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Medical Fuzzy Expert System for Diagnosis And Distribution of Doctors in Rural Areas in Morocco: COVID-19 Case Study

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ABSTRACT

In this paper, we propose a computer-aided diagnostic system based on a fuzzy expert system, in order to help physicians, make the right diagnosis and o← er an opportunity to improve access to health care in rural areas in Morocco, where there is a lack of infrastructure and medical experts. The system is mainly based on the diagnoses of various physicians. We collect different diagnostic decisions of a specific disease according to its relevant symptoms for different physicians. Diagnostic decisions of different experts and severity levels of each symptom are modeled using linguistic fuzzy values. Then we form a system based on fuzzy rules to combine the different expert diagnoses and obtain a general diagnosis. Moreover, we propose an application to COVID-19 disease to test how well the proposed model may be applied in practice for different diseases.

Key words: Computer-aided diagnostic system, fuzzy expert system, diagnostic decisions, fuzzy rules, COVID-19.

1. INTRODUCTION

The objective of any health policy is to take into consideration all the health problems of the population, rural or urban, in order to improve living conditions. The major problem for developing countries, including Morocco, is to guarantee access to healthcare, affordability, and the best quality of care. However, until today a large number of people do not receive the necessary medical care especially in rural areas [10]. In general, the country's rural public health systems are struggling to attract, retain, and ensure the regular presence of highly qualified health professionals. It is well known that many physicians are unwilling to work in rural areas because of the lack of facilities, even if they receive high salaries. In Morocco, data from the Ministry of Health estimates a deficit of 16,000 doctors and nurses and that 45% of doctors are located in the region between Casablanca and Rabat [11]. Nevertheless, many of the health problems experienced by rural populations are preventable and easily treatable.
So far more than 40% of the country's population lives in rural areas, access to care is often difficult, if not impossible, to put into practice [3]. This critical problem has prompted us to reflect on adopting a strategy that can guarantee the resolution of the problem of access to care based on digital tools and in particular on Medical Informatics. The health fields have found their place among these fields to use computer science. The intersection between informatics and healthcare has been formulated in a new field called "medical IT" [7], where medical data is collected, stored, processed, analyzed, recovered, and used in various medical operations. Different disciplines have emerged to cover the wide range of specialties required by the field of medical informatics [16, 12]. One of the areas where medical IT shows its great influence on healthcare is the aid to the diagnosis of diseases according to certain rules implemented on huge quantities of medical records of patients. Sometimes these diagnoses can help improve and speed up the provision of a required medical assistant, which would help improve the quality of life for humans. In order to reach a satisfactory decision, the medical decision-making process involves different actions to be taken, that can help improve patient care outcomes, such as diagnosis, prognosis, treatment, and therapeutic follow-up [17]. One of the most common problems in medical diagnosis is uncertainty. The use of the fuzzy set theory helps dealing with this uncertainty. Fuzzy logic was applied in medical systems [13] almost 20 years after its introduction by Zadeh [22]. Moreover, it has recently prompted interesting implementations [4, 6, 1, 23]. The fuzzy logic is considered a valuable tool for describing medical concepts [19, 18]. It is an approach that provides "degrees of truth" and not the common

binary solutions true or false. Decision-making systems based on fuzzy logic approach the way a human being makes decisions, with levels of truth or certainty, according to [5, 21, 2]. Leung et al. have defined a general structure of the fuzzy system, describing the necessary steps to follow for the use of fuzzy logic [8].

In this study, we develop an efficient method to generate fuzzy expert systems for medical diagnosis [14, 15], based on membership functions and rules instead of applying Boolean logic for reasoning about data. The general structure of our system is as follows:

- Step 1: The patient will first enter the specialty and then will be asked about a set of symptoms related to a predefined set of suspected diseases.
- Step 2: The fuzzy help decision system, that we propose, will treat the inputs (Patient's Symptoms) using the fuzzy inference and obtain a decision fuzzy set for each disease, and subsequently crisp decision values to determine the certainty of the existence of each disease.
- Step 3: The Chief Medical Officer must interpret the percentages provided by the fuzzy system and therefore send the appropriate physician to the patient in the case of an emergency, otherwise in the case of a less urgent illness, the Chief Medical Officer may provide a prescription including the necessary medicines.

2. MODEL FORMULATION

In this section we describe the method used to build the decision support system. The decision of this system is mainly based on the comments of experts in different specialties. At the beginning we propose a system based on the opinions of h experts, and later we apply the model with three experts. Indeed, the structure of the fuzzy system is as follows:

- The experts are asked to give their diagnosis of the suspect diseases according to each symptom.
- The experts' opinions are combined according to each disease.
- The system uses the combined opinions of each symptom to make an overall diagnosis of the disease.

Let’s D be a set of m diseases and F a collective set of n features relevant to these diseases.

$$D = \{d_1, d_2, d_3, \ldots\ldots, d_n\} \text{ and } F = \{f_1, f_2, f_3, \ldots\ldots, f_m\}$$

With any given disease d_i has a set R_i of $k \leq m$ related features. Example for disease d_1, its related features are defined by a subset of F as follow:

$$F_1 = \{f_1, f_2, f_3, \ldots\ldots, f_k\}$$

After selecting the specialty, the patient has to fill a questionnaire, where he is tested against all symptoms in set F. He may assign a fuzzy value, chosen from a set V, to each feature. For example, one feature can be determined as < Headache, High >. Where V is defined as follow:

$$V = \{Null, Very\ Low, Low, Moderate, High, Very\ High\}$$

At the end of filling out the form, we might obtain a set of patient's m symptoms defined as follow:

$$T_m = \{< f_1, v_1 >, < f_2, v_2 >, < f_3, v_3 >, \ldots\ldots, < f_n, v_m >\}$$

With vi is the fuzzy value assigned to the i^{th} feature f_i. We give in table 1 bellow an example of typical symptoms of COVID-19 entered by an imaginary patient (see Table 1).

Table 1: Typical symptoms entered by an imaginary patient

Feature	Fuzzy value
Headache	High
Cough	Moderate
Dyspnea	Very High
Fever	High
Diarrhoea	Low
Sore throat	Very Low
Anosmia	Moderate
Fatigue	High
Rhinorrhea	Moderate
Gastrointestinal reaction	Null
Abdominal pain	Moderate

3. ADAPTATION OF FUZZY MODEL

A scientific committee composed of h experts, corresponding to each specialty, must give comments for each disease in the set of diseases considered D, called disease profiles. These tables are composed of suitable linguistic values for every feature. These linguistic values are chosen from the following set:

{No Risk, Low Risk, Medium Risk, High Risk}

Table 2 presents a typical profile table for a disease, based on an expert's experience.

Linguistic variables *No Risk*, *Low Risk*, *Medium Risk*, *High Risk*, are presented as trapezoidal fuzzy sets (see figure 1). Defined in equations 1-4.

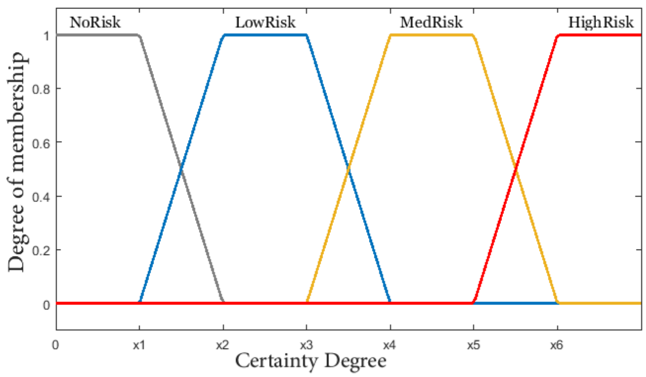

Figure 1: The fuzzy sets, *NoRisk, LowRisk, Medium Risk* and *HighRisk*, for the certainty of disease presence.

Each, comment, trapezoidal fuzzy number C_{ijk} is defined by four points:

$$C_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk}, d_{ijk})$$

These crisp values correspond to the level of certainty predefined. Denoted in membership functions (1-4) by x_1, x_2,…., x_6. In order to know the overall assessment of the experts C_{ij}, we need to combine the h comments of the scientific committee. We use the method used by Tsaur in his paper [20]. Collective fuzzy diagnosis of the certainty level of disease d_i regarding j^{th}, f_j can be calculated as:

$$C_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$$

Feature	Null	Very Low	Low	Moderate	High	Very High
Headache	No Risk	No Risk	Low Risk	Meduim Risk	High Risk	High Risk
Cough	No Risk	Low Risk	Meduim Risk	Meduim Risk	High Risks	High Risk
Dyspnea	Low Risk	Meduim Risk	Meduim Risk	High Risk	High Risk	High Risk
Fever	No Risk	Low Risk	Meduim Risk	Meduim Risk	High Risk	High Risk
Diarrhoea	Low Risk	Meduim Risk	Meduim Risk	Meduim Risk	Meduim Risk	High Risk
Sore throat	No Risk	Low Risk	Low Risk	Medium Risk	High Risk	High Risk
Anosmia	No Risk	Low Risk	Meduim Risk	High Risk	High Risk	High Risk
Fatigue	No Risk	Low Risk	Meduim Risk	Meduim Risk	High Risk	High Risk
Rhinorrhea	No Risk	Low Risk	Meduim Risk	Meduim Risk	High Risk	High Risk
Gastrointestinal reaction	Low Risk	Meduim Risk	Meduim Risk	Meduim Risk	Meduim Risk	High Risk
Abdominal pain	Low Risk	Meduim Risk	Meduim Risk	Meduim Risk	Meduim Risk	High Risk

Table 2: Profile for Covid-19 disease based on an expert's experience

$$\mu_{Norisk}(x) = \begin{cases} \Phi_1 & = 1 \qquad x < x_1 \\ \Phi_2 & = \dfrac{x_2 - x}{x_2 - x_1} \qquad x_1 \leq x < x_2 \end{cases} \tag{1}$$

$$\mu_{Lowrisk}(x) = \begin{cases} \Psi_1 & = \dfrac{x - x_1}{x_2 - x_1} \qquad x_1 \leq x < x_2 \\ \Psi_2 & = 1 \qquad x_2 \leq x < x_3 \\ \Psi_3 & = \dfrac{x_4 - x}{x_4 - x_3} \qquad x_3 \leq x < x_4 \end{cases} \tag{2}$$

$$\mu_{Mediumrisk}(x) = \begin{cases} \Lambda_1 & = \dfrac{x - x_3}{x_4 - x_3} \qquad x_3 \leq x < x_4 \\ \Lambda_2 & = 1 \qquad x_4 \leq x < x_5 \\ \Lambda_3 & = \dfrac{x_6 - x}{x_6 - x_5} \qquad x_5 \leq x < x_6 \end{cases} \tag{3}$$

$$\mu_{Highrisk}(x) = \begin{cases} \Upsilon_1 & = \dfrac{x - x_5}{x_6 - x_5} \qquad x_5 \leq x < x_6 \\ \Upsilon_2 & = 1 \qquad x \geq x_6 \end{cases} \tag{4}$$

In order to know the overall comment of the committee, we have to combine the comments of the *h* experts. The comment of the scientific committee concerning the symptom fi on the possibility of the disease d_j, is calculated as:

{No Risk, Low Risk, Medium Risk, High Risk}

Where $i \in \{1, 2,…., n\}$, $j \in \{1, 2,….., m\}$ and $k \in \{1, 2,…., h\}$.

With

$$a_{ij} = \sum_{k=0}^{h} a_{ijk},\ b_{ij} = \sum_{k=0}^{h} b_{ijk},\ c_{ij} = \sum_{k=0}^{h} c_{ijk}$$

And

$$d_{ij} = \sum_{k=0}^{h} d_{ijk}$$

Next, using the method of the center of the area, we assign the defuzzification of C_{ij} to C_{ij}. Thus, the goal is to find a reasonable interval, so that if C_{ij} is classified in this interval, we can determine whether it belongs to the linguistic variable *No Risk, Low Risk, Medium Risk* or *High Risk*. Using membership functions (1-4), we calculate these intervals:

$$\Phi_2(a) = \Psi_1(a) \rightarrow a = \frac{x_1 + x_2}{2}$$

$$\Psi_3(b) = \Lambda_1(b) \rightarrow b = \frac{x_3 + x_4}{2}$$

$$\Lambda_3(c) = \Upsilon_1(c) \rightarrow c = \frac{x_5 + x_6}{2}$$

Hence, the rule base may be presented as follow:

- if $\gamma_{ij} \in$ [0, a] then the overall fuzzy decision is No Risk.
- if $C_{ij} \in$]a, b] then the overall fuzzy decision is Low Risk.
- if $C_{ij} \in$]b, c] then the overall fuzzy decision is Medium

Risk.

- if $C_{ij} \in]c, 100]$ then the overall fuzzy decision is High Risk.

We then draw up a hybrid profile table for each disease d_i with the combined observations, noted T_{ic}, in order to facilitate the further utilization of these hybrid diagnosis, see figure 2.

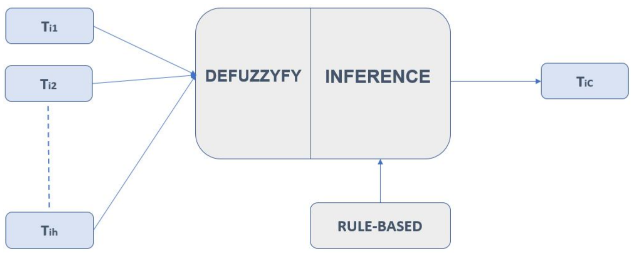

Figure 2: The fuzzy design of the system, with T_{ik}: Profile table according to expert number k, and T_{ic}: Combined profile table based on all experts

4. FINAL FUZZY DECISION

The combined decision of the i^{th} disease based on the j^{th} feature is calculated as:

$$\gamma_{ij} = C_{ij}$$

With C_{ij} is the hybrid decision (comment) of h experts, it can be directly obtained from the hybrid profile table:

$$T_{ij}[f_{ij}, s[f_{ij}]]$$

$s[f_{ij}]$ the crisp number obtained of the value v_j which is obtained from the patient's symptoms for the feature f_{ij}.
Note q_i the number of related features of the i^{th} disease. The total diagnosis decision is calculated as follow:

$$\Gamma_i = \frac{1}{q_i} \sum_{j=1}^{j=q_i} \gamma_{ij} \tag{6}$$

Using the following formula, which is based on center area method, we obtain the crisp values r_i that represent the certainty of existence for every disease d_i in set D.

$$r_i = \frac{c_i}{c_h} \times 100\% \tag{7}$$

With ci is the centroid of the overall diagnosis decision fuzzy set and c_h the centroid for the *High Risk* fuzzy set.

5. APPLICATION

In this section, we consider in a set of fuzzy tables the comments of four experts on a set of diseases D. The level of certainty of the existence of the disease di is indicated using four trapezoidal fuzzy sets (*No Risk*, *Low Risk*, *Medium Risk*, *High Risk*), see figure 3. Membership functions of these sets are defined in equations 8-11.

$$\mu_{Norisk}(x) = \begin{cases} \Phi_1 &= 1 & x < 15 \\ \Phi_2 &= 2 - \frac{x}{15} & 15 \leq x < 30 \end{cases} \tag{8}$$

$$\mu_{Lowrisk}(x) = \begin{cases} \Psi_1 &= \frac{x}{15} - 1 & 15 \leq x < 30 \\ \Psi_2 &= 1 & 30 \leq x < 45 \\ \Psi_3 &= 4 - \frac{x}{10} & 45 \leq x < 60 \end{cases} \tag{9}$$

$$\mu_{Mediumrisk}(x) = \begin{cases} \Lambda_1 &= \frac{x}{15} - 3 & 45 \leq x < 60 \\ \Lambda_2 &= 1 & 60 \leq x < 75 \\ \Lambda_3 &= 6 - \frac{x}{15} & 75 \leq x < 90 \end{cases} \tag{10}$$

$$\mu_{Highrisk}(x) = \begin{cases} \Upsilon_1 &= \frac{x}{15} - 5 & 75 \leq x < 90 \\ \Upsilon_2 &= 1 & x \geq 90 \end{cases} \tag{11}$$

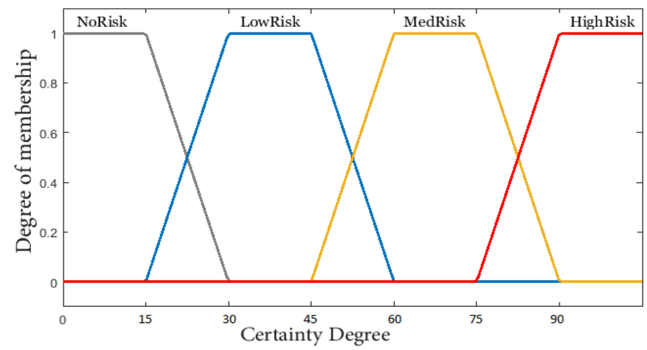

Figure 3: The fuzzy sets for the certainty of disease presence. Interval for *No Risk* = (0, 0, 15, 30), *Low Risk* = (15, 30, 45, 60), *Medium Risk* = (45, 60, 75, 90) and *High Risk* = (75, 90, 100, 100).

In order to apply and validate our model we consider a disease di with 11 symptoms, $q_i = 11$. Using method considered in section 3 we combine comments of the four experts and obtain hybrid profile for the disease d_i. We consider the example of 10 patients. According to the values of symptoms attributed by patients during the questionnaire. We represent the combined decisions in Table 3.

Table 3: The combined decisions of 10 patients

	No Risk	Low Risk	Medium Risk	High Risk
Patient 1	2	1	3	5
Patient 2	4	2	3	2
Patient 3	1	1	3	6
Patient 4	3	3	3	2
Patient 5	1	2	4	4
Patient 6	5	3	2	1
Patient 7	3	1	5	2
Patient 8	3	6	1	1
Patient 9	2	2	4	3
Patient 10	6	3	1	1

we notice that the results of the defuzzification validate the robustness of our model. According to table 3, we observe that the percentage of certainty of the presence of disease, r_h, varies according to the combined diagnosis of the experts. For patient 3 we have according to the combined diagnosis 6 out of 11 of the symptoms are of *High risk* and therefore a percentage of 80.24% is obtained after defuzzification. For patient 7 we have according to the combined diagnosis 5 out of 11 of the symptoms are of *Medium risk* and therefore a percentage of 60% is obtained after defuzzification, etc.

Table 4: The percentage of certainty of the presence of disease for 10 patients

	r_h=certainty of the presence of disease
Patient 1	67.75%
Patient 2	54.65%
Patient 3	80.24%
Patient 4	50.3%
Patient 5	68.7%
Patient 6	32.8%
Patient 7	60%
Patient 8	43%
Patient 9	65.2%
Patient 10	17.16%

5.1 Details of Calculation

We present in this section the details of calculation of the certainty of the presence of the considered disease for Patients 3, 8 and 10.

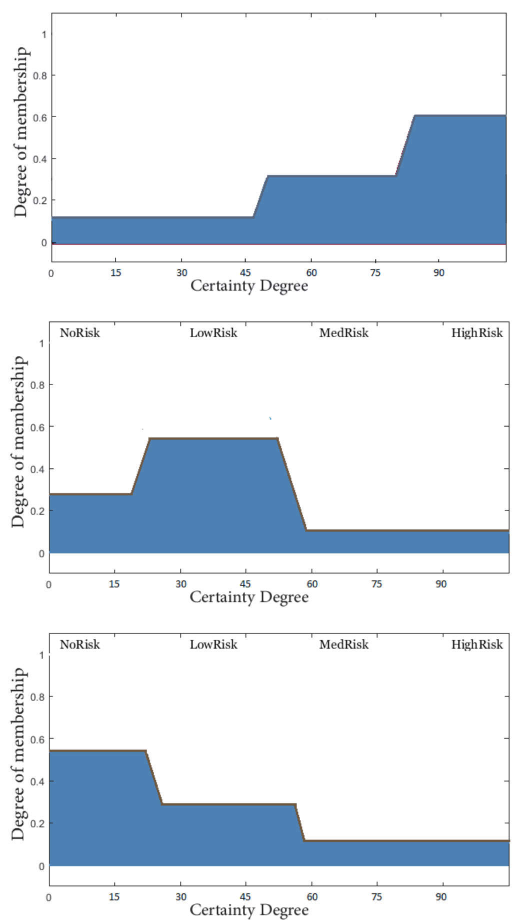

Figure 5: The visualization of certainty of the presence of disease for patient 3, 8 and 10.

• **Patient 3:**

The overall diagnostic decision of the first patient is:

Γ_i = (1 No Risk + 1 Low Risk + 3 Medium Risk + 6 High Risk) /11

Using the center of area method for defuzzification we obtain:

	No Risk	Low Risk	Medium Risk	High Risk	Overall diagnosis
Centroid area	14.17	37.5	67.5	89.36	71.71

Applying equation (7) we obtain the certainty of the presence of the considered disease is r_h = 80.24%.

• **Patient 8:**

The overall diagnostic decision of the second patient is:

Γ_i = (3 No Risk + 6 Low Risk + 1 Medium Risk + 1 High Risk) / 11

Using the center of area method for defuzzification we obtain:

	No Risk	Low Risk	Medium Risk	High Risk	Overall diagnosis
Centroid area	14.81	37.47	67	87.99	38.22

Applying equation (7) we obtain the certainty of the presence of the considered disease is r_h = 43%.

• **Patient 10:**

The overall diagnostic decision of the third patient is:

Γ_i = (6 No Risk + 3 Low Risk + 1 Medium Risk + 1 High Risk) / 11

Using the center of area method for defuzzification we obtain:

	No Risk	Low Risk	Medium Risk	High Risk	Overall diagnosis
Centroid area	15.5	37.3	67	87.99	15.1

Applying equation (7) we obtain the certainty of the presence of the considered disease is r_h = 17.16%.

6. DISCUSSION AND CONCLUSION

The present study aimed to develop a new method in fuzzy logic that can be used to diagnose different diseases. The method presented is mainly based on the experience of different physicians. The comments of the physicians are saved in fuzzy tables to indicate disease profiles. First, we get a disease profile table associated with each expert and then using the basic rules of the proposed expert fuzzy system we combined the different tables into a hybrid profile table. After that, we join the hybrid diagnoses decisions of each relevant symptom, to obtain an overall final diagnosis decision of the suspect disease. And finally the center of area method is considered to obtain the certainty for every suspected disease specified by a crisp percentage value. The proposed system aims to help physicians make faster and more accurate medical diagnoses and could be applied to several typical diseases only by entering their associated symptoms' values as the input cases. Furthermore, this study offers an opportunity to improve access to health care in rural areas in Morocco, where there is a lack of infrastructure and medical experts.

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