzy logic forecasting model using FL to analyze exchange rate data.

The aim of this paper was to estimate or predict risk levels for blood pressure and thyroid hormone. The contributions here were represented by the exploited artificial intelligence methods as follows:

- FL system was created to calculate blood pressure and thyroid hormone risk levels. It has two inputs of the LDLC and diabetes with one output which is the risk.
- ANFIS method was suggested. It combines the FL with multiple-layer NN to learn and evaluate blood pressure and thyroid hormone risks.

The paper is organized as follows: Section 1 presents introduction, Section 2 describes the utilized exploited artificial intelligence methods, Section 3 provides findings and discussions and Section 4 declares conclusions.

II. EXPLOITED ARTIFICIAL INTELLIGENCE

A. Fuzzy Logic Method

A fuzzy set is the foundation of FL. Fuzzy refers to a collection without a definite, well-defined boundary. Elements that are just partially member may present. One of the main requirements is the membership function, which ranges between 0 and 1. An arbitrary curve can serve as the function itself and its shape can be described as a function that works well in terms of convenience, simplicity, efficiency and speed [24] [25]. A fuzzy set is created by expanding a classical set. If Z is the discourse universe and its elements are indicated by z, then a fuzzy set G in Z is defined as a collection of ordered pairs.

$$G = \{z,\ \mu G(z) \backslash\ z \in Z\} \quad (1)$$

G is z's membership function μ in $G(z)$. Each component of Z is given a membership value by the membership function, which ranges from 0 to 1. Additionally, the statement G AND H may be resolved using the minimum (min) function, provided that G AND H are limited to the range [0,1]. In other words, G AND H is equivalent to $min(G, H)$. The same reasoning may be used to replace the OR operator with the maximum (max) function, making G OR H equal to $max(G, H)$. The operation NOT G becomes the operation 1-G. A binary mapping T that combines the following two fuzzy sets G and H is widely used to describe their intersection.

$$\mu G \cap H(Z) = T\left(\mu G(Z), \mu H(Z)\right) \quad (2)$$

The fuzzy union operator, like fuzzy intersection, is usually made available through a binary mapping S:

$$\mu G \cap H(Z) = S\left(\mu G(Z), \mu H(Z)\right) \quad (3)$$

The defuzzification procedure uses the fuzzy set of inputs (the aggregate output fuzzy set) and an integer is produced as the result.

B. Adaptive Neuron-Fuzzy Inference System Method

An enhanced method of decision-making is the ANFIS. In essence, it combines the FL with the NN by dividing various NN layers into various FL processes. In other words, the ANFIS is made up of common FL parts that are dispersed throughout NN layers. It essentially has the following five layers: inputs, membership functions for the inputs, rules, membership functions for the outputs and output. The first layer is assigned for ANFIS's input data. Inputs membership functions of the embedded FL are allocated at the second layer. The rules are established at the third layer. The analyzed rule outputs are provided with a fourth layer. The ANFIS's combined output is presented at the final layer. Sugeno type is usually used with the ANFIS as a normal procedure. Equations that are equivalents to the formal ANFIS structure are represented as follows [20]:

$$f_1 = a_1 x + b_1 y + c_1 \quad (4)$$

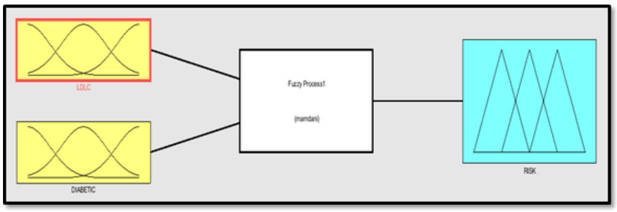

Fig. 1. The employed Mamdani FL method

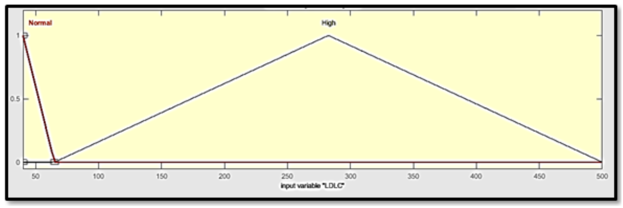

Fig. 2. Membership functions for the first input of the employed FL method

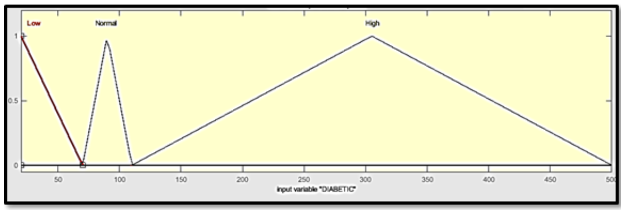

Fig. 3. Membership functions for the second input of the employed FL method

$$f_2 = a_2 x + b_2 y + c_2 \tag{5}$$

where: f_1 and f_2 are linear output functions of Sugeno, a_1, b_1, c_1, a_2, b_2, and c_2 are the linear parameters, and x and y are ANFIS inputs. Thus, as indicated in the following equations, the parameters $\bar{w_1}$ and $\bar{w_2}$ are employed to normalize the firing strengths of ANFIS nodes by taking into account the membership function layer analyses of w_1 and w_2.

$$\bar{w_1} = \frac{w_1}{w_1 - w_2} \tag{6}$$

$$\bar{w_2} = \frac{w_2}{w_1 - w_2} \tag{7}$$

The following equation may be used to express the total output of the ANFIS:

$$f = \bar{w_1} f_1 - \bar{w_2} f_2 \tag{8}$$

where: f is the ANFIS total output function. Alternately, the following equations can be used for a more thorough explanation:

$$f = \frac{w_1}{w_1 - w_2} f_1 - \frac{w_2}{w_1 - w_2} f_2 \tag{9}$$

$$f = \frac{w_1 f_1 - w_2 f_2}{w_1 - w_2} \tag{10}$$

III. RESULTS AND DISCUSSION

A. Results for the Fuzzy Logic

The employed FL method has two inputs and a single output. LDLC [26], [27], [28], and [29] and diabetes are the two inputs, whereas, risk is the output. This means that, as illustrated in Figure 1, the suggested method exploits delivering the proportion of risks for the two inputs of the LDLC and diabetes by using the FL of type Mamdani.

Triangle forms serve as the foundation for the proposed membership functions. Two membership functions are considered for the first input: one for the normal and another for the high. The entire range is shown in Figure 2 to be between 40 and 500 as confirmed by medical centers in Iraq. Three membership functions are included in the second input: one for the low, one for the normal range and one for the high. The full range is shown in Figure 3 between 20 to 500, again this is confirmed by medical centers. Two membership functions are provided for the output: one for the normal and another for the high. As seen in Figure 4, the total range corresponds to percentages between 0 and 100. So, the output represents a risk percentage.

It is known that if the FL considers “low” for the second input with “high” of the first input, this may produce “normal” output. This cannot be true for medical purposes as both “low” and “high” refers to risk. Therefore, the key idea of our strategy is to consider any “low” or “high” as risk. This has been considered in the essential FL rules as follows:

- If (LDLC is Normal) or (DIABETIC is Normal) then (RISK is Normal).
- If (LDLC is Low) or (DIABETIC is Low) then (RISK is High).
- If (LDLC is Low) or (DIABETIC is High) then (RISK is High).

Fuzzy relationships surface of the employed FL method is shown in Figure 5. Figure 6 demonstrates an example of simulation implementation of the employed FL method, where columns represent the first input, second input and output, respectively. Referring name is shown at the top of each column. Input values can be provided at the left-bottom space and the calculated risk value is shown at the top right of the last column.

B. Results for the Adaptive Neuron-Fuzzy Inference System Method

Firstly, the architecture network of the employed ANFIS method is demonstrated in Figure 7. It consists of five layers: input, input membership function (inputmf), rule, output membership function (outputmf) and output, respectively.

Likewise the previous FL method, the employed ANFIS has two inputs of the LDLC and diabetes, and a

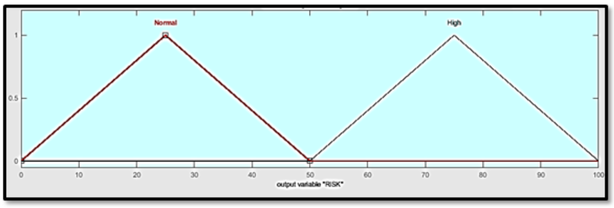

Fig. 4. Membership functions for the output of the employed FL method

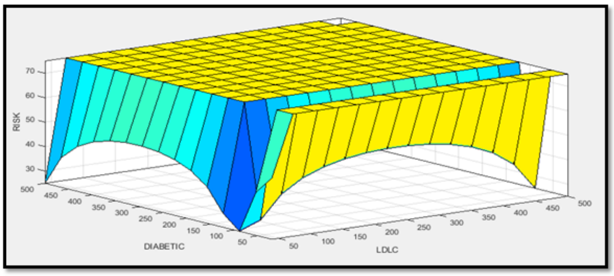

Fig. 5. 3D relationships between the inputs and output of the employed FL method

single output of the risk. However, it uses the type Sugino instead of Mamdani. In fact the results of the employed FL method are exploited as ground-truth for the ANFIS machine learning. That is, the values of inputs and resulted outputs of the previous FL method are partitioned into learning and evaluating datasets. the employed ANFIS method uses the learning dataset for its training stage and utilizes the evaluating dataset for its testing stage. The inputs and output membership functions of the ANFIS are explored by comparing all possible ANFIS membership function types. TableIshows training and testing performances for the employed ANFIS after examining the different membership function types. A hybrid network of the backpropagation algorithm and Mean Square Error (MSE) is considered with 600 epochs of training for the ANFIS. Furthermore, as the previous FL method the number of membership functions are set as 2 and 3 for the first input and second input, respectively. The highlighted values in TableI indicate the best membership function input and output types with their performances, where the gaussian bell membership functions in the inputs and linear membership function in the output are found to have the best performances with minimum training and testing errors.

TableI reveals that after comparing all possible membership function types for the inputs and output, the generalized bell-shaped membership function type for the inputs with the linear membership function type for the output benchmarks the highest ANFIS performances. Lowest MSE error of 5.90 is achieved for each of the ANFIS training and testing. Moreover, it can be observed that the linear membership function type for the ANFIS Sugino output performs better than the constant membership function type in all training and testing stages. In other words, this has been verified in all of the cases that have been explored. Therefore, the linear membership function

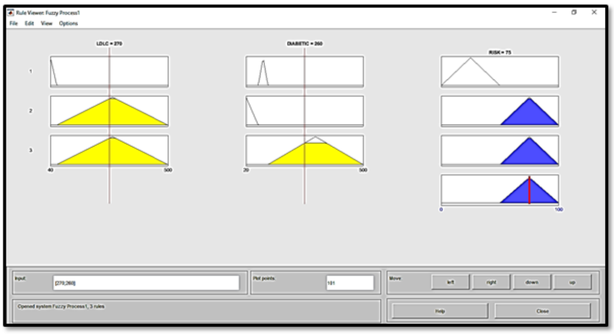

Fig. 6. An example of simulation implementation of the employed FL method

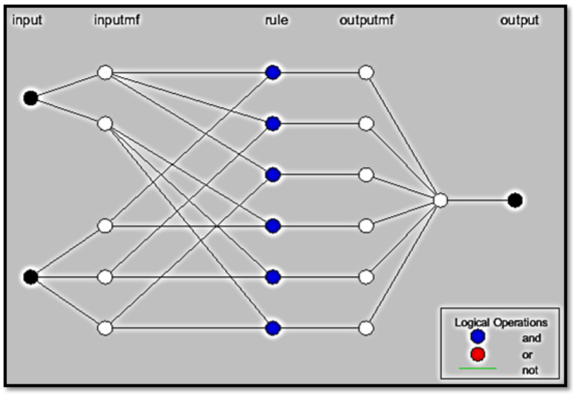

Fig. 7. The network architecture of the employed ANFIS method

type is selected for the output and generalized bell-shaped membership function type is chosen for the inputs of the employed ANFIS method. This is due to the superior training and testing results that have produced by these types compared to the results of all other types as it is investigated. Figure 8 shows the training curve of the employed ANFIS method for the determined membership function types.

Figure 9 depicts the triple relationships between the two inputs and outputs of the employed ANFIS method. It further proof the effectiveness of the applied ANFIS as the produced 3D relationships surface is well formed for utilized FL values. It also shows a developed relationships between the inputs and outputs. Finally, another example of simulation implementation of the employed ANFIS method is given in Figure 10. Similar to the previous FL method values of inputs can be provided and an output value is generated. It can be observed that the generated output value for the ANFIS method is close to the output value for the FL method.

IV. CONCLUSIONS

In this paper, two artificial intelligence methods are considered and employed for estimating or predicting risk levels for blood pressure and thyroid hormone of humans. Firstly, a FL method was provided and determined as a ground-truth or basis. Secondly, an ANFIS method is learned and evaluated. Two inputs were used in each method. These are the LDLC

TABLE I. Training and testing performances for the employed ANFIS after examining all possible membership function types

Inputs Membership FT	Output Membership FT	MSE Training	MSE Testing
Triangle	Constant	8.92	8.92
Triangle	Linear	8.11	8.11
Trapezoidal	constant	8.72	8.72
Trapezoidal	Linear	7.36	7.36
Generalized bell-shaped	constant	8.60	8.60
Generalized bell-shaped	**Linear**	**5.90**	**5.90**
Gaussian	constant	8.87	8.87
Gaussian	Linear	7.27	7.27
Gaussian 2	constant	8.75	8.75
Gaussian 2	Linear	7.38	7.38
Pi	constant	8.73	8.73
Pi	Linear	7.49	7.49
Difference sigmoidal	constant	8.72	8.72
Difference sigmoidal	Linear	6.30	6.30
Product sigmf	constant	8.72	8.72
Product sigmf	Linear	6.30	6.30

Fig. 8. Training curve of the employed ANFIS method

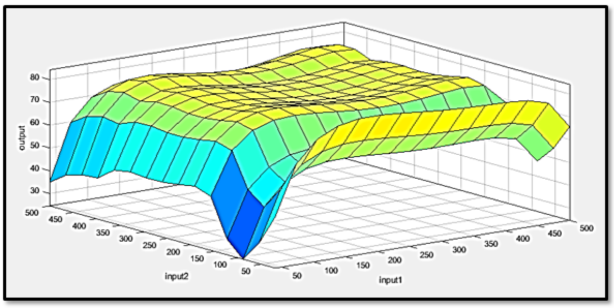

Fig. 9. 3D relationships between the inputs and output of the employed ANFIS method

and diabetic. Whilst, a single output was utilized. It is assigned for risk percentages. After constructing the FL, values of inputs and output were collected. Then, they were divided into two sets: learning dataset (for training) and evaluating dataset (for testing). Many comparisons were investigated to find out the best membership function types for the inputs and outputs of the employed ANFIS method. Finally, the generalized bell-

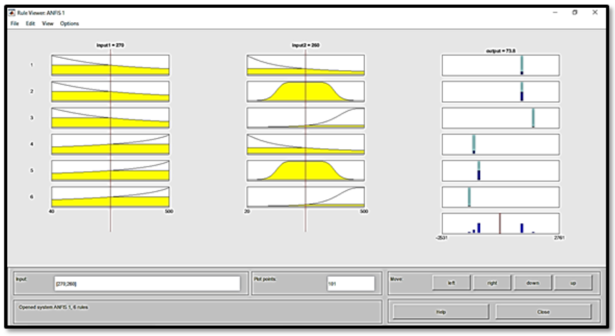

Fig. 10. An example of simulation implementation of the employed ANFIS method

shaped membership function type is selected for the inputs and the linear membership function type is chosen for the output as they leaded to achieve best training and testing performances compared to all other possible types under fair conditions.

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