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, 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. As the uncertainty of respiratory sounds increased, changes in fuzzy entropy similarity measures and expected credibility values were observed. In addition, a model for uncertain respiratory sounds was created and numerical numbers supported the diagnosis of the physician. Sound data were analyzed and interpreted using fuzzy multipurpose decision methods. Respiratory sounds were shown to be an indicator in diagnosing with the created model.

Keywords: Fuzzy set · Fuzzy entropy · Fuzzification · Credibility distribution · Expected value · Fuzzy reasoning

1 Introduction

Fuzzy set theory was introduced by L.A. Zadeh (Zadeh 1965), in 1965. Fuzzy logic (Barnabas 2013) has been previously studied since Lukasiewicz and Tarski (Pelletier 2000) in the 1920s. De Luca and Termini (Luca and Termini 1972a) proposed a measure of the degree of fuzziness (entropy) in 1972. With fuzzy set theory, medical diagnosis and uncertain information can often be formalized. Fuzzy logic provides reasoning methods that can make approximate inferences. Fuzzy set theory suggests that it may be a suitable basis for the development of a computerized diagnostic system. It is verified by experiments with the medical expert system CADIAG-2 (Adlassnig 1986), which uses fuzzy set theory and the diagnostic process to model it. 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 often made in a situation of uncertainty. There are two mathematical systems to deal with uncertainty in a logical way. One is probability theory Kolmogorov (Chaudhuri and Ghosh 2016; Kolmogorov 1933) and the other is uncertainty theory Liu (Liu 2015). Probability is interpreted as frequency, while uncertainty is interpreted as personal belief degree (Yuanguo 2019). Fuzzy entropy (Zimmermann 1991) is used to represent the mathematical values of the fuzziness of fuzzy sets. Also, fuzzy entropy plays an important role in fuzzy decision making. Many physiological signals in the human or animal body are now widely used in fuzzy entropy applications. Especially ECG and EEG signals are one of the most important data used in the diagnosis of diseases. Credibility is recommended by Li (Li and Ralescu 2009) a measure of
confidence for resolve uncertainties in the fuzzy environment.

Some uncertain situations may have difficulty in the decision-making process, the same is true in the diagnosis of diseases in medicine. The same is true for the interpretation of uncertain respiratory sounds. Respiratory sounds have an important place in the detection of respiratory diseases, researches have been done and still continue. Sovijarvi (Sovijarvi and Dalmasso 2000) defined the terms for breath sounds. Shi (Shi et al. 2019) proposed a lung sound recognition algorithm based on deep learning and transfer learning. Jayalakshmy and Sudha (Jayalakshmy and Sudha 2020) studied the Scalogram-based prediction model for respiratory disorders. Fraiwan (Fraiwan et al. 2021) studied the recognition of multiple lung diseases from lung sounds.

Respiratory diseases researches are still continuing increasingly. Respiratory sounds attracted attention and the characteristics of the sounds were examined. It is known that EKG (Electrocardiogram) is used to diagnose heart disease and EEG (electroencephalogram) is used to help evaluate the electrical activity of the brain. The effect of respiratory sounds in the diagnosis of respiratory diseases is examined. In addition, considering that it is easy and reliable to detect diseases with sound data analysis, it has been interesting to examine respiratory sounds. For this reason 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 (Lowen 1980).

\[
A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \frac{\mu_A(x_3)}{x_3} + \cdots + \frac{\mu_A(x_n)}{x_n}
\]

Fuzzy entropy is defined as the 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 (Luca and Termini 1972b) 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 new fuzzy entropy. The fuzzy entropy proposed by De Luca and Termini is shown in Eq. (2.1). It is defined based on the concept of membership function, \( i = 1, 2, 3, \ldots, n \) where there are \( n \) membership function \( (\mu_i) \).

\[
H_A = -K \sum_{i=1}^{n} \{ \mu_i \log(\mu_i) + (1 - \mu_i) \log(1 - \mu_i) \} \tag{2.1}
\]

The four properties of this fuzzy entropy are:

1. if \( A \) is a crisp set \( (\mu_i = 0 \text{ or } 1) \forall x_i \in A \).
2. \( H_A \) is maximum if \( \mu_i = 0.5 \forall x_i \in A \).
3. \( H \geq H^* \) where \( H^* \) is the entropy of \( A^* \), a sharpened version of \( A \).
4. \( H = H^c \) where \( H^c \) is the entropy of the complement set \( A \) (Zadeh 1971; Zimmermann 1996).

Zadeh extended the Shannon entropy to be applied as a fuzzy entropy on a fuzzy subset \( A \) for the finite set \( X = \{x_1, x_2, \ldots, x_n\} \) with respect to the probability distribution \( P = \{p_1, p_2, \ldots, p_n\} \) such an entropy is expressed as \( H = -\sum_{i} \mu_A(x_i)p_i \log(p_i) \) or \( e(A) = \int h(A(x))p(x)dx \) (Zadeh 1989). Where \( A(x) \) is the membership function of \( A \):

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

| Symbol | Definition |
|--------|------------|
| \( \mu_A(x) \) | Membership Function |
| \( H_A \) | Fuzzy entropy |
| \( C_r \) | Credibility |
| \( E(\xi) \) | Expected value of a fuzzy variable |
| \( \Phi(x) \) | Credibility distributions function of a fuzzy variable |
Inequality \( e(A) = \int h_1(A(x))p(x)dx, \ k \in [0, 1] \) and \( p(x) = k \) if \( h_1(x) = 4x(1-x) \) then (Zimmermann 1991)

\[
h_1(A(x)) = \begin{cases} 
4 \left[ h_a(x-a) + h_b \right] & \text{if } x \in [a, b] \\
-4h_a(x-b) + h_a & \text{if } x \in [b, c] \\
0, & \text{otherwise}
\end{cases}
\]

\[
e(A) = \int 4 \left[ h_a(x-a) + h_b \right] k \cdot dx + \int 4 \left[ -h_a(x-b) + h_a \right] k \cdot dx = k \left( 2h_a - \frac{4}{3} h_b \right) E(A)
\]

Example 2.1. Let \( \xi \) be a triangular fuzzy variable. The credibility distribution function of a fuzzy variable \( \xi \) is:

\[
\Phi(x) = \text{Cr}(\theta \in \Theta/\xi(\theta) \leq x)
\]

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

Example 2.2. The expected value is:

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

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

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

The expected value may not exist for some fuzzy variables. Let the fuzzy variable \( \xi \) has membership function \( \mu(x) = \frac{1}{1+|x|}, \forall x \in \mathbb{R} \). The expected value \( \xi \) does not exists because both integrals \( \int_{-\infty}^{\infty} \text{Cr}(\xi \geq r) \) and \( \int_{-\infty}^{\infty} \text{Cr}(\xi \leq r) \) 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. It is important that respiratory diseases do not progress and circulatory diseases do not occur. 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, roncus, crepitans) were determined. Their age and gender were also covered (Dwyer, 2000; Mason and Murray, 2010, Pasterkamp et al., 1997).

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 (Cao et al., 2020) (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.

In the Fuzzy Decision Model in Fig. 2, first of all, respiratory sounds are entered into the model. Sound waves are digitized. Then, the maximum values are fuzzificated and fuzzy sequences are created. The similarity measures, fuzzy entropies, credibility distributions and expected values of the created fuzzy sequences are found. A degree between 0 and 1 is obtained by using the max–min method, one of the fuzzy multi-purpose decision making methods. If there is uncertainty, other fuzzification methods are used. The decision-making process begins, taking into account the patient’s character (age, gender, sound type).

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:

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

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. This patient was randomly selected. The data of this patient were fuzzificated, and the table below was prepared. Based on these data, transactions were carried out (Sanlhuba, 2019).

\[ h_A, h_B, h_C, h_D \] are the peak values of respiratory sound waves, that is, their maximum values. 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.

Figure 3 is reduced by 1/10 the maximum points of the sound waves. \( h_A \) is the height of the fuzzy membership function, \( u_A \) is the coordinates of the fuzzy number on the x axis. Then, triangular fuzzy sets are created in Fig. 4 and the datas obtained from the fuzzification are written in Table 2.

**Step 1: Entropies are calculated**

The entropies of the fuzzy sequences created with the respiratory graph of the patient given in Fig. 4 are calculated one by one using the entropy function \[ e(A) = k(2h_A - \frac{3}{2}h_A^2), L(A) \] in (2.1) and (2.2).
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**Fig. 2** Fuzzy decision model

**Fig. 3** Respiratory sound wave graph of the patient
Fuzzification sound waves

Table 2 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 |

$e(u_1) = k \left( 2h_A - \frac{4}{3}h_A^2 \right) \cdot I(A)$

$= 1 \left( 2.0, 16 - \frac{4}{3}(0, 16)^2 \right) \cdot (0, 812 - 0, 276)$

$= 0.155$

$e(u_2) = k \left( 2h_B - \frac{4}{3}h_B^2 \right) \cdot I(B)$

$= 1 \left( 2.0, 28 - \frac{4}{3}(0, 28)^2 \right) \cdot (1, 033 - 0, 276)$

$= 0.348$

$e(u_3) = k \left( 2h_C - \frac{4}{3}h_C^2 \right) \cdot I(C)$

$= 1 \left( 2.0, 31 - \frac{4}{3}(0, 31)^2 \right) \cdot (1, 472 - 0, 812)$

$= 0.324$

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 Fig. 4. 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.

Similarities of fuzzy sequences created with the data in Fig. 4 and Table 3 are found.

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

$S(u_1, u_2) = \frac{0.16}{0.28} \left[ 1 - \frac{1}{3} \left( (0, 276 - 0) + (0, 812 - 0.276) \right) + (1, 033 - 0.812) = 0, 374 \right]$

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.

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

$\mathcal{P} \circ \mathcal{R} = \max \{ \min \{ ((0, 155), (0, 374)), ((0, 348), (0, 582)), ((0, 324), (0, 171)) \} \}$

$\mathcal{P} \circ \mathcal{R} = \max \{ ((0, 155)), ((0, 348)), ((0, 171)) \} = 0, 348$

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.

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, ronkus)

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

These calculations are made one by one for other patients and their results are processed (Fig. 5).

Step 4 Credibility distribution and expected value are calculated

There are several measures in fuzzy set theory. These are similarity measure, divergence measure, subhood measure and fuzzy entropy (Li et al. 2016). As an alternative measure of a fuzzy event, credibility was 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.

Table 3 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)] |
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 (Sen-gonul et al. 2016).

After the maximum values of the data in Table 4 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).

Expected value (in Figs. 5 and 6);

$$E(\xi_{15}) = \frac{a + 2b + c}{4} = \frac{0 + 2 \cdot (0.44) + 0.91}{4} = 0.44$$

In Table 5, Fuzzy Entropy Similarity Measures and Expected Credibility Values were found for some of the patients and the data were shown. In addition, the data in Table 5 took values between 0 and 1 (Fig. 6).

Respiratory sounds of 100 patients were listened to with an electronic stethoscope and the type of respiratory sounds of the patients were determined with the help of a physician. Then, the characteristics of 100 patients (Age, gender, sound type) were listed one by one in Table 6. In addition, the data created in Table 5 and Table 6 were not taken from another publication and were used for this study.

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 in Tables 5 and 6 were examined and some analyzes were made below.

| Patient | $h_A$ | $u_A$ | $h_B$ | $u_B$ | $h_C$ | $u_C$ | $h_D$ | $u_D$ |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|
| Patient 14 | 0.16 | 0.276 | 0.28 | 0.812 | 0.31 | 1.033 | 0.26 | 1.472 |
| Patient 15 | 0.19 | 0.05 | 0.31 | 0.49 | 0.27 | 0.96 | 0.29 | 1.45 |
| Patient 16 | 0.22 | 0.05 | 0.29 | 0.36 | 0.30 | 0.84 | 0.35 | 1.26 |
| Patient 17 | 0.12 | 0.06 | 0.36 | 0.51 | 0.17 | 1.11 | 0.16 | 1.82 |
| Patient 18 | 0.38 | 0.07 | 0.43 | 0.66 | 0.29 | 1.32 | 0.31 | 1.95 |
| Patient 19 | 0.21 | 0.02 | 0.30 | 0.70 | 0.32 | 1.25 | 0.31 | 1.68 |
| Patient 20 | 0.29 | 0.24 | 0.28 | 0.85 | 0.32 | 1.17 | 0.32 | 1.52 |
| Patient 21 | 0.31 | 0.43 | 0.29 | 0.89 | 0.28 | 1.14 | 0.20 | 1.77 |
| Patient 22 | 0.30 | 0.45 | 0.25 | 1.10 | 0.19 | 1.64 | 0.24 | 1.98 |
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 respiratory sounds were an indicator.

### 4 Conclusions and suggestions

Decision-making and interpretation process in respiratory sounds are developing. If the studies on respiratory sounds are compared with the studies conducted in this article, the main difference can be listed as follows: The studies are mostly related to the determination of the type of respiratory sounds. In addition, when examined in more detail, some diseases were decided by looking at the concepts related to the frequency, intensity, height and wavelength of respiratory sounds. It was made by looking at the sounds that are usually certain. In this study, on the other hand, vague and uncertain sound waves were interpreted with the help of fuzzy processes. In addition, fuzzy entropy similarity measures and expected credibility values were used in the decision-making process of respiratory sounds, paving the way for versatile and consistent evaluation.

It is easy to listen and save respiratory sounds with a stethoscope. If risky patients are identified through uncertain respiratory sounds before respiratory diseases progress, both the disease will not progress and large treatment costs can be avoided.

### Table 5  Fuzzy entropy similarity measures and expected credibility values

| Patient | Fuzzy entropy similarity measures | Expected credibility values |
|---------|-----------------------------------|-----------------------------|
| 15      | 0.45                              | 0.44                        |
| 16      | 0.37                              | 0.42                        |
| 17      | 0.32                              | 0.48                        |
| 18      | 0.37                              | 0.67                        |
| 19      | 0.46                              | 0.52                        |
| 20      | 0.42                              | 0.32                        |
| 21      | 0.44                              | 0.43                        |
| 22      | 0.38                              | 0.50                        |

### Fig. 6  Patient 15’s credibility distribution graph
Table 6 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) |
Considering the data in Table 5 and Table 6, with the help of the model shown in Fig. 2 risky patients were identified.

The conclusions are summarized in 5 items below:

1. When looking at the data obtained, it was noted that there are approaches to (0,5). It is clear that this value is the most uncertain situation and the risk is high. Therefore, 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.

5. When the uncertainty of patients approaching Fuzzy Entropy Similarity measures (0.5) is high, if the credibility value is numerically greater than (0.5), it is concluded that these patients should be paid attention to. This indicates the presence of a respiratory problem. Because as the uncertainty of respiratory sounds increases, entropy and credibility changes in sound data are seen in the data. When the data are examined in detail and the results of the decision-making practices are examined, it is understood from the analyzes that respiratory sounds are an indicator.

With this study, numerical documents were obtained to guide the physician in the diagnosis of respiratory diseases. With the created model, risky patients were determined and these patients were examined more. The work of the physician in making the diagnosis is made easier. Respiratory sounds were shown to be important and an indicator in the diagnosis of disease.

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, it was thought to be important to be evaluated at the decision stage with the credibility rating made in the diagnosis of the disease. Because the higher the Credibility value, the more likely it is for a fuzzy event to occur. 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 toward 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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Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest I. Şanlıbaba declares that he has no conflict of interest.

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

Informed consent Not applicable.

Table 6 (continued)

| Number of Patient | Age | Gender | Sound Type | Number of Patient | Age | Gender | Sound Type |
|-------------------|-----|--------|------------|-------------------|-----|--------|------------|
| 49                | 74  | F      | RONKUS     | 99                | 50  | M      | RAL        |
| 50                | 57  | F      | RAL        | 100               | 50  | M      | RONKUS     |
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