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Similarity Measurement of Fuzzy Entropies of Respiratory Sounds and Risk Measurement According to Credibility Distributions

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Abstract: In this paper, we have provided some definitions and theorems about fuzzy set, fuzzy set operations, the uncertainty theory used in fuzzy environments, and the credibility theory which exists on the base of the mathematical knowledge. Then, the definition and applications of fuzzy set operations, fuzzification, defuzzification, similarity, credibility distribution were included in diagnostic medicine. Sounds of respiratory patients were transferred to computer by recording and converted into numerical data. In particular, the entropies, similarities, credibility distributions and expected values of sounds were analyzed using fuzzification and defuzzification methods to analyze respiratory sound data via fuzzy operations and to make sense of uncertain sound data. In addition, a model for respiratory sounds was created and numerical numbers supported the diagnosis of the physician. Sound data were analyzed and interpreted using fuzzy multipurpose decision methods.

Key words: Fuzzy set, fuzzy entropy, fuzzification, credibility distribution, expected value, fuzzy reasoning.

1. Introduction

Fuzzy set theory was introduced by L.A. Zadeh [1] in 1965. Fuzzy logic has been previously studied since Lukasiewicz and Tarski [2] in the 1920s. Expert system was come across in fuzzy sets. In general, Expert system is an interactive computer-aided decision tool based on information obtained from an expert using events and experiences to solve complex problems. Expert systems provide expert advice and pioneer a wide range of activities from computerized diagnostics to sensitive medical surgery. The complexity and uncertainty in medical diagnosis complicates the learning, teaching and application of the diagnostic process. Fuzzy logic methods have gained widespread application in various medical fields due to its success in modeling certain types of uncertainty.

Real decisions are usually made in the state of indeterminacy. For modelling indeterminacy, there exist two mathematical systems, one is probability theory Kolmogorov [3,4] and the other is uncertainty theory Liu [5]. Probability is interpreted as frequency, while uncertainty is interpreted as personal belief degree [6]. Some uncertain situations may have difficulty in the decision-making process, the same is true in the diagnosis of diseases in medicine. In particular, the meaning of the respiratory sounds, when they are uncertain, the interpretation steps are important. In this study, the interpretation process of respiratory sounds was examined by using multi-directional decision mechanisms and some convenience was provided in the decision process.

2. Some Basic Theorems and Applications Regarding Entropies, Credibility Distribution, Expected Value of the Sequence of Fuzzy Sets

A fuzzy set is defined by its membership function $\mu_A(x)$ which assigns to each element x a real number $\mu_A(x)$ in the interval $[0,1]$, where the value of $\mu_A(x)$ represents the grade of membership of x in the fuzzy set.

$$A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \frac{\mu_A(x_3)}{x_3} + \dots + \frac{\mu_A(x_n)}{x_n} = \sum \frac{\mu_A(x_n)}{x_n} \quad [7].$$

Fuzzy entropy is a term used with regard to indicating the degree of uncertainty. Finding the entropy of a set is one of the important applications in fuzzy set theory. The degree of fuzziness is important in the theory of fuzzy sets and there stand out several methods for measuring the degree of fuzziness of fuzzy sets. Although the measure of fuzziness was initially considered as the distance between the non- fuzziness set, the concept of entropy was later used. In fact, fuzzy set theory is the generalized version of classical set theory.

In 1972, De Luca and Termini [8] defined fuzzy entropy based on Shannon's function, and they introduced a set of properties which a fuzzy entropy should satisfy. The properties of fuzzy entropy are widely accepted and have become a criterion for defining any new fuzzy entropy. The fuzzy entropy proposed by De Luca and Termini is shown in equation (2.1). It is defined based on the concept of membership function (μ_i).

$$H_A = -K \sum_i^n \{\mu_i \log(\mu_i) + (1 - \mu_i) \log(1 - \mu_i)\} \quad (2.1)$$

The four properties of this fuzzy entropy are:

- P-1 $H_A = 0$ if A is a crisp set ($\mu_i = 0$ or $1 \forall x_i \in A$).
- P-2 H_A is maximum if $\mu_i = 0.5 \forall x_i \in A$
- P-3 $H \geq H^*$ where H^* is the entropy of A^* , a sharpened version of A .
- P-4 $H = \bar{H}$ where $\bar{H}$ is the entropy of the complement set $\bar{A}$ [9], [10].

Zadeh extended the Shannon entropy to be applied as a fuzzy entropy on a fuzzy subset A for the finite set $X = \{x_1, x_2, \dots, x_n\}$ with respect to the probability distribution $P = \{p_1, p_2, \dots, p_n\}$ such an entropy is expressed as $H = -\sum_i^n \mu_A(x_i) p_i \log(p_i)$ or $e(A) = \int h(A(x)) p(x) dx$ [11].

Where $A(x)$ is the membership function of A :

$$A(x) = \begin{cases} \frac{h_A(x-a)}{b-a}, & x \in [a, b] \\ -\frac{h_A(x-c)}{c-b} + h_A, & x \in [b, c] \\ 0, & - \end{cases}$$

In equality $e(A) = \int h_1(A(x)) p(x) dx$, $k \in [0,1]$ and $p(x) = k$ if $h_1(x) = 4x(1-x)$ then

$$h_1(A(x)) = \begin{cases} 4 \left[\frac{h_A(x-a)}{b-a} \right] \left[1 - \frac{h_A(x-a)}{b-a} \right], & x \in [a, b] \\ 4 \left[-\frac{h_A(x-b)}{c-b} + h_A \right] \left[1 - \frac{h_A(x-b)}{c-b} + h_A \right], & x \in [b, c] \\ 0, & - \end{cases}$$

$$e(A) = \int 4 \left[\frac{h_A(x-a)}{b-a} \right] \left[1 - \frac{h_A(x-a)}{b-a} \right] k \cdot dx + \int 4 \left[-\frac{h_A(x-b)}{c-b} + h_A \right] \left[1 - \frac{h_A(x-b)}{c-b} + h_A \right] k \cdot dx$$

$$e(A) = k \left(2h_A - \frac{4}{3} h_A^2 \right) \cdot l(A) \quad [12]. \quad (2.2)$$

Define the function S as follows, where the notations h_A and h_B denote maximum height of the fuzzy sets A and B .

$$S: \mathcal{F} \times \mathcal{F} \rightarrow \mathbb{R}, S(A, B) = \frac{\min(h_A, h_B)}{\max(h_A, h_B)} \left[1 - \frac{1}{3} \sum_{k=0}^2 |A_k - B_k| \right] \quad [13].$$

In fuzzy sets, often the similarity and entropy are calculated separately and are included in the evaluation together. Finding the entropies and similarities of a fuzzy set is called the measure of similarity of the fuzzy entropies.

The credibility distribution shows the difficulty or degree of difficulty in predicting the specific value of the fuzzy variable. Liu and Liu [14] also defined credibility distributions function of a fuzzy variable ξ :

$$\Phi: \mathbb{R}^n \rightarrow [0,1]$$

$$\Phi(x) = Cr\{\theta \in \Theta / \xi(\theta) \leq x\}$$

Where $\Phi(x)$ is the credibility that the fuzzy variable ξ takes a values less than or equal to x .

Example 2.1. Let ξ be a triangular fuzzy variable. The credibility distribution function of fuzzy variable ξ is:

$$\Phi(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{2(b-a)} & \text{if } a \leq x < b \\ \frac{x+c-2b}{2(c-b)} & \text{if } b \leq x < c \\ 1 & \text{if } x \geq c \end{cases}$$

It can be represented in the graphic that follows:

Figure 2.1. Distribution function of a triangular fuzzy variable

Let ξ be a fuzzy variable. Then, the expected value of a fuzzy variable ξ is defined by

$$E(\xi) = \int_0^\infty Cr\{\xi \geq r\}dr - \int_{-\infty}^0 Cr\{\xi \leq r\}dr \quad (2.3)$$

provided that at least one of the two integrals is finite. The expected value $E(\xi^k)$ is called the k^{th} moment of fuzzy variable where k is a positive integer [15].

$$E(\xi^k) = k \int_0^\infty r^{k-1} Cr\{\xi \geq r\} dr \quad (2.4)$$

Example 2.2. The expected value is;

$$\text{If } \xi \text{ is an equipossible fuzzy variable } E(\xi) = \frac{a+b}{2}, \quad (2.5)$$

$$\text{If } \xi \text{ is a triangular fuzzy variable } E(\xi) = \frac{a+2b+c}{4}, \quad (2.6)$$

$$\text{If } \xi \text{ is a trapezoidal fuzzy variable } E(\xi) = \frac{a+b+c+d}{4}. \quad (2.7)$$

The expected value may not exist for some fuzzy variables. Let the fuzzy variable ξ has membership function $\mu(x) = \frac{1}{1+|x|}$, $\forall x \in \mathbb{R}$. The expected value ξ does not exists because both integrals $\int_0^\infty Cr\{\xi \geq r\} dr$ and $\int_{-\infty}^0 Cr\{\xi \leq r\} dr$ are infinite.

3. Respiratory Sounds and Decision making process

As an important equipment to guide the physician, stethoscope is an indispensable equipment, which is used effectively in the examination of the respiratory tract, abdominal and cardiovascular system. Electronic stethoscope is a very useful device to identify and diagnose lung sounds

The data of the Ministry of Health have entered into the statistics that 26.8% of all cancer deaths are caused by lungs, and it is the most common cause in males today. Therefore, in order to carry out studies that will guide the physician in the treatment of this disease, respiratory sounds from different regions of 100 patients were listened to via electronic stethoscope and recorded in a computer environment with the help of a physician who deals with respiratory patients. In addition, the type of patients' respiratory sounds (ral, ronus, crepitan) were determined. Their age and gender were also covered.

In this study, it was tried to develop the process of making sense of respiratory sounds belonging to 100 patients and making decision making process to facilitate the diagnosis of these sounds. First of all, uncertain breathing sounds were converted into computerized numerical data. There are filter processes in order to get rid of the sounds called unwanted sounds in the environment, but small unwanted sounds will not matter because the maximum sounds will be considered in this study. The maximum sounds of the patient were fuzzification to the range [0,1], fuzzy sequences were created. Fuzzy similarity measures and entropies of the fuzzy sequences created were found. Max-min approach is one of the fuzzy multi-purpose decision making methods. The main point of the max-min approach in Zimmerman [16] (1978) is to maximize the minimums of the membership function values of each function. So, the basic logic of this approach is to maximize the minimum satisfaction levels of each goal simultaneously.

As a result, we will encounter a value between 0 and 1. If the obtained numerical number is not very meaningful or evokes uncertainty, then other fuzzification methods can be applied and the above-mentioned processes can

be continued again. The physician's work in the diagnosis of the disease is made easier by taking into consideration the numerical value obtained and the characteristics of the patient.

The fuzzy decision making model according to the sound created now is given below.

Figure 3.1. Fuzzy Decision Model

The sounds of a patient's respiratory are obtained through an electronic stethoscope. Ambient or unwanted sounds are neglected, not filtered because small sound waves are unimportant or negligible due to the processing of maximums of the sound data. These sound waves were converted into digital data by computer programs. Firstly, fuzzy sequences were created by the fuzzification of the converted sound data. The entropies of the fuzzy sequences created and the similarities of the sequences were found. Then, when fuzzy multi-purpose decision making methods were investigated, the most appropriate and valid decision making method, max-min approach, was used. The reason for using this method is:

$$p: \text{entropy} \quad q: \text{risk} \quad r: \text{similarity} \quad t: \text{consistence}$$

$p \uparrow \rightarrow q \uparrow$, $r \uparrow \rightarrow t \uparrow$ As entropy increases, risk increases, while similarity increases, consistency increases. In other words, when comparing entropy and similarity, if the similarity is large, entropies are taken into consideration, if entropies are large, the degree of similarity is taken into account and consistency is calculated.

Below is the sound graph of the 14th patient. The data of this patient were fuzzificated, and the table below was prepared. Based on these data, transactions were carried out [17].

Figure 3.2. Respiratory sound wave graph of the patient

By taking the maximum of the sound data belonging to the patient, the data were digitized in computer environment and triangular fuzzy sets were made. In the fuzzification process, the table and graph of triangular fuzzy sets are shown below, by looking at the value of the maximum sounds and at what time they occur.

Table 3.1. Fuzzification sound waves

h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
0,16	0,276	0,28	0,812	0,31	1,033	0,26	1,472

Figure 3.3. Respiratory sound wave graph of the patient

Step 1. Entropies are calculated

The entropies of the fuzzy sequences created with the respiratory graph of the patient given in figure 3.3. are calculated one by one using the entropy function $e(A) = k \left(2h_A - \frac{4}{3}h_A^2 \right) \cdot l(A)$ in (2.1) and (2.2).

$$e(u_1) = k \cdot \left(2h_A - \frac{4}{3}h_A^2 \right) \cdot l(A) = 1 \cdot \left(2 \cdot 0,16 - \frac{4}{3} \cdot (0,16)^2 \right) \cdot (0,812 - 0,276) = 0,155$$

$$e(u_2) = k \cdot \left(2h_B - \frac{4}{3}h_B^2 \right) \cdot l(B) = 1 \cdot \left(2 \cdot 0,28 - \frac{4}{3} \cdot (0,28)^2 \right) \cdot (1,033 - 0,276) = 0,348$$

$$e(u_3) = k \cdot \left(2h_C - \frac{4}{3}h_C^2 \right) \cdot l(C) = 1 \cdot \left(2 \cdot 0,31 - \frac{4}{3} \cdot (0,31)^2 \right) \cdot (1,472 - 0,812) = 0,324$$

Step 2. Similarities are calculated

Calculation of similarity of fuzzy sequences and degree of similarity are important for comparison. With the similarity calculation, one more step is taken in multidirectional predictions. Let h_A be the height of the fuzzy membership function and the coordinates of the fuzzy number u_1, u_2, u_3, u_4 on the x axis in Figure 3.3. Appropriate triangular fuzzy numbers were selected by reference to the range and intensity values in the respiratory graph, and then the values were calculated in the determined entropy function. In the next step, a generating function has been built that will speed up this calculation. In this study, respiratory sounds expressed by fuzzy numbers are considered as a finite time series. Then, entropy values were calculated for comparison. In conclusion, the effect of changes in respiratory sound h_A and h_B waves in respiratory disorders is discussed with the help of increases and decreases in entropy.

Table 3.2. Fuzzy entropy values

u_1	$[(0), (0,276), (0,812)]$
u_2	$[(0,276), (0,812), (1,033)]$
u_3	$[(0,812), (1,033), (1,472)]$
u_4	$[(1,033), (1,472), (1,911)]$

Similarities of fuzzy sequences created with the data in Figure 3.3 and Table 3.2 are found.

$$S(u_1, u_2) = \frac{\min(h_A, h_B)}{\max(h_A, h_B)} \left[1 - \frac{1}{3} \sum_1^3 (A_i - B_i) \right]$$

$$S(u_1, u_2) = \frac{0,16}{0,28} \left[1 - \frac{1}{3} \cdot [(0,276 - 0) + (0,812 - 0,276) + (1,033 - 0,812)] \right] = 0,374$$

Step 3. Fuzzy entropy and similarities found *max-min* composition

After finding fuzzy entropy and similarities, Zimmermann's max-min approach, which is one of the fuzzy multipurpose decision making methods, is preferred. The reason is that the minimums of entropy and similarity values are desired to be maximized.

$$\begin{aligned} \mathcal{P} \circ \mathcal{R} &= \max\{\min\{\mu \mathcal{P}(x, y), \mu \mathcal{R}(x, y)\}\} \mathcal{P} \circ \mathcal{R} = \\ &\max\{\min\{[(0,155), (0,374)], [(0,348), (0,582)], [(0,324), (0,171)]\}\} \mathcal{P} \circ \mathcal{R} = \\ &\max\{[(0,155)], [(0,348)], [(0,171)]\} = 0,348 \end{aligned}$$

A sample group is selected from the respiratory sound data of 100 patients and the numerical data of $h_A, u_A, h_B, u_B, h_C, u_C, h_D, u_D$ values are written using the computer programs. Later, these raw sound data are converted to triangular fuzzy processes, and the resulting sequences are written in the table below.

Table 3.3. Some patients' respiratory values after fuzzification

	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 14	0,16	0,276	0,28	0,812	0,31	1,033	0,26	1,472
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 15	0,19	0,05	0,31	0,49	0,27	0,96	0,29	1,45
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 16	0,22	0,05	0,29	0,36	0,30	0,84	0,35	1,26
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 17	0,12	0,06	0,36	0,51	0,17	1,11	0,16	1,82
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 18	0,38	0,07	0,43	0,66	0,29	1,32	0,31	1,95
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 19	0,21	0,02	0,30	0,70	0,32	1,25	0,31	1,68
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 20	0,29	0,24	0,28	0,85	0,32	1,17	0,32	1,52

	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 21	0,31	0,43	0,29	0,89	0,28	1,14	0,20	1,77
	h_A	u_A	h_B	u_B	h_C	u_C	h_D	u_D
patient 22	0,30	0,45	0,25	1,10	0,19	1,64	0,24	1,98

According to the table above, when the calculations of step 1 (entropy calculation), step 2 (similarity calculation) and step 3 (fuzzy entropy and max-min composition of similarities) are made, the following graphs are attained.

Patient 15 (Age 61, male, ronküs)

Figure 3.4. Respiratory sound graph of patient 15

$$(\mathcal{P} \circ \mathcal{R})_{15} = \max\{\min\{\mu \mathcal{P}(x, y), \mu \mathcal{R}(x, y)\}\} = 0,45$$

These calculations are made one by one for other patients and their results are processed..

Step 4. Credibility distribution and expected value are calculated

As an alternative measure of a fuzzy event, credibility has recently been proposed as a measure of confidence in the fuzzy environment to resolve uncertainties in fuzzy environments and predict future events. The optimization model, the method of making the best decisions to achieve specific goals, was accepted as a competent measure of the level of confidence in fuzzy constraints. Because the credibility is self-dual, when the credibility value of a fuzzy event reaches 1, the fuzzy event will definitely occur. When using the credibility measure, fuzzy events occurring in different possibilities will have different credibility values. The fuzzy event with high credibility is more likely to occur.

After the maximum values of the data in Table 3.3 are set, the fuzzy set start point is set to zero and the graph's credibility distributions and expected values are shown below.

Patient 15 (Credibility distribution and expected value calculation)

Figure 3.5. Patient 15 's credibility distribution graph

Expected value;

$$E(\xi_{15}) = \frac{a + 2b + c}{4} = \frac{0 + 2 \cdot (0,44) + 0,91}{4} = 0,44$$

Table 3.4. Fuzzy Entropy Similarity Measures and Expected Credibility Values

	Patient 15	Patient 16	Patient 17	Patient 18	Patient 19	Patient 20	Patient 21	Patient 22
Fuzzy Entropy Similarity Measures	0,45	0,37	0,32	0,37	0,46	0,42	0,44	0,38
Expected Credibility Values	0,44	0,42	0,48	0,67	0,52	0,32	0,43	0,50

Table 3.5. Patient characteristics

Number of Patient	Age	Gender	Sound Type	Number of Patient	Age	Gender	Sound Type
1	28	M	RAL	51	84	M	RONKUS
2	65	M	RONKUS	52	51	F	RONKUS
3	52	F	RAL	53	73	M	RAL(KREPİTAN)
4	32	M	RAL	54	72	M	RAL(KREPİTAN)
5	62	F	RAL(KREPİTAN)	55	35	M	RAL
6	28	F	RAL	56	47	F	RONKUS
7	47	M	RAL	57	58	F	RONKUS
8	58	M	RONKUS	58	70	F	RAL(KREPİTAN)
9	74	M	RAL(KREPİTAN)	59	50	M	RAL
10	67	F	RONKUS	60	43	F	RONKUS
11	76	M	RONKUS	61	27	M	RAL
12	37	M	RAL	62	39	F	RAL
13	62	F	RAL	63	68	M	RAL(KREPİTAN)
14	49	M	RAL	64	56	M	RAL(KREPİTAN)
15	61	M	RONKUS	65	40	M	RAL
16	30	M	RAL	66	23	F	RAL
17	71	M	RAL+RONKUS	67	39	F	RAL
18	82	M	RAL	68	34	F	RAL
19	56	F	RAL(KREPİTAN)	69	74	M	RAL
20	50	M	RONKUS	70	34	F	RAL
21	72	F	RONKUS	71	63	M	RONKUS
22	79	F	RONKUS	72	70	F	RAL
23	62	F	RAL(KREPİTAN)	73	52	F	RONKUS
24	47	F	RAL	74	44	F	RONKUS
25	65	M	RONKUS	75	48	F	RAL
26	79	M	RAL(KREPİTAN)	76	40	F	RONKUS
27	83	F	RAL(KREPİTAN)	77	47	M	RAL
28	30	M	RAL	78	51	M	RAL
29	61	F	RAL	79	57	M	RAL
30	64	F	RAL	80	59	M	RAL
31	70	M	RAL	81	27	M	RONKUS
32	62	M	RONKUS	82	23	M	RAL
33	74	M	RAL	83	19	M	RONKUS
34	45	F	RONKUS	84	66	M	RONKUS
35	70	M	RAL(KREPİTAN)	85	69	F	RAL(KREPİTAN)
36	84	M	RAL(KREPİTAN)	86	19	M	RAL
37	53	M	RAL	87	32	M	RONKUS
38	48	M	RONKUS	88	24	M	RAL
39	79	M	RONKUS	89	39	M	RONKUS
40	48	M	RAL	90	77	F	RAL
41	65	M	RONKUS	91	27	M	RONKUS
42	55	M	RAL	92	62	M	RONKUS
43	58	M	RAL(KREPİTAN)	93	79	M	RAL(KREPİTAN)
44	36	F	RAL	94	34	M	RAL
45	62	M	RONKUS	95	75	M	RONKUS
46	75	M	RAL(KREPİTAN)	96	69	F	RONKUS
47	44	F	RAL	97	37	F	RAL
48	50	F	RONKUS	98	82	M	RAL(KREPİTAN)
49	74	F	RONKUS	99	50	M	RAL
50	57	F	RAL	100	50	M	RONKUS

Fuzzy entropy and similarities were found in order to fuzzificate the sound data with the model created and eliminate the uncertainty that exists. Fuzzy reasoning methods were tried using fuzzy entropies and similarities. Respiratory sounds of the patients were tabulated by looking at the max-min combination, which is one of the

fuzzy inference methods, and graphics and numerical numbers were obtained. In other words, respiratory sound data were digitized to assist physicians in making decisions.

Respiratory sounds of a total of 100 patients were examined and some analyzes were made below.

- i. It was observed that the age values of the patients whose fuzzy entropy similarity measure approached the number 0.5 were high.
- ii. When the patients whose credibility values was over 0.5 was considering, Ral (crepitan) sounds were intense and the age value was high.
- iii. Looking at the table and examining it in detail, it was seen that the ral (crepitan) sound of the men was more, and partially less of the women. This was shown to us again that these sounds increased respiratory ailments and that treatment should be started, and that the respiratory diseases of the world health organization are more common in men.
- iv. As respiratory sounds increase and uncertainty of respiratory sounds increase, entropy and credibility changes in the sound data are seen in the data. When the data were examined in detail, it was understood from the analyzes that breathing sounds were an indicator.

4. Conclusions and Suggestions

The conclusions are summarized in 4 items below:

1. When looking at the data obtained, it was noted that there are approaches to (0,5). It was concluded that the physician should pay more attention to the patients with respiratory sound data, where there are approaches to (0,5).
2. It was thought that it was important to listen to the respiratory sounds of the patients approaching the Fuzzy Entropy Similarity Measures (0,5) and to observe the credibility values of these patients since the uncertainty value was high.
3. Considering the credibility value, it was decided that the uncertainty about the patients having numerically high value is low, and that the diagnosis of the disease can be made easily.
4. It was observed that the uncertainty and credibility experienced in the respiratory sound data were found to be eliminated significantly with the fuzzy entropy similarity measures.

In order to measure the confidence level of these uncertain sound data and to predict future events, the measures of the credibility theory, which measures uncertain data and is another decision-making criterion, were used. The credibility distributions and expected values were calculated and it was thought to be important to be evaluated at the decision stage with the credibility rating made in the diagnosis of the disease. Therefore, the fuzzy entropy with the numerical data obtained was written one after the other with similarity data. Considering that it is easier to estimate the ones with high credibility, a physician was guided through a bilateral evaluation.

Fuzzy inferences made are not a diagnosis, but a numerical document presented to the physician for the grading of the disease. Thanks to the model created and the deficiencies to be eliminated, the diagnosis of diseases goes towards computerized diagnosis. The importance of fuzzy sets in medicine is gradually increasing, instead of

relative evaluation in medicine and other fields or the realization of an event, it paves the way for graded evaluation about credibility.

Respiratory sounds are also an evaluation criterion by themselves. It is our suggestion to take into account the heart sounds and make sense of the heart sounds.

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Ethics

No Potential conflicts of interest and is an article with a single author. There are human data whose names are unknown. The data was created by giving numbers to people respectively. Therefore, there is no need for any approval.

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