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A type-2 fuzzy rule-based model for diagnosis of COVID-19

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Abstract: In this study, a type-2 fuzzy logic-based decision support system comprising clinical examination and blood test results that health professionals can use in addition to existing methods in the diagnosis of COVID-19 has been developed. The developed system consists of three fuzzy units. The first fuzzy unit produces COVID-19 positivity as a percentage according to the respiratory rate, loss of smell, and body temperature values, and the second fuzzy unit according to the C-reactive protein, lymphocyte, and D-dimer values obtained as a result of the blood tests. In the third fuzzy unit, the COVID-19 positivity risks according to the clinical examination and blood analysis results, which are the outputs of the first and second fuzzy units, are evaluated together and the result is obtained. As a result of the evaluation of the trials with 60 different scenarios by physicians, it has been revealed that the system can detect COVID-19 risk with 86.6% accuracy.

Key words: COVID-19, fuzzy logic, decision support system, diagnosis

1. Introduction

COVID-19 is a disease caused by the SARS-CoV-2 virus, which can be transmitted to animals and humans, and spread to the world in 2019 and became a pandemic. COVID-19, which has taken the whole world under its influence and caused many people to die, continues to maintain its effect with different mutations. The rate of spread is extremely high since it is transmitted by respiratory and contact routes. According to the information presented daily by the World Health Organization, as of 20 October 2022, the number of cases reported worldwide was 620 million, while more than 6 million people died. Early diagnosis of COVID-19 is important in quarantining patients in the early period and thus reducing the spread of the virus. In the diagnosis of COVID-19, reverse transcription polymerase chain reaction (RT-PCR) tests, lung radiology images, blood tests, and clinical findings are evaluated. In the guide published by the World Health Organization [1], it is recommended to apply RT-PCR tests primarily in the diagnosis of COVID-19. However, due to the high demand for these tests, supply problems have arisen in various countries. In addition, it is seen that the accuracy of the test results varies between 42.9% and 88.9% according to the area where the swab was taken (nose, throat), the person taking the swab, and the period the swab was taken [2]. RT-PCR tests, which are not performed properly, especially during test-intensive periods, give false results and cause false negativity. In addition, the emergence of various variants also affects the accuracy of RT-PCR tests.

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In addition to RT-PCR tests, the COVID-19 diagnosis can be made by evaluating chest radiology images. In Ai et al. [3]'s work, computed tomography and RT-PCR test results were compared on 1014 cases and it was revealed that radiological imaging showed higher diagnostic performance than RT-PCR tests. In the literature, there are various studies on the diagnosis of COVID-19 from artificial intelligence-based algorithms and radiology images [4–9]. However, it is stated that radiological imaging may give false results, especially in the early stages of the disease [10]. In addition, the high cost and damage of radiation taken into the body in radiological imaging—especially in computed tomography—stand out as the limitations of this method [11].

Another method used in the diagnosis of COVID-19 is the evaluation of clinical findings. In addition to the evaluation of symptoms such as fever, cough, diarrhea, loss of smell/taste, joint pain, and sore throat, various tests are also performed. In many clinical studies in the literature, it was stated that there were significant changes in the blood values of COVID-19 patients and that early diagnosis is possible with the detection and analysis of these values [12–16]. There are various studies in which artificial intelligence methods are used in the evaluation of clinical findings and blood tests for the diagnosis of COVID-19. Shaban et al. [17] developed a method called hybrid diagnostic strategy by combining fuzzy logic and deep neural network method. In this system, the effect of each parameter on the disease was determined by the deep neural network method and sent to the fuzzy logic structure. As a result of the tests, it was shown that the average accuracy of the system is 97.6%. Batista et al. [18] compared machine learning algorithms for the diagnosis of COVID-19 from blood samples. As a result of the tests performed with 235 blood samples (102 of them COVID-19–positive) taken from Albert Einstein Hospital in Brazil, it was revealed that the algorithm that gave the best performance was the support vector machine with 85% accuracy and 68% sensitivity. Brinati et al. [19] investigated the COVID-19 prediction performance of seven different machine learning algorithms. In the study conducted with 279 blood samples (177 positive) taken from San Raffaele Hospital in Italy, 15 different features were used. The random forest algorithm modified by the authors was the algorithm that gave the best performance with 82% accuracy and 92% precision. Mariam et al. [20] developed a system called the ensemble learning model for the prediction of COVID-19 from blood samples. A two-layer prediction model was used in the model. An accuracy rate of 99.88% was achieved in the system developed with the data of 5644 patients. Jiang et al. [21] used machine learning techniques to predict the clinical severity of COVID-19. Eleven clinical features were considered and logistic regression, k nearest neighborhood, decision trees, random forests, and support vector machines classifiers were applied. Best accuracy was obtained with SVM classifier with 80%. Ahamad et al. [24] developed a model that employs machine learning algorithms to identify the features predicting the COVID-19. These features are age, gender, fever, travel history, cough, and incidence of lung infection. They applied different machine learning algorithms and found that the eXtreme gradient boosting (XGBoost) algorithm performed with the 85% accuracy in detecting the COVID-19. Arpaci et al. [25] presented a study for COVID-19 diagnosis based on 14 clinical features. This research employs machine learning classification algorithms. The results showed that the classification via regression (CR) metaclassifier was the most accurate classifier for predicting the positive and negative COVID-19 cases with an accuracy of 84.21%. Wu et al. [26] developed a machine learning-based diagnostic system. Of the 110 blood samples taken from Tongji Hospital in China, 88 were used for training and 22 for testing. In the system, 7 different features were used. The model has 0.99 AUC, 98% sensitivity and 91% specificity in predicting COVID-19 disease. Shatnawi et al. [27] developed a fuzzy logic model in which symptoms were evaluated in the detection of COVID-19. In the system, only clinical findings such as fever, dry cough, fatigue, diarrhea, headache, respiratory distress, loss of taste/smell,

eye redness, and sore throat are evaluated. Considering that these symptoms were similar to those in upper respiratory tract infections, it was an important limitation that additional parameters such as blood samples are not taken into account. When we look at the studies in general, it is seen that most of them are based on machine learning algorithms. For these algorithms to work with high performance and to determine that their outputs can reach acceptable accuracy values, a large number of data must be available. Most of the studies have been done with a small number of data. This limits its applicability in real life. The results of studies on artificial intelligence-based COVID-19 diagnosis are compared in Table 1.

Table 1. Comparison of different algorithms for COVID-19 diagnosis.

Publication	**Method**	**Accuracy (%)**
Shaban et al. [17]	Fuzzy logic and deep neural network	97.6
Batista et al. [18]	Support vector machine	85
Brinati et al. [19]	Modified random forest	82
Mariam et al. [20]	Ensemble learning model	99.88
Jiang et al. [21]	Support vector machine	80
Abdulkareem et al. [22]	Support vector machine	95
Alakus and Turkoglu [23]	CNNLSTM	92.3
Ahamad et al. [24]	eXtreme gradient boosting	85
Arpaci et al. [25]	classification via regression metaclassifier	84.21
This work	**Type-2 fuzzy logic**	**86.6**

In this study, a type-2 fuzzy logic-based decision support system that health professionals can use in addition to existing methods in the diagnosis of COVID-19 has been developed. The developed decision support system consists of three fuzzy units. The first fuzzy unit is based on the respiratory rate, loss of smell, and body temperature values obtained in the clinical examination, and the second fuzzy unit is based on the C-reactive protein (CRP), lymphocyte (LYM), and D-dimer (DD) values obtained as a result of the blood tests. It produces a person's COVID-19 positivity risk as a percentage. In the third fuzzy unit, the COVID-19 positivity risks due to the clinical examination and blood analysis results, which are the outputs of the first and second fuzzy units, are evaluated together and the final result of the system is obtained. As a result of the evaluation of the results of the trials with 60 different scenarios by physicians, it is revealed that the system showed a diagnosis performance of 86.6% for the COVID-19 disease.

The contributions of the study to the literature are:

- The development of a type-2 fuzzy logic-based decision support system for the detection of COVID-19 risk,
- Clinical examination and blood samples are evaluated together for the first time.

The limitations of the study are given below:

- The data used during the testing of the system are not real patient data but are scenarios created by physicians.
- The clinical examination and blood analysis data used in the developed system have not been tested with different artificial intelligence methods and have not been compared.

This article is organized as follows: details of the fuzzy inference mechanism, input variables, and rules are provided. Finally, the experimental results and the conclusion are given.

2. Materials and methods

In this section, the details of the developed system and the data used are given. Interval type-2 fuzzy system approach is used in the model. Interval type-2 (IT2) fuzzy logic systems developed by Liang and Mendel [28] are the generalized form of type-1 fuzzy sets. Type-2 fuzzy systems [29, 30], which were presented to the literature in the early 2000s and showed successfully deal with uncertainties, parameter changes, and disturbance effects, were used in disease diagnosis [31–34], fault detection [35–37], control of unmanned aerial vehicles [38], and in solving many other engineering problems. In Figure 1, the membership function of the IT2 fuzzy logic is shown.

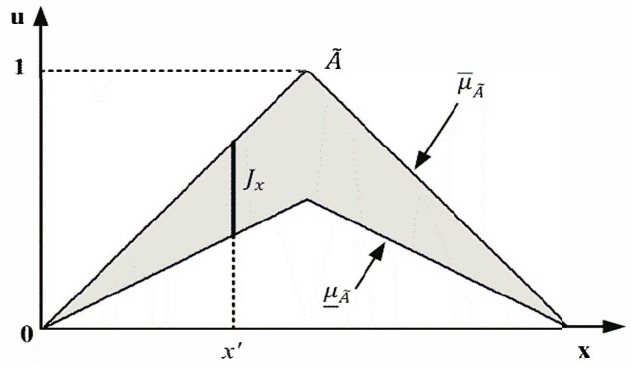

Figure 1. IT2 membership function.

$\tilde{A}$ shown in Figure 1 is characterized by the membership function $\mu_{\tilde{A}}(x,u)$ defined as follows:

$$\tilde{A} = ((x,u), \underline{\mu}_{\tilde{A}}(x,u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1] \tag{1}$$

Here $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$ and primary membership value is a value in the $u \in J_x \subseteq [0,1]$. In a continuously defined space, the set $\tilde{A}$ is expressed as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \frac{\mu_{\tilde{A}}(x,u)}{x,u} J_x \in [0,1] \tag{2}$$

Here $\int \int$ denotes the intersection of all x and u values in the domain. J_x is defined as the primary membership function of x, and $\mu_{\tilde{A}}(x,u)$ is defined as the secondary membership function of x. In type-2 fuzzy logic ($\tilde{A}$), the uncertainty is expressed in a region in the primary membership function. This set is defined by an upper membership function $\overline{\mu}_{\tilde{A}}$ and a lower membership function $\underline{\mu}_{\tilde{A}}$. If $\mu_{\tilde{A}}(x,u) = 1$ for $\forall u \in J_x \subseteq [0,1]$, an interval type-2 fuzzy system is obtained.

In this study, a type-2 fuzzy logic-based decision-making mechanism is developed on MATLAB, based on the feedback received from infectious diseases specialists. Interval Type-2 Fuzzy Toolbox [39], which was developed by Taşkın and Kumbasar in 2015, is used for Type-2 Toolbox in MATLAB. In the fuzzy system, the Takagi-Sugeno-Kang model is selected. The fuzzy inference system includes three subunits. Clinical examination results of the patient are evaluated in the first unit, and blood samples are evaluated in the second unit. In the

third unit, the output of the system is obtained by evaluating the results of these two units together. The block diagram of the fuzzy inference mechanism is given in Figure 2.

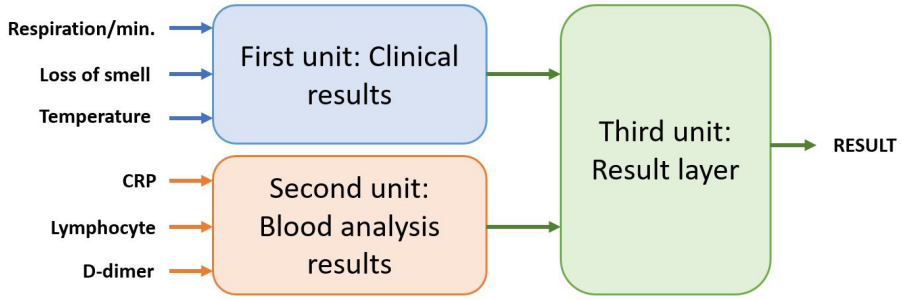

Figure 2. Fuzzy inference mechanism block diagram.

The first unit has three inputs. These are respiratory rate per minute, loss of smell, and body temperature.

Respiratory rate/min.: According to the information received from physicians, the respiratory rate per minute for healthy people varies between 12 and 20, while this number rises to 25–30 in patients. IT2 membership function is created according to these values.

Loss of smell: It is seen that short- and long-term loss of smell and taste occurs in some of the COVID-19 cases [40]. The senses of smell and taste are closely related. When the nerves related to the sense of smell are affected for any reason and the sense of smell is partially or completely lost, the sense of taste is also affected. For this reason, the presence of loss of smell in the developed system is taken as an input. The input for the presence or absence of loss of smell can be defined as 0 and 1. By blurring this definition, the loss of smell membership function is defined between 0 and 1.

Body temperature: One of the effects of COVID-19 disease is an increase in body temperature [41]. Normal body temperature in healthy people is 36.8 $\pm$ 0.4 degrees. According to these values, the membership function of the input is created.

The input membership functions of the first unit, which consists of 8 rules in total, are given in Figure 3. At the first unit output, the prediction for COVID-19 is obtained as a percentage. This output is the first input of the third unit, which will give the actual result.

The rules of the first fuzzy unit are given below.

- IF respiratory rate is LOW, taste-smell loss is LOW, Body temperature is LOW, THEN Result NS
- IF respiratory rate is LOW, taste-smell loss is LOW, Body temperature is HIGH, THEN Result NB
- IF respiratory rate is LOW, taste-smell loss is HIGH, Body temperature is LOW, THEN Result MS
- IF respiratory rate is LOW, taste-smell loss is HIGH, Body temperature is HIGH, THEN Result MB
- IF respiratory rate is HIGH, taste-smell loss is LOW, Body temperature is LOW, THEN Result MOS
- IF respiratory rate is HIGH, taste-smell loss is LOW, Body temperature is HIGH, THEN Result MOB
- IF respiratory rate is HIGH, taste-smell loss is HIGH, Body temperature is LOW, THEN Result SS
- IF respiratory rate is HIGH, taste-smell loss is HIGH, Body temperature is HIGH, THEN Result SB

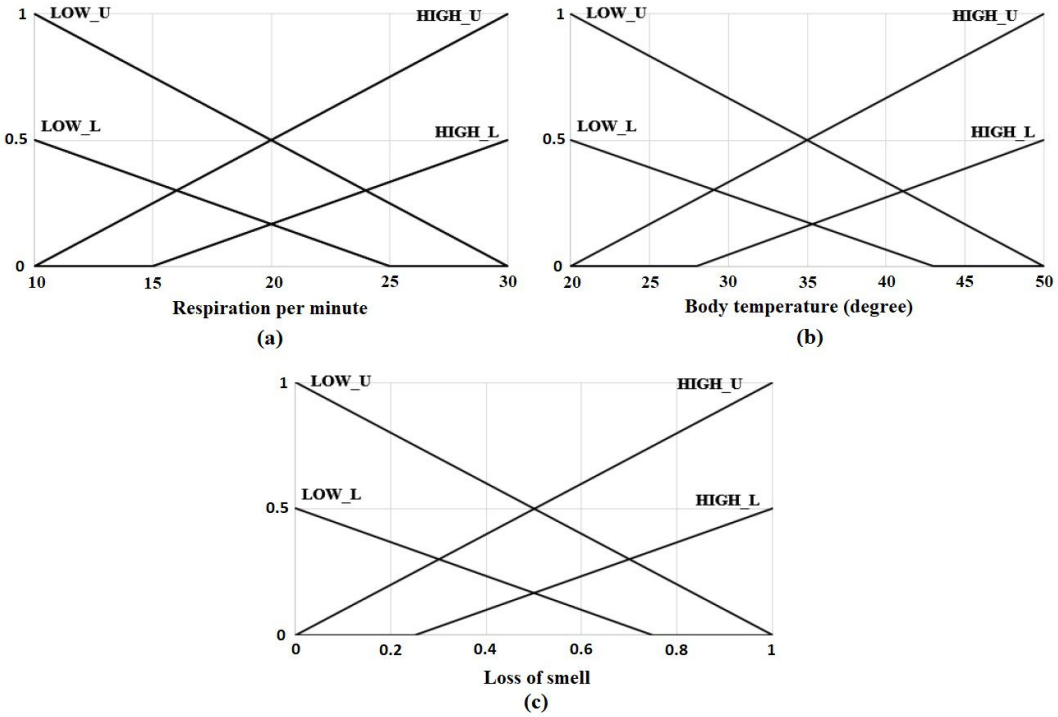

Figure 3. Input membership functions of the first unit (a) respiratory rate per minute; (b) loss of smell; (c) body temperature.

Here, NS, NB, MS, MB, MOS, MOB, SS, SB represent normal small, normal big, mild small, mild big, moderate small, moderate big, severe small, and severe big, respectively.

In the second unit, blood analysis results are evaluated. The inputs of this unit are determined as C-reactive protein (CRP), lymphocyte (LYM), and D-dimer (DD) according to physicians opinions.

CRP: The blood level of CRP, a protein produced in the liver, is used as a highly sensitive marker in the detection of many diseases in the body. As a defense response to eliminate the factor causing the infection in the body, to activate the repair mechanism and to reduce the damage in the tissues, markers such as an increase in the amount of CRP, an increase in body temperature, and an increase in the number of white blood cells appear. The normal CRP value in a healthy person is 1.0 mg/L. According to these values, the membership function is created.

LYM: Lymphocytes produced by the bone marrow are white blood cells. The main task of lymphocytes is to destroy pathogens (bacteria, viruses, parasites, etc.) that have entered the body. The amount of lymphocytes in healthy people varies between 1000 and 4800 μL. In COVID-19 patients, this value can increase to 9000 μL. According to these values, the membership function of the input regarding the lymphocyte level is established.

DD: D-dimer test is a hematology test used to investigate whether there is a disorder in the blood clotting cycle. According to the results of scientific research, there is a predisposition to coagulation disorder in COVID-19 patients [42]. The DD value in healthy people is 500 μg/L. It is seen that this value increases to 2500 μg/L in COVID-19 patients. According to these values, the membership function of the input is created.

The membership functions of the second unit, which consists of 8 rules in total, are given in Figure 4. At the second unit output, the prediction for COVID-19 is obtained as a percentage. This output is the second input of the third unit, which will produce the actual result.

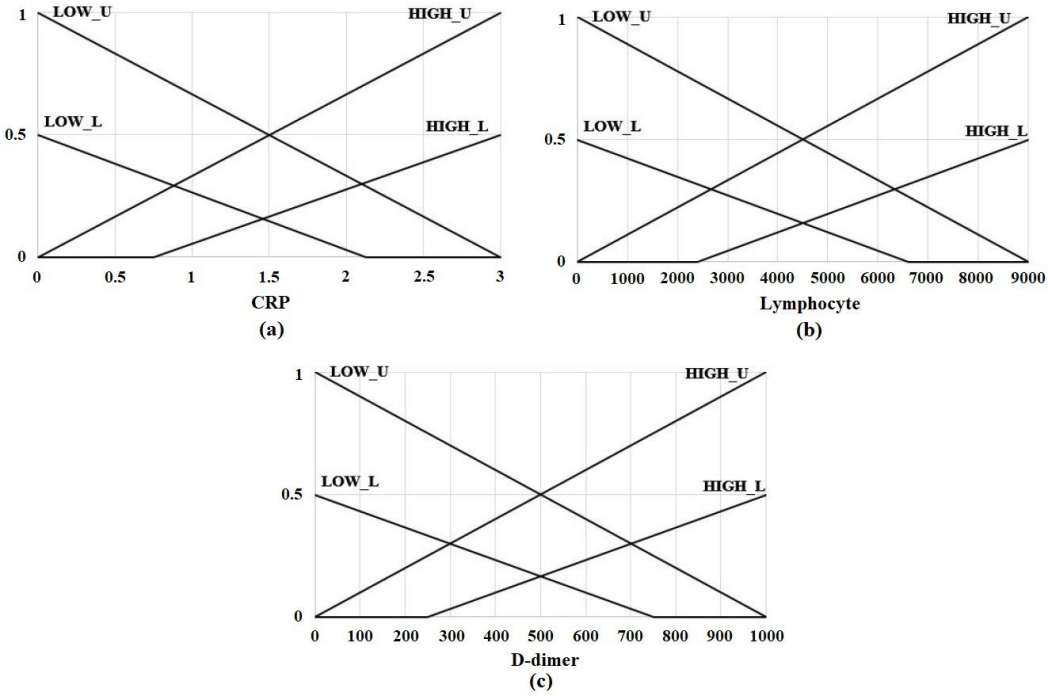

Figure 4. Input membership functions of the second unit (a) CRP; (b) lymphocyte; (c) D-dimer.

The rules of the second fuzzy unit are given below.

- IF CRP value is LOW, Lymphocyte value is LOW, D-Dimer value is LOW, THEN Result NS
- IF CRP value is LOW, Lymphocyte value is LOW, D-Dimer value is HIGH, THEN Result NB
- IF CRP value is LOW, Lymphocyte value is HIGH, D-Dimer value is LOW, THEN Result MS
- IF CRP value is LOW, Lymphocyte value is HIGH, D-Dimer value is HIGH, THEN Result MB
- IF CRP value is HIGH, Lymphocyte value is LOW, D-Dimer value is LOW, THEN Result MOS
- IF CRP value is HIGH, Lymphocyte value is LOW, D-Dimer value is HIGH, THEN Result MOB
- IF CRP value is HIGH, Lymphocyte value is HIGH, D-Dimer value is LOW, THEN Result SS
- IF CRP value is HIGH, Lymphocyte value is HIGH, D-Dimer value is HIGH, THEN Result SB

The output membership functions of the first and second units are given in Figure 5.

The first unit output and the second unit output, which are given as input to the third unit, consist of 2 membership functions and 9 rules. The output of the third unit is the final output of the system and gives the decision about the patient's condition. The membership functions of the third unit inputs are given in Figure 6.

The rules of the third fuzzy unit are given below.

- IF Output-1 value is LOW, Output-2 value is LOW, THEN system output LS

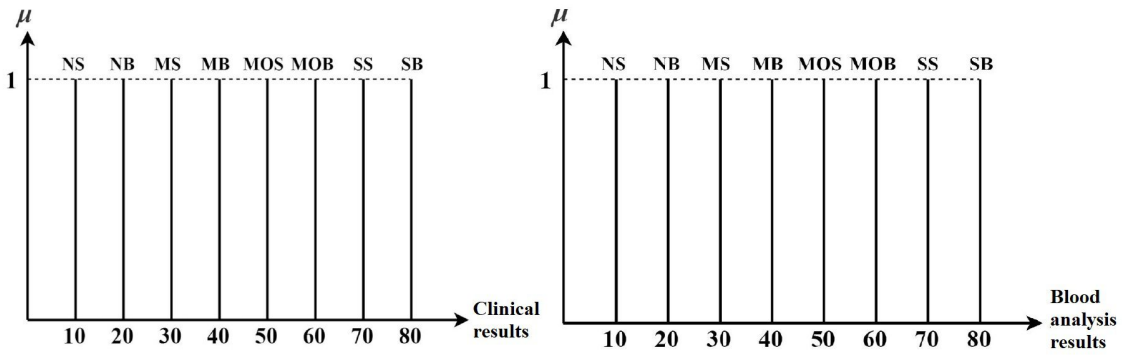

Figure 5. Output membership functions of the first and second units.

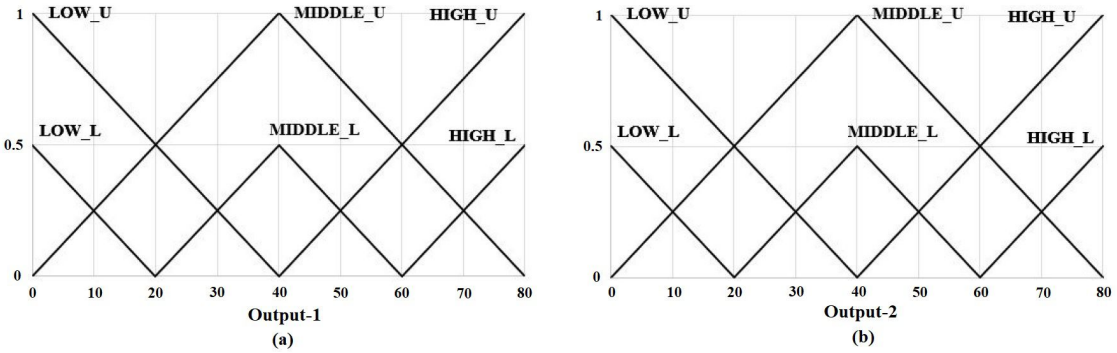

Figure 6. Input membership functions of the third unit (a) output of the first unit; (b) output of the second unit.

- IF Output-1 value is LOW, Output-2 value is MEDIUM, THEN system output LM
- IF Output-1 value is LOW, Output-2 value is HIGH, THEN system output LB
- IF Output-1 value is MEDIUM, Output-2 value is LOW, THEN system output MS
- IF Output-1 value is MEDIUM, Output-2 value is MEDIUM, THEN system output MM
- IF Output-1 value is MEDIUM, Output-2 value is HIGH, THEN system output MB
- IF Output-1 value is HIGH, Output-2 value is LOW, THEN system output HS
- IF Output-1 value is HIGH, Output-2 value is MEDIUM, THEN system output HM
- IF Output-1 value is HIGH, Output-2 value is HIGH, THEN system output HB

Here, LS, LM, LB, MS, MM, MB, HS, HM, and HB represent low small, low medium, low big, moderate small, moderate medium, moderate big, high small, high medium, and high big, respectively. The output membership function of the third unit is given in Figure 7. The percentages in the final output of the system and the suggestions to be made according to the information received from the physicians are given below.

- IF 0 < Result <= 50, THEN "The person is in good health"
- IF 50 < Result <= 60, THEN "The person should self-quarantine"

- IF 60 < Result <= 70, THEN "The person should go to the hospital"
- IF 70 < Result <= 85, THEN "The person should be given antiviral drug"
- IF 85 < Result, THEN "The person should be taken to intensive care"

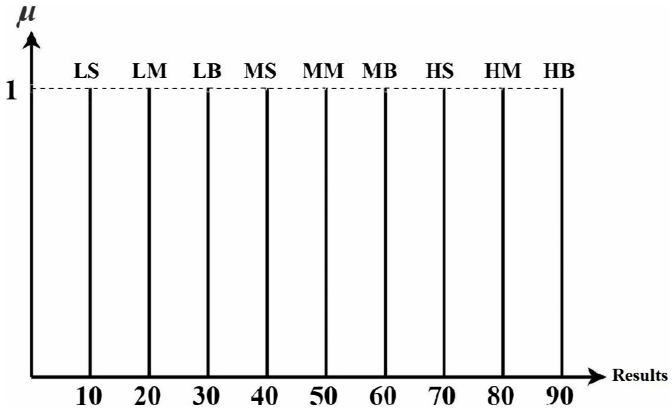

Figure 7. Output membership function of the third unit.

3. Resuls and discussion

In order to test the performance of the developed system, inputs belonging to 60 different scenarios are given to the system and outputs are obtained. These outputs are evaluated by physicians and the results are revealed regarding the performance of the system. The data is entered through the user interface given in Figure 8. The inputs, system output, and physician opinions regarding 60 scenarios are given in Table 2. In the first three columns of the table, there are respiratory rate, loss of smell, and body temperature, which are clinical examination data. In the next three columns, there are CRP, lymphocyte, and D-dimer values obtained as a result of blood tests. In the last two columns, there are the percentage results of the COVID-19 risk obtained by the system and the physician opinion evaluating this result. Incorrect results are marked in yellow.

Fifty-two of the results obtained in 60 different scenarios were found to be correct by the physicians. It was stated that eight results were wrong. In scenario 8 seen in Table 2, the system output is determined as 44.87% (the person's health condition is good). However, this person's CRP and D-dimer values are higher than normal. This result shows that people may be in contact, it is stated by physicians that they should be quarantined. In scenario number 10, CRP, lymphocyte, and D-dimer values are higher than normal. The system result is 40.62% (the person's health condition is good). It is recommended by the physicians to go to the health institution, since the lymphocyte value is high as well as the CRP and D-dimer values. In scenario 15, body temperature and lymphocyte value are high. Although the system output is 55.76% (person should self-quarantine), physicians recommended that the person go to a health institution. In scenario 29, the lymphocyte value is high. Although the system output is 37.35% (the person's health status is good), it is recommended by the physicians to go to a health institution to investigate the reason for the high lymphocyte value. Since other parameters were within normal limits, it is stated that the reason for the lymphocyte elevation is high due to a disease other than COVID-19. Likewise, in scenarios 40, 44, 49, and 54, it is concluded that the persons' health status are good despite the high body temperature, CRP, lymphocyte, and D-dimer values. When the wrong results are evaluated, it is seen that the system output is 37.35 minimum and 56.06 maximum. The average

value is found to be 46.79. These values show that the system makes errors in values between healthy and low-grade disease suspicion. In some studies in the literature, it has been observed that some biomarkers have different values and rates in COVID-19–positive and –negative states in people with diabetes, coronary artery, cerebrovascular and cardiovascular disease, hypertension, chronic respiratory disease, chronic renal disease, and high body-mass index and in pregnant women [43–46]. As can be seen after scenario 30 in the table, some input values are kept constant and their effects on the result are observed. When these results are evaluated, it is seen that the accuracy rate of the system is 86.6%.

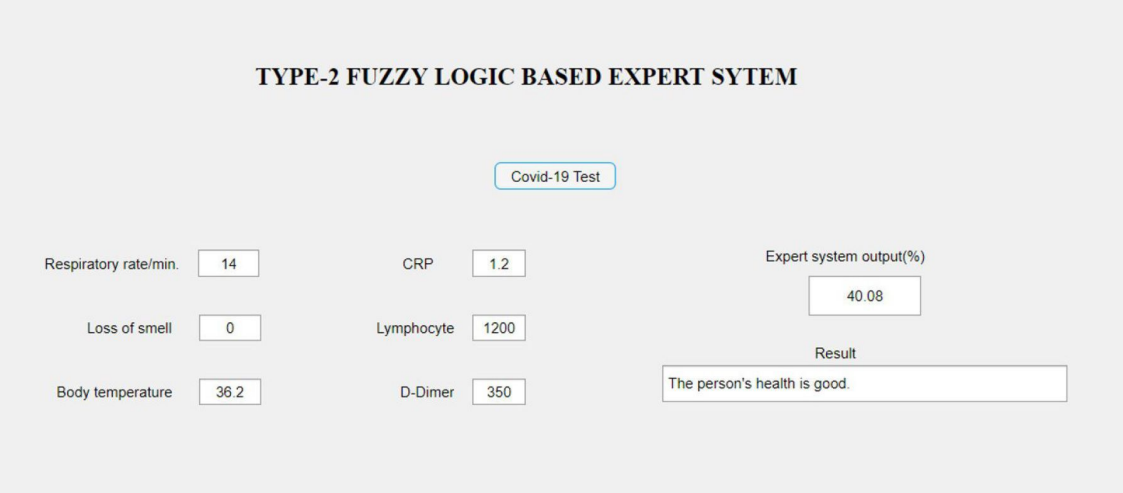

Figure 8. COVID-19 diagnosis interface.

Table 2. The system inputs and results.

	Respiratory rate	**Smell loss**	**Temperat. (°C)**	**CRP (mg/L)**	**LYM (μL)**	**D-dimer (μg/L)**	**Result (%)**	**Physician opinion**
1	14	0	36.2	1.2	1200	350	40.08	**TRUE**
2	18	0.1	36.8	2.6	2900	125	43.89	**TRUE**
3	20	0.8	38.5	3.7	3500	740	66.61	**TRUE**
4	15	0.9	39.4	4.5	1650	450	60.79	**TRUE**
5	26	0.3	37.5	8.7	4885	525	72.97	**TRUE**
6	21	0.2	38.9	5.9	6460	686	60.16	**TRUE**
7	18	0.7	41.6	6.2	5825	745	72.01	**TRUE**
8	15	0.4	36	5.6	3600	490	44.87	**FALSE**
9	28	0.9	41.8	8.7	5200	600	80.02	**TRUE**
10	16	0.1	36.5	9.3	4500	675	40.62	**FALSE**
11	24	0	37.2	2.1	8535	395	51.95	**TRUE**
12	26	0.5	38.6	3.6	3465	470	65.91	**TRUE**
13	18	0.8	39.7	9.4	4640	990	74.78	**TRUE**
14	17	0.6	40.6	5.7	6720	625	68.39	**TRUE**
15	14	0.5	41.8	3.4	4550	355	55.76	**FALSE**
16	28	0.6	40.7	5.5	7410	665	79.85	**TRUE**
17	30	0.9	41.4	8.5	8645	915	86.18	**TRUE**
18	15	0.1	36.8	5.8	3980	150	42.93	**TRUE**
19	30	0.4	37.3	7.3	6785	910	80.01	**TRUE**
20	13	0.6	38.4	1.9	3695	375	45.28	**TRUE**

Table 2. (Continued).

	Respiratory rate	Smell loss	Temperat. (°C)	CRP (mg/L)	LYM (μL)	D-dimer (μg/L)	Result (%)	Physician opinion
21	18	0.3	39.1	4.6	3560	485	62.44	**TRUE**
22	16	0	36.3	5.7	2650	500	42.54	**TRUE**
23	25	0.2	38.5	9.1	7815	690	71.28	**TRUE**
24	22	0.5	37.2	8.3	5535	860	71.6	**TRUE**
25	14	0.3	38.7	2.5	4980	235	45.06	**TRUE**
26	17	0	40.5	4.6	2750	440	50.73	**TRUE**
27	22	0.4	41.5	5.7	7915	650	75.2	**TRUE**
28	19	0.5	38.1	4.7	4825	375	73.61	**TRUE**
29	12	0.1	36	3.8	6071	340	37.35	**FALSE**
30	30	1	42	9.5	8559	940	94.43	**TRUE**
31	20	0.3	36.5	6.1	3567	480	51.93	**TRUE**
32	20	0.7	40	3.2	4789	640	67.08	**TRUE**
33	20	0.5	39.8	4.1	2456	190	60.82	**TRUE**
34	20	0.8	38.4	7.6	5832	350	72.18	**TRUE**
35	20	0.6	39.1	2.2	3794	265	60.43	**TRUE**
36	14	0.7	41.2	6.3	7195	850	69.11	**TRUE**
37	16	0.7	40.9	7.4	6384	430	70.58	**TRUE**
38	22	0.7	36.5	9.4	2745	265	68.37	**TRUE**
39	28	0.7	40.1	6.6	4967	745	79.45	**TRUE**
40	17	0.7	36.4	2.6	6974	595	56.06	**FALSE**
41	20	0.2	39.5	5.6	3864	415	56.15	**TRUE**
42	24	0.4	39.5	7.2	5754	635	73.75	**TRUE**
43	18	0.5	39.5	6.9	2478	230	61.66	**TRUE**
44	19	0.1	39.5	3.8	7723	510	49.23	**FALSE**
45	23	0.8	39.5	5.7	6142	680	76.16	**TRUE**
46	16	1	38.8	6.3	8541	255	73.11	**TRUE**
47	17	0.5	40.8	6.3	5241	505	64.89	**TRUE**
48	19	0.7	36.7	6.3	7382	275	64.18	**TRUE**
49	14	0.3	38.9	6.3	6385	765	42.70	**FALSE**
50	18	0	36.5	6.3	4752	330	43.99	**TRUE**
51	24	0.4	39.8	5.3	6250	570	68.47	**TRUE**
52	29	0.6	38.5	6.8	6250	650	79.85	**TRUE**
53	17	0.9	37.2	1.9	6250	410	61.74	**TRUE**
54	18	0.1	38.7	4.3	6250	530	47.76	**FALSE**
55	20	1	40.5	3.2	6250	180	69.17	**TRUE**
56	16	0.6	41.5	7.4	8541	250	72.35	**TRUE**
57	27	0.3	39.6	4.2	3465	250	62.02	**TRUE**
58	19	0.9	38.7	5.9	8634	250	73.38	**TRUE**
59	24	0.2	41.2	6.7	5457	250	68.48	**TRUE**
60	12	0.5	37.6	1.8	3475	250	40.91	**TRUE**

4. Conclusion

The COVID-19 disease continues to spread with various mutations and poses a threat to the health of millions of people. Early detection of the disease is extremely important for the control of the epidemic. There are 3 different approaches to the diagnosis of COVID-19. These are PCR tests, radiological image evaluation, and blood tests. In this study, a type-2 fuzzy rule-based decision support system was developed to assist health professionals in the diagnosis of COVID-19. In the system, clinical examination data (respiratory rate, loss of

smell, and body temperature) and blood analysis data (CRP, lymphocyte, D-dimer) were evaluated and the results regarding the risk of COVID-19 were revealed as a percentage. As a result of experiments with 60 different scenarios, it was determined that the system had an accuracy value of 86.6%. The developed system creates an idea about the necessity of advanced tests for the diagnosis of COVID-19.

In future works, the performance of the system will be evaluated and improved by increasing the diversity of clinical examination and blood analysis data. By weighting the data within itself, it will be ensured that the parameters with high effect value affect the result more. Actual patient data and test results will be used for performance testing of the system.

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