



An alternative approach to determination of Covid-19 personal risk index by using fuzzy logic

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Abstract

COVID-19 disease is an outbreak that seriously affected the whole world, occurred in December 2019, and thus was declared a global epidemic by WHO (World Health Organization). To reduce the impact of the epidemic on humans, it is important to detect the symptoms of the disease in a timely and accurate manner. Recently, several new variants of COVID-19 have been identified in the United Kingdom (UK), South Africa, Brazil and India, and preliminary findings have been suggested that these mutations increase the transmissibility of the virus. Therefore, the aim of this study is to construct a support system based on fuzzy logic for experts to help detect of COVID-19 infection risk in a timely and accurate manner and to get a numerical output on symptoms of the virus from every person. The decision support system consists of three different sub and one main Mamdani type fuzzy inference systems (FIS). Subsystems are Common- Serious symptoms (First), Rare Symptoms (Second) and Personal Information (Third). The first FIS has five inputs, fever-time, cough-time, fatigue-time, shortness of breath and chest pain/dysfunction; the second FIS has four inputs, Loss of Taste/Smell, Body Aches, Conjunctivitis, and Nausea/Vomiting/Diarrhea; and the third FIS has three inputs, Age, Smoke, and Comorbidities. Then, we obtain personal risk index of individual by combining the outputs of these subsystems in a final FIS. The results can be used by health professionals and epidemiologists to make inferences about public health. Numerical output can also be useful for self-control of an individual.

Keywords COVID-19 · Risk index · Fuzzy inference · Symptoms

1 Introduction

COVID-19 is the disease caused by a new coronavirus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This new virus was emerged in Wuhan, China in December 2019 and has spread all over the World in a short time. The disease was declared a global epidemic by the World Health Organization (WHO) on March 11, 2020 due to deep concern both with alarming levels of spread and severity and alarming inertia levels, [1]. Until now, there have been approximately 241 million confirmed cases, including 4.9 million deaths, reported to WHO, [2]. According to WHO, *the most common symptoms of COVID-19* detected in confirmed cases are Fever, Dry cough and

Fatigue; *serious symptoms of COVID-19* are difficulty breathing or shortness of breath, chest pain or pressure in the chest and dysfunction or confusion; and *other symptoms of COVID-19* are loss of taste or smell, nasal congestion, conjunctivitis, sore throat, headache, muscle or joint pain, different types of skin rash, nausea or vomiting, diarrhea and chills or dizziness, [3]. It was determined that the symptoms and the severity of the disease differ according to age, chronic disease, immune system or genetic factors. We see the various characteristic and situation of COVID-19 from the systematic, comprehensive reviews and meta-analysis articles, [4–8]. Recently, several new variants of COVID-19 have been identified in the United Kingdom (UK), South Africa, India and Brazil, and preliminary findings have been suggested that these mutations increase the transmissibility of the virus, [9–11]. The Delta variant, first reported in India, has been affecting currently in most of countries around the World, [12]. Studies on the variants of COVID-19 virus have been continuing and new mutants and variants are emerging.

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The severity of COVID-19 symptoms can range from very mild to severe. Some people may have only a few symptoms, and some people may have no symptoms at all, called asymptomatic. Some people may experience worsened symptoms, such as worsened shortness of breath and pneumonia. Because some of the symptoms of flu and COVID-19 are similar, it may be hard to tell the difference between them based on verbal, ambiguous and intuitive responses. On the other hand, older people are at higher risk of serious illness from COVID-19, and the risk increases with age. People with existing medical conditions may have a higher risk of serious illness. In [13], the symptoms of 46,248 COVID-19 infected patients were examined. Chronic diseases accompanying infected patients were frequently associated with 17% hypertension, 8% diabetes, 5% cardiovascular diseases and 2% respiratory diseases. In [14], it was found that of 76,993 patients infected with COVID-19, 16.37% had hypertension, 12.11% had cardiovascular disease, 7.63% had a history of smoking, and 7.87% had a history of diabetes. Asymptomatic or mildly symptomatic individuals are not aware of their contagion, causing them not to seek healthcare professional support and an increase in the number of infected people. At the same time, rapid detection, isolation, and contact tracing of community COVID-19 cases are essential measures to limit the community spread of COVID-19, [15].

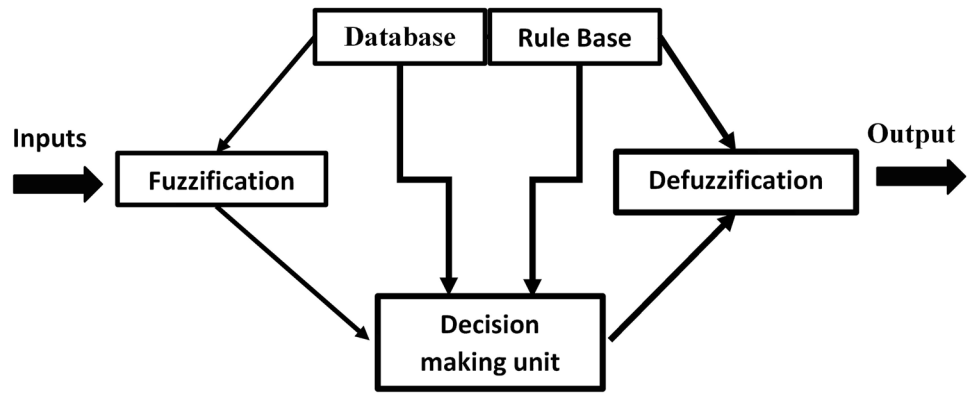
In the medical field, many of the concepts are fuzzy, making them difficult to model and objectify. Moreover, medical diagnosis is a complex process since the associated symptoms can be complex and the vague, and indirect-unknown relationships of the symptoms with the final output is very difficult to recognize and work with, [16]. Today, medical diagnosis processes are carried out with the help of computer-related technologies based on human reasoning, which is increasing day by day. These systems are mostly based on the principles of artificial intelligence and are designed not only to make a diagnosis based on symptoms but also to prescribe treatments based on it. Fuzzy modelling is deemed to be an appropriate technique for modelling the uncertainty in the medical domain, [17]. Thus, fuzzy approach is the most suitable technique for modelling and supporting the medical diagnostic decision. On the other hand, the outputs of this approach will help both to gain awareness and to be able to separate information by synthesizing and to choose the best / right among the options. Consequently, alternative studies on smart systems that provide rapid results regarding COVID-19 symptoms are very important to help detect in time whether a person has been infected or not with the virus.

Some of the researches based on the relationship between the fuzzy approach and medical field can be seen as follows. In [18], design and development of a fuzzy rule-based expert system to identify the current stage of chronic kidney disease is proposed. The development of a medical diagnostic

system using fuzzy logic is covered in [19] in order to enhance the accuracy and precision of medical diagnosis. In [20], a new Hybrid Diagnose Strategy (HDS) that consists of two classifiers; fuzzy inference engine and Deep Neural Network (DNN) is introduced for COVID-19. In the study [21], an intelligent fuzzy inference system for the primary diagnosis of COVID-19 is proposed, which infers the likelihood level of COVID-19 infection based on the symptoms. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed in [22] as a key rule for automatic COVID-19 detection from chest X-ray images based on the characteristics derived by texture analysis. In another similar study [23], a fuzzy rule-based inference system is presented to support medical diagnoses, to minimize health costs and to maximize health resources based on real data selected by medical groups in the health market. In [24], an intelligent medical diagnostic system to diagnose renal cancer is developed by using fuzzy and neuro-fuzzy techniques. A fuzzy model for a bone disease to have the right diagnosis answer is proposed in [25]. Based on the references of 173 articles from 124 journals, the development trend and application potential of fuzzy expert system in the medical field over the past two decades are reviewed in [26]. In [27], fuzzy inference systems to improve the quality of the day-by-day clinical care of type-2 diabetic patients of Anti-Diabetes Centre (CAD) of the Local Health Authority ASL Naples 1 are presented. Govindan et al. [28] developed a decision support system based on physicians' knowledge and fuzzy inference system (FIS) in order to help with the demand management in the healthcare supply chain and to break down the COVID-19 propagation. Mangla et al. [29] cover three important types of factors, risk factors, clinical factors, and miscellaneous factors, that influence the mortality rate of COVID-19 under the Mamdani-based fuzzy expert system. In [30], a fuzzy expert system, a clinical decision support system, is developed for diagnosis and prediction of chronic kidney disease.

There are many studies and researches on various issues related to COVID-19 in fuzzy environment. Al-Qaness et al. [31] presents a forecasting model to estimate the number of confirmed cases of COVID-19 in the upcoming ten days based on the previously confirmed cases recorded in China by using ANFIS. By using fuzzy logic, Boucenna et al. [32] dealt with the analysis of the spread of COVID-19 and the people likely to be affected. Chowdhury et al. [33] worked on the assessment of the effective role of various environmental conditions in the spread of COVID-19 with the help of the fuzzy inference system. Fu and Liang [34] analyzed household medical products using fuzzy logic for the COVID-19 anti-epidemic normalization. Gemmar [35] compared alternative and advanced model approaches with models proposed in literature in order to estimate the state of health and to predict patient mortality risk. Painuli et al. [36] tried to propose a fuzzy rule based system to give predictions

Fig. 1 Fuzzy Inference System



related to whether one is suffering from COVID-19 or not. Shaban et al. [37] introduced a new Hybrid Diagnose Strategy (HDS) relying on fuzzy logic and deep neural network to detect COVID-19 patients. Chowdhury et al. [38] used the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the long short-term memory (LSTM) to predict the newly infected cases of COVID-19 in Bangladesh. Castillo and Melin [39] offer a hybrid intelligent approach for forecasting COVID-19 time series combining fractal theory and fuzzy logic. Ardabili et al. [40] described a comparative analysis of MLP and ANFIS models to predict the COVID-19 outbreak. Sharma et al. [41] proposed a mediative fuzzy correlation mathematical technique providing a relation between the increments of COVID-19 positive patients in terms of the incremental transition with respect to time.

The aim of this article is to construct more practical and useable Mamdani-type fuzzy inference intelligent technique for experts to help detect of COVID-19 infection risk and to get a numerical output on symptoms of the virus from every person coming testing for COVID-19. The paper is organized as follows. In Section 2, the structure of fuzzy logic inference system is explained. The proposed method is presented in Section 3. Finally, discussion and conclusion are given in Section 4.

2 About fuzzy logic

Fuzzy Logic provides artificial intelligence methods that resemble human reasoning for handling the various type uncertainties. Fuzzy Inference Systems produce an output by processing incomplete, ambiguous fuzzy inputs of a problem that can be defined by linguistic parameters. Fuzzy inference system consists of a **fuzzification interface** which transforms the crisp inputs into degrees of match with linguistic values; a **rule base** containing a number of fuzzy IF–THEN rules; a **database** defining the membership functions of the fuzzy sets used in the fuzzy rules; a **decision-making unit** performing the inference

operations on the rules; and finally a **defuzzification interface** which transforms the fuzzy results of the inference into a crisp output (Fig. 1). More information about this concept can be found in the literature, [42–45].

A **fuzzy set** \tilde{A} in a universe of discourse X is defined by a membership function

$$\mu_{\tilde{A}} : X \rightarrow [0, 1]$$

such that it associates a real number giving a membership degree of each element x in the range $[0, 1]$. **Fuzzy numbers** are special fuzzy sets satisfying the following conditions (Fig. 2);

- Convex fuzzy set (if $\mu_{\tilde{A}}(\lambda x_1 + (1 - \lambda)x_2) \geq \mu_{\tilde{A}}(x_1) \wedge \mu_{\tilde{A}}(x_2)$ for all $\lambda \in (0, 1]$ and $x_1, x_2 \in X$, then \tilde{A} is a convex fuzzy set.),
- Normalized fuzzy set (if $Core(\tilde{A}) = \{x \in X : \mu_{\tilde{A}}(x) = 1\} \neq \emptyset$, then \tilde{A} is normalized.),
- It's membership function is piecewise continuous,
- It is defined in the real number.

There are different classes of fuzzy numbers such as Triangular, Trapezoidal, Gaussian, S-shaped, G-bell, Z-shaped, Sigmoidal fuzzy numbers, which appear in real-world

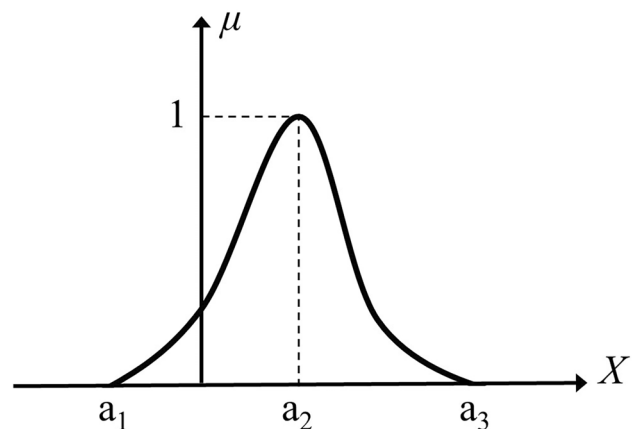


Fig. 2 Fuzzy number

problems. Fuzzy numbers are used in **fuzzification interface** of an inference system; namely, inputs are described by fuzzy numbers in the system.

A fuzzy **rule base** consist of a set of fuzzy IF-THEN rules, which are the main theme of the FIS. All other components such as membership functions are used to implement these rules in a reasonable, realistic and efficient manner. A fuzzy IF-THEN rule generally assumes the form

$$R : \text{If } x_1 \text{ is } \tilde{A}_1 \text{ AND (OR) } x_2 \text{ is } \tilde{A}_2, \text{ THEN } y \text{ is } \tilde{B},$$

where, \tilde{A}_1 , \tilde{A}_2 and \tilde{B} are linguistic variables of the FIS defined by fuzzy numbers on input and output universes, respectively. Logical operators AND, OR are known as the fuzzy intersection or conjunction (AND), and fuzzy union or disjunction (OR), respectively and defined as follows:

$$\begin{aligned} \tilde{A}_1 \text{ AND } \tilde{A}_2 &: \min \left\{ \mu_{\tilde{A}_1}, \mu_{\tilde{A}_2} \right\}, \\ \tilde{A}_1 \text{ OR } \tilde{A}_2 &: \max \left\{ \mu_{\tilde{A}_1}, \mu_{\tilde{A}_2} \right\}. \end{aligned}$$

After determining the rule base, we apply the process by which the fuzzy sets that represent the outputs of each rule are combined into a **single fuzzy number** (set), which is known as **aggregation** of rules. Aggregation could be done by different operators, such as Max, Sum or Probor. The Max operator is generally preferred when compensation between input variables is desirable. The Max operator is given by:

$$\mu_{output} = \max \left\{ \mu_{rule^1}, \mu_{rule^2}, \dots, \mu_{rule^r} \right\}.$$

The last step is the **defuzzification interface** such that output fuzzy set obtained after the aggregation step is changed to a crisp number. Defuzzification techniques used in Mamdani based fuzzy inference system are generally Center of area or centroid (CoA), Bisector of area, Small of maxima (SoM), Mean of maxima (MoM), and Largest of maxima (LoM). **The Mean of maxima** (Fig. 3) gives a defuzzified crisp value x^* as the element with the highest membership values such that the mean value of the maxima is taken when there are more than one element having maximum membership values.

All these mathematical operations explained above can be done using the MATLAB Fuzzy Logic Toolbox. In this paper, Mamdani type fuzzy inference system is used for the personal risk index of COVID-19, which is the most common in practice and in the literature. We apply **max–min inference** method for composition and minimum operator for implication. Gaussian Fuzzy numbers whose membership function is defined in (1) are used generally for the inputs and the aggregation is determined as the Max operator. As the defuzzification method, the Mean of maxima is taken for the proposed Mamdani type Fuzzy Inference Systems discussed below.

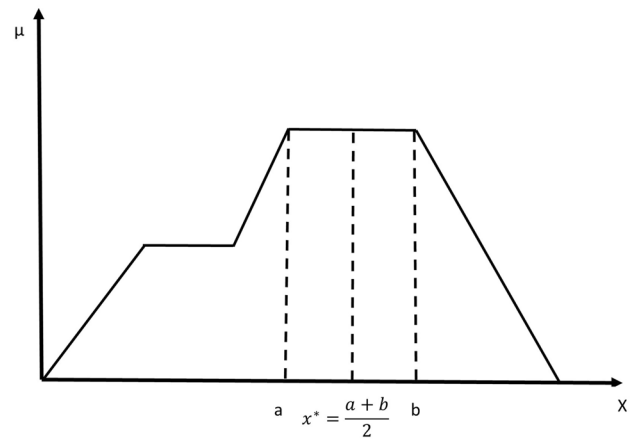


Fig. 3 The mean of maxima defuzzification

$$f(x; \sigma, c) = \exp \left(\frac{-(x - c)^2}{2\sigma^2} \right), \tag{1}$$

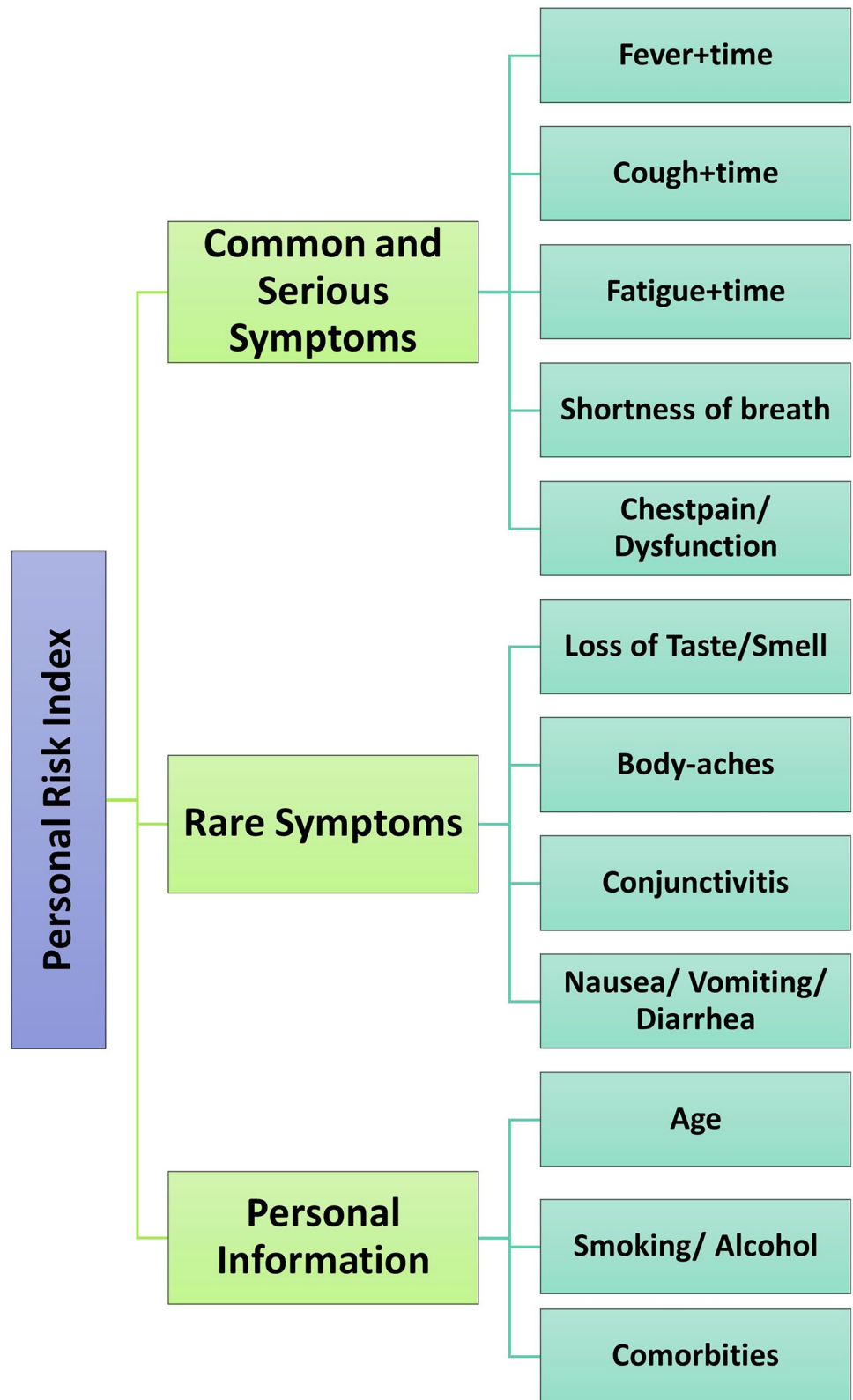
where c and σ are the parameters of the Gaussian fuzzy number, which determine the membership ship center (the peak of the curve) and the membership function width, respectively.

3 Proposed fuzzy inference system

COVID-19 is a contagious pandemic with an estimated reproduction number of 2.87, [46], and thus is spreading over multiple countries or continents. In order to know whether or not you have the virus, two types of tests are applied: molecular tests (also called PCR tests, viral RNA tests, nucleic acid tests) and antigen testing, [47, 48]. The decision on whether to test for COVID-19 can be made based on the individual applicant’s verbal expression of whether he/she has symptoms of the virus and how severe the symptoms are. Therefore, an inference system bringing out appropriate human reasoning capabilities can be developed in order to support the decision of whether to test or not, in order to further clarify the virus symptoms of the person, in order to make them numerical data and to obtain comparative results, and in order to better manage growing demand and make quick decisions. In this paper, we construct such a system based on the FIS, expert knowledge, related literature and last information from WHO for describing a personal risk index of COVID-19 pandemic. The recommended system consists of three sub-fuzzy inference systems and a final system (Fig. 4):

- The First FIS: Common and Serious Symptoms,
- The Second FIS: Rare Symptoms,
- The Third FIS: Personal Information.

Fig. 4 Structure of Proposed System



Moreover, the First FIS has three sub-fuzzy inference systems, which are the Fever-Time, Cough-Time and Fatigue-Time Mamdani-type inference systems. The first system

provides an inference on common and serious symptoms, the second gives an output on rare symptoms, and finally the third fuzzy inference system is built in which personal

Table 1 Fuzzy Classification of Input and Output Variables for Common and Serious Symptoms

		Linguistic Variables	Fuzzy Membership Functions		
Input-1	Fever-Time Range: [0 10]		Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
			[1 0 1 1]	[1 4.5]	[4.5 8.5]
			Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
Input-2	Cough-Time Range: [0 10]		Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
			[1 0 1 1]	[1 4.5]	[4.5 8.5]
			Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
Input-3	Fatigue-Time Range: [0 10]		Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
			[1 0 1 1]	[1 4.5]	[4.5 8.5]
			Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
Input-4	Shortness of Breath Range: [0 10]		Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
			[1 0 1 1]	[1 4.5]	[5 8.2]
			Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
Input-5	Chestpain/ Dysfunction Range: {0, 1}		No	Yes	-
			0	1	-
			Mild	Moderate	Severe
			Gauss2mf	Gaussmf	S-shapedmf
			[1 0 1 1]	[1.5 4.5]	[4.5 8.5]

information is collected. The Fever-Time, Cough-Time and Fatigue-Time FISs are formed to evaluate the relationship between the common symptoms and time. The inputs in the first and second fuzzy inference systems were created by evaluating the symptoms announced by WHO, [3]. The inputs in the third fuzzy inference system were determined as age, chronic disease and smoking-alcohol habits that affect the risk of COVID-19 disease transmission. The COVID-19 personal risk index is obtained by transforming the outputs of these sub-fuzzy inference systems into a single output in a final fuzzy inference system.

3.1 The first FIS: common and serious symptoms

In this FIS, we aim to get a numerical output for the common and serious symptoms of COVID-19. There are five inputs in the system; fever-time, cough-time, fatigue-time, shortness of breath and chest pain/dysfunction. The structure of the First FIS is shown in Fig. 5. Three membership functions are used for explaining linguistic variables of inputs-outputs. Paek et al. [49] formed a review study for better understanding of fatigue and also gave significant detection methods and systematic approaches to figure out the impacts and causes of fatigue such that it is explained that Karolinska sleepiness scale (KSS), a nine-point scale, has a different measure of fatigue for each point and is the most frequently used drowsiness and fatigue scale. In other study, [50], subjective and objective tests to evaluate the sense of smell, which are commonly used in patients, were discussed like Visual Analogue Scale (VAS, 0-10 scale). On the other hand, Fontana and Widdicombe [51] investigated how to measure the cough intensity or frequency and

concluded that there are many methods for measuring and assessing cough such that the choice of them, apart from practical and financial considerations, must depend on the question being asked. Therefore, we aim to collect data on the severity of pain by scoring the severity of pain in the range of 0-10, which is also called a Likert scale. The Table 1 gives the information about the linguistic variables and fuzzy membership functions of Common and Serious Symptoms. 17 rules, several of which are given in Table 2, are formed in total for the first FIS. The mean of maxima (MoM) is chosen as the defuzzification method. The Figs. 6 and 7 show the impact of the symptoms on personal risk evaluation in 3D form as a rule surface performed in MATLAB on Cough-time and Fever-time; Shortness of Breath and Chestpain/Dysfunction, respectively.

For the fever, cough and fatigue, which are common symptoms, three separate corresponding sub-fuzzy inference systems were formed to include in the system how long a person

Table 2 A Few Rules for the first FIS: Common and Serious Symptoms

Inputs					Output
Fever-T	Cough-T	Fatigue-T	S. of Breath	Chestpain/ Dysfunc.	Risk Value
Mild	Mild	Mild	Mild	No	Mild
Moderate	Moderate	Mild	Mild	No	Moderate
Mild	Moderate	Moderate	Mild	No	Moderate
⋮	⋮	⋮	⋮	⋮	⋮
Severe	Severe	Severe	Mild	No	Severe
Severe	Severe	Severe	Severe	Yes	Severe

Fig. 5 Diagram of the First FIS

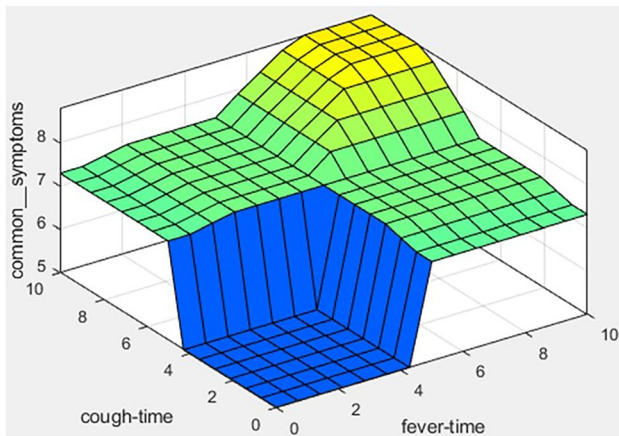
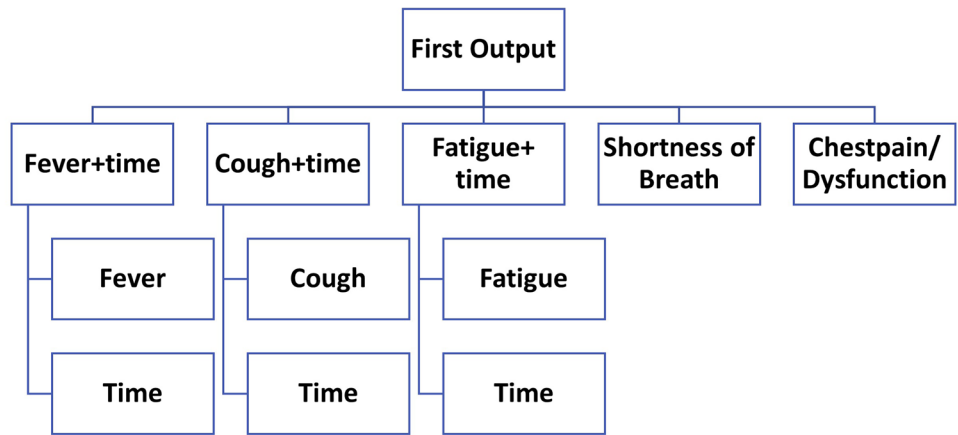


Fig. 6 Surface View of the Rule Base of the Common Symptoms (Fever-time and Cough-time)

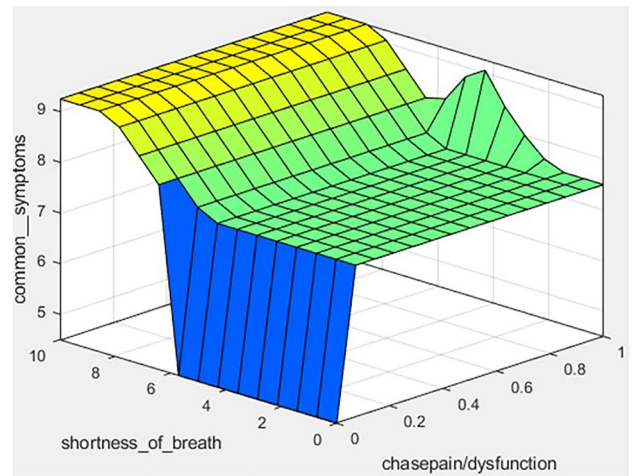


Fig. 7 Surface View of the Rule Base of the Serious Symptoms (Shortness of Breath and Chasepain/Dysfunction)

has had these symptoms. Linguistic variables and fuzzy membership functions of fever-time gathered in Table 3. Table 4 has some rules about fever-time sub-fuzzy inference system. There are 8 rules for this sub-fuzzy inference system and the defuzzification method is the mean of maximum. The surface view of the rule base of the fever-time is given in Fig. 8. Similar sub-FIS can be formed for the cough-time and

fatigue-time, which surface views of the rule base for them are shown in Figs. 9 and 10. As a result, we get the outputs for common symptoms: fever, cough and fatigue, by using the sub-fuzzy inference systems and then we reach the risk index for the common and serious symptoms by using the first FIS.

Table 3 Fuzzy Classification of Input and Output Variables for fever-time

	Linguistic Variables	Fuzzy Membership Functions		
Input-1	Fever ($^{\circ}C$) Range: [36 40]	Mild	Moderate	Severe
		Gauss2mf [0.1 36 0.4 36.6]	Gaussmf [0.33 37.7]	S-shapedmf [37.7 38.7]
Input-2	Time (Hour) Range: [0 36]	Beginning	Middle	High
		Z-shapedmf [3 12]	Gaussmf [4.5 16]	S-shapedmf [16 30]
Output	Fever-Time Range: [0 10]	Mild	Moderate	Severe
		Gauss2mf [1 0 1 1]	Gaussmf [1 4.5]	S-shapedmf [4.5 8.5]

Table 4 A Few Rules for Fever-time

Inputs		Output
Fever	Time	Fever-Time
Mild	Beginning	Mild
Moderate	Middle	Moderate
⋮	⋮	⋮
Severe	High	Severe

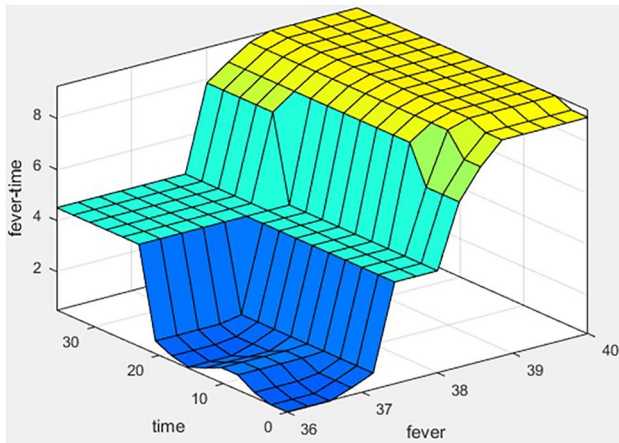


Fig. 8 Surface View of the Rule Base of the Fever-time

3.2 The second FIS: other symptoms that are less common

In this FIS, we aim to get a numerical output for the rare symptoms of COVID-19. There are four inputs in the system; Loss of Taste/Smell, Body Aches, Conjunctivitis, and Nausea/Vomiting/Diarrhea. The Table 6 explains the linguistic variables of inputs-output and the corresponding membership functions of the fuzzy inference system. In total, 32 rules are formed for the rare symptoms, several of which are given in Table 5. The mean of maximum (MOM) is chosen as the defuzzification method. Figs. 11 and 12 show the impact of the symptoms on risk evaluation in 3D form as a rule surface performed in MATLAB.

Table 5 A Few Rules for the second FIS: Rare Symptoms

Inputs				Output
Loss of Taste/Smell	Body-Aches	Conjunctivitis	Nause/Vomitting/ Diarrhea	Risk Value
Mild	Moderate	Yes	No	Moderate
Mild	Severe	No	Yes	Severe
Moderate	Moderate	No	Yes	Severe
⋮	⋮	⋮	⋮	⋮
Moderate	Severe	No	Yes	Severe
Severe	Mild	No	No	Severe

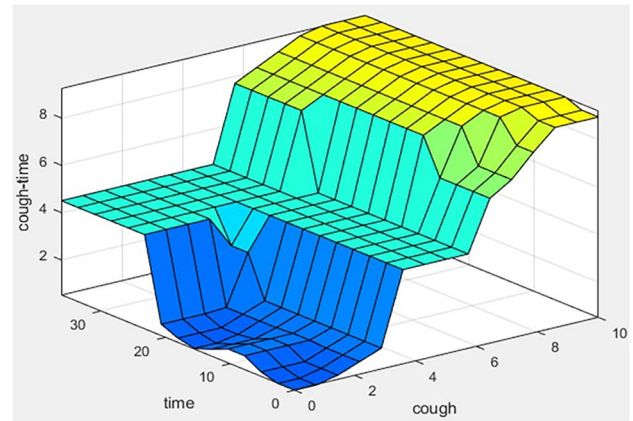


Fig. 9 Surface View of the Rule Base of the Cough-time

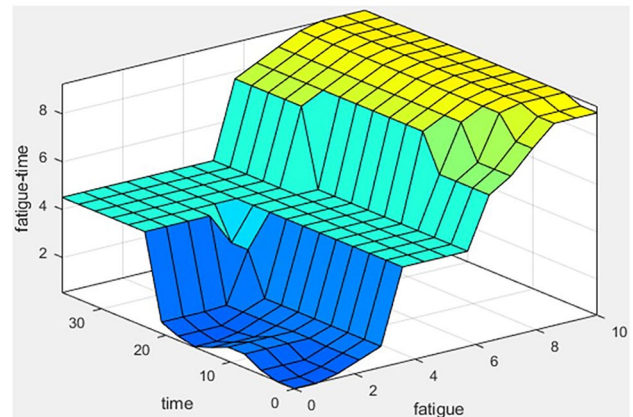


Fig. 10 Surface View of the Rule Base of the Fatigue-time

3.3 The third FIS: personal information

In this FIS, we aim to get a numerical output for the personal information affecting the risk value of COVID-19. There are three inputs in the system; Age, Smoke, and Comorbidities. The Table 7 explains the linguistic variables of inputs-output and the corresponding membership functions of the fuzzy

Table 6 Fuzzy Classification of Input and Output Variables for Rare Symptoms

-		Fuzzy Membership Functions		
Linguistic Variables		Fuzzy Membership Functions		
Input-1	Loss of Taste/Smell	Mild	Moderate	Severe
	Range: [0 10]	Gauss2mf [1 0 1 1]	Gaussmf [1 4.5]	S-shapedmf [4.5 8.5]
Input-2	Body-Aches	Mild	Moderate	Severe
	Range: [0 10]	Gauss2mf [1 0 1 1]	Gaussmf [1 4.5]	S-shapedmf [4.5 8.5]
Input-3	Conjunctivitis	No	Yes	-
	Range: {0, 1}	0	1	-
Input-4	Nause/Vomitting/Diarrhea	No	Yes	-
	Range: {0, 1}	0	1	-
Output	Risk Value of Rare Symp.	Mild	Moderate	Severe
	Range: [0 10]	Gbellmf [1.7 2 0.1]	Gaussmf [0.9 5]	Gbellmf [2 2.6 9.4]

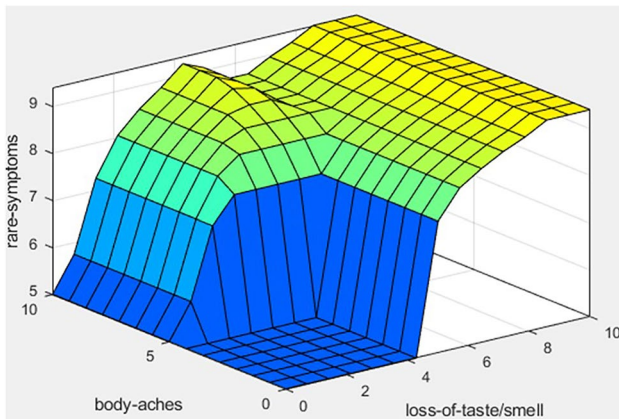


Fig. 11 Surface View of the Rule Base of Rare Symptoms (Loss of Taste/Smell and Body-Aches)

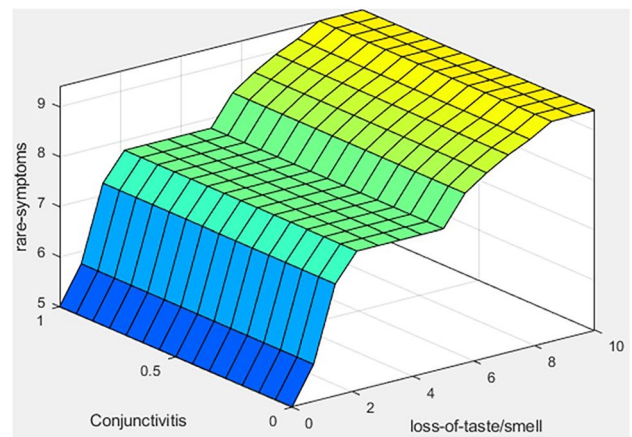


Fig. 12 Surface View of the Rule Base of Rare Symptoms (Loss of Taste/Smell and Conjunctivitis)

inference system. In total, 13 rules are formed for the personal information, several of which are given in Table 8. The mean of maximum (MOM) is chosen as the defuzzification method. Figure 13 illustrates the impact of the symptoms on risk evaluation in 3D form as a rule surface performed in MATLAB.

3.4 Personal risk index of COVID-19

Now, we can obtain the COVID-19 personal risk value by combining the fuzzy inference systems explained above. We present a final fuzzy inference system whose inputs are the

Table 7 Fuzzy Classification of Input and Output Variables for Personal Information

-		Fuzzy Membership Functions		
Linguistic Variables		Fuzzy Membership Functions		
Input-1	Age	Young	Middle-Age	Old
	Range: [18 80]	Gaussmf [5 18]	Gaussmf [5.4 40]	S-shapedmf [35 65]
Input-2	Smoke	No	Yes	-
	Range: {0, 1}	0	1	-
Input-3	Comorbidities	None	One	More than one
	Range: {0, 0.5, 1}	0	0.5	1
Output	Risk Value of Personal Info	Mild	Moderate	Severe
		Gaussmf [1.5 0]	Gaussmf [1.2 4.5]	Gbellmf [3 2.5 10]

Table 8 A Few Rules for the third FIS: Personal Information

Inputs			Output
Age	Smoke	Comorbidities	Risk Value
Young	Yes	More than one	Severe
Middle-age	No	One	Moderate
Old	No	One	Severe
⋮	⋮	⋮	⋮
Old	No	No	Severe

outputs obtained by the first, second and third fuzzy inference systems. There are 16 rules and the mean of maximum (MOM) is chosen as the defuzzification method. The Table 9, Figs. 14, 15, and 16 give the structure of the final system like the previous ones.

Then, we can discuss the performance of the proposed approach. The following questions can be asked to the person to determine the input values of the FISs in the proposed system.

- How many hours do you have a fever? (The temperature is determined by a medical thermometer)
- How many hours do you have a dry cough? And can you determine the cough severity with a decimal number between 0-10?
- How many hours do you have a fatigue? And can you determine the fatigue severity with a decimal number between 0-10?
- Can you determine the severity of shortness of breath with a decimal number between 0-10 if exist?
- Do you have a chest pain or dysfunction?
- Do you have a loss of Taste/Smell? If you have, can you determine the severity of loss of taste/smell with a decimal number between 0-10?
- Do you have Body-aches? If you have, can you determine the body ache severity with a number between 1-10?
- Do you have a Conjunctivitis?

Table 9 Fuzzy Classification of Input and Output Variables for Risk Index of COVID-19

	Linguistic Variables	Fuzzy Membership Functions		
Input-1	Com. and Ser. Symp. Range: [0 10]	Mild	Moderate	Severe
		Gauss2mf	Gaussmf	S-shapedmf
		[1 0 1 1]	[1.5 4.5]	[4.5 8.5]
Input-2	Rare Symp. Range: [0 10]	Mild	Moderate	Severe
		Gbellmf	Gaussmf	Gbellmf
		[1.7 2 0.1]	[0.9 5]	[2 2.6 9.4]
Input-3	Personal Info Range: [0 10]	Mild	Moderate	Severe
		Gaussmf	Gaussmf	Gbellmf
		[1.2 0.01]	[1.1 4.5]	[3 2.5 10]
Final Output	Personal Risk Value Range: [0 10]	Mild	Moderate	Severe
		Gaussmf	Gaussmf	Gauss2mf
		[1.5 0.1]	[1.1 4.5]	[1.3 8.4 1.2 10]

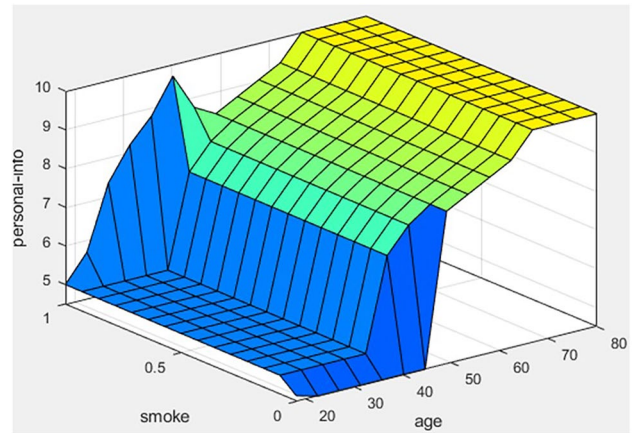


Fig. 13 Surface View of the Rule Base of the Personal Info (Age and Smoke)

- Do you have a Nausea or Vomiting or Diarrhea?
- How old are you?
- Do you use cigarettes or alcohol?
- Do you have any chronic diseases?

According to the input values obtained by the responses for these questions, we compute the outputs of the fuzzy inference systems and using the final inference system explained above, we get the final output that is the personal risk value for COVID-19 disease. The input values can be obtained by a person coming for testing, practically. Or, input information for helping the medical diagnosis can also be obtained by the patient’s practical and quick response to the questions given above under the control of a physician in a digital environment. For example, the answers given by two people to the above questions may be as in Table 10.

The outputs for the input values of the Table 10 are presented in the Table 11.

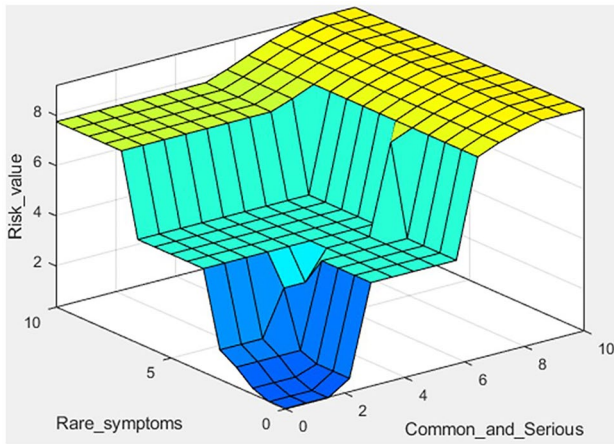


Fig. 14 Rule Base of the Risk Index (Common,-Serious and Rare Symptoms)

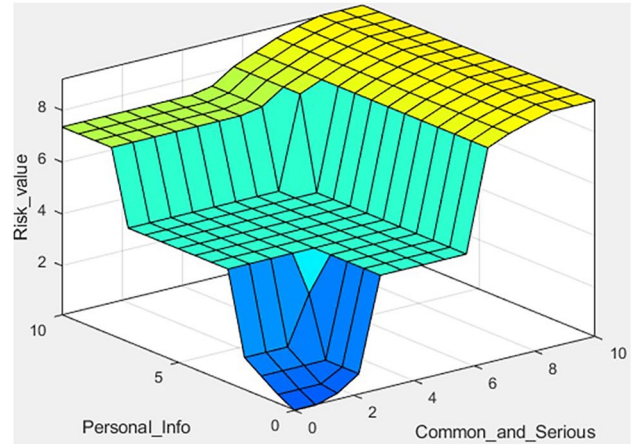


Fig. 16 Rule Base of the Risk Index (Common,-Serious and Personal Info)

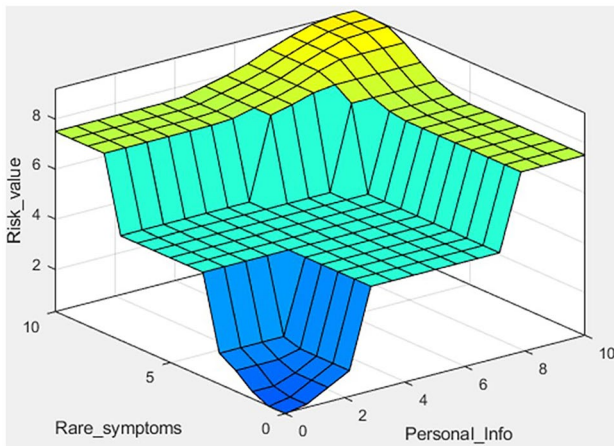


Fig. 15 Rule Base of the Risk Index (Rare Symptoms and Personal Info)

The results show that Person-1 should take the COVID-19 test and must quarantine herself/himself. Person-2 should be careful and don't need to take the test. As a result, the proposed system has a reasonable potential and usefulness and its performance is justified.

4 Discussion and conclusion

In this paper, a fuzzy logic inference system was proposed to get a numerical output on COVID-19 symptoms disease so that more specific data is obtained before testing for COVID-19. The data aimed to be obtained with the fuzzy inference system created in the study helps the segregation of individuals at risk of COVID-19 from the society. The data are obtained by evaluating the severity of symptoms mapped on Likert scale 0-10. The proposed approach has three sub-fuzzy inference system; namely, Common and Serious Symptoms, Rare Symptoms and Personal Information. In the last step, the data obtained from the sub-fuzzy inference systems are used for determining the personal risk index by means of the final inference system.

The resulting numerical data can be used by health professionals and epidemiologists to make inferences about public health. Numerical output can also be useful in terms of self-control of an individual to help him/her make decisions about seeking appropriate medical care such as Centers for Disease Control and Prevention, 2021, [52]; Columbia University 2021, [53]; and John Hopkins Medicine 2021, [54]. In other words, the proposed approach can

Table 10 Input Data of Two People

FIS type	First FIS					Third FIS		
Inputs	<i>Fever-T</i>	<i>Cough-T</i>	<i>Fatigue-T</i>	<i>Short.of.B.</i>	<i>CP/Dys.</i>			
Person-1	38.2-8	8-7	6-4	1	No			
Person-2	36.5-36	3-18	4-10	0	No			
FIS type	Second FIS				Third FIS			
Inputs	<i>Loss of T/S</i>	<i>Body-A.</i>	<i>Con.</i>	<i>N/V/D</i>	<i>Age</i>	<i>Smoke</i>	<i>Com.</i>	
Person-1	5	7	No	No	60	Yes	No	
Person-2	2	6	No	Yes	33	No	Yes (One)	

Table 11 COVID-19 Risk Index Results for Two People with Input Data in Table 10

	<i>First FIS</i>	<i>Second FIS</i>	<i>Third FIS</i>	Final FIS
Person-1	9.15	8.9	9.15	9.2
Person-2	4.5	5	4.5	4.5

be a COVID-19 Self-Checker, which is a tool to help make decisions on when to seek testing and appropriate medical care. According to experts' opinions and new studies, improvements and updates can be practically made on the rule base and inputs, as well. On the other hand, this study may be used by epidemiologists for different types of diseases and outbreaks by updating the inputs and rule base. A mobile or digital application of this study can easily be formed in digital health including digital care programs like Health Pass, HES (Life Fits Home Application) in Turkey, which is the convergence of digital technologies with health, healthcare, living, and society to improve the efficiency of healthcare delivery to make medicine more personalized and precise.

Nandal et al. [55] proposed a deep learning framework for Covid-19 detection by using chest X-ray images by first enhancing the image by using fuzzy logic which improves the pixel intensity and suppresses background noise. In addition, Al-ali et al. [22] implemented an (Adaptive Neuro-Fuzzy Inference System) ANFIS-Net based binary classification process for automatically detecting COVID-19 infection from chest X-ray images. Classifier outputs of these systems can also be used as an input-4 of our approach in the final system by referring to an X-ray image value in order to obtain more advanced and improved result for experts and physicians. This satisfies an evaluation that considers the symptoms and X-ray images together. On the other hand, in the studies [56] and [57], a novel automatic cough frequency monitoring system combining a triaxial accelerometer and a stretchable strain sensor AND the development of a machine learning-based analysis framework to connect multimodal wearable sensor data are presented for the cough and fatigue respectively. Based on these researches, we can obtain more measured and improved responses for the severity of fatigue and cough especially in the first FIS. Similarly, smell-odor sensors and other technological devices corresponding to the other inputs can be used to obtain more real and numerical results and to improve the efficiency of the proposed fuzzy approach.

Govindan et al. [28] proposed a similar decision support system based on physicians' knowledge and fuzzy inference system by considering the time as an input value for the most common symptoms. Also, users were divided

into subgroups with respect to age and chronic disease. In our system, we consider other symptoms of COVID-19 and the severity of the symptoms in addition to the time of most common symptoms in the first FIS. Shatnawi et al. [21] represent a single FIS including the symptoms of COVID-19 that have two membership functions and this system does not include age, chronic disease and smoke. Also, constructing and updating a rule base are more difficult for such system having more inputs. However, the proposed system represents a practical and updatable fuzzy approach. On the other hand, we can also consider other important preventive, inhibiting factors and concepts affecting the spread of COVID-19 like immune response, mask use, social distance, nanoparticles, environmental factors and so on. Then, we can construct a final protection index system from COVID-19 pandemic using these factors and following similar structures. We can see some of the researches investigating such factors in [29, 58–60]. Abstract mathematical and statistical approaches, which can be seen some studies in [61, 62], are another important ways for fighting COVID-19, as well.

In this paper, three membership functions have been considered for input variables where it is possible to promote the accuracy of the proposed system by increasing the number of membership functions. Another limitation is that some of the answers given by users to the questions mentioned in the Section 3.4 may not be absolutely correct.

Summary Points

What is already known on the topic?

- Reliable and comparable information on the symptoms of COVID-19 virus is important.
- Since linguistic concepts and variables are handled by physicians in deciding the diagnosis and prognosis, the medical area has a great compatibility with fuzzy logic technology and fuzzy logic is used in the medical decision-making process.

What this study added to our knowledge?

- A decision support system in fuzzy environment is being developed. This system consists of three sub fuzzy inference systems, Common-Serious symptoms, Rare Symptoms and Personal Information, and one main system combining the subsystems.
 - COVID-19 personal risk index of an individual is obtained by running the proposed inference system.
 - Results obtained from each subsystem and main system can assist healthcare professionals in a more detailed assesment of symptoms.
-

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