Fuzzy case-based reasoning approach for finding COVID-19 patients priority in hospitals at source shortage period

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ABSTRACT

In this research article, we introduced an algorithm to evaluate COVID-19 patients admission in hospitals at source shortage period. Many researchers have expressed their conclusions from different perspectives on various factors such as spatial changes, climate risks, preparedness, blood type, age and comorbidities that may be contributing to COVID-19 mortality rate. However, as the number of people coming to the hospital for COVID-19 treatment increases, the mortality rate is likely to increase due to the lack of medical facilities. In order to provide medical assistance in this situation, we need to consider not only the extent of the disease impact, but also other important factors. No method has yet been proposed to calculate the priority of patients taking into account all the factors. We have provided a solution to this in this research article. Based on eight key factors, we provide a way to determine priorities. In order to achieve the effectiveness and practicability of the proposed method, we studied individuals with different results on all factors. The sigmoid function helps to easily construct factors at different levels. In addition, the cobweb solution model allows us to see the potential of our proposed algorithm very clearly. Using the method we introduced, it is easier to sort high-risk individuals to low-risk individuals. This will make it easier to deal with problems that arise when the number of patients in hospitals continues to increase. It can reduce the mortality of COVID-19 patients. Medical professionals can be very helpful in making the best decisions.

1. Introduction

A novel COrona VIrus Disease-2019 (COVID-19) is the reason for the massive pandemic situation all over the world, which has been named and declared by World Health Organization (WHO) on January, 2020 when it reached over 2,00,000 cases around 160 countries. COVID-19 was first identified at the end of 2019 in Wuhan, China, then it spreads rapidly and caused death due to the respiratory failure or other related complications in the Wuhan city and some other countries which are in contact with Wuhan. Severe Acute Respiratory Syndrome (SARS) associated with the largest known RNA virus called corona virus emerges periodically in recent years around the world. Globally, as of 3:46 PM CET, 02 November 2020 there have been 46,403,652 confirmed cases of COVID-19, including 1,198,569 deaths received by WHO from national authorities. Day to day, the number of COVID-19 patients rate is increasing rapidly in worldwide. Many scientific and

research communities are involved in processing and developing the mathematical model to mitigate the wide spread of the COVID-19 outbreak. The available results about the spread of the infectious disease COVID-19 using previously proposed some mathematical models for analysis reveals the exponential growth rate of the affected and death cases and the requirements of the equipment for serious respiratory illness patients is abundant. The countries most affected by COVID-19 suffer from a shortage of hospital resources and have trouble allocating hospital facilities, beds, ICU facilities and ventilators for severe COVID-19 patients (Nardo et al., 2020). During this COVID-19 pandemic, hospitals have to make rapid decisions on allocation the isolation beds and respiratory equipment for the better claim patients can be done with some mathematical approaches. This kind of decisions and allocation are routine feature for the health care sectors and public authorities even when there is no pandemic situation. The expert opinion is based on a thorough study of two indicators, age and pre-

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existing diseases among patients, which helps the healthcare department to break down the spread chain of the epidemic COVID-19 (Govindan, Mina, & Alavi, 2020). For the first time, improves the practical decision-making support system for healthcare demand and supply management. The medical knowledge and Fuzzy Inference System (FIS) to reduce stress among the community. Good resource allocation in hospitals is essential for better management. Hospital resources are classified as all materials, funds, facilities and all other sources which can be used for providing services in hospitals. Hospital resource are limited resources due to the increase in demand day by day, because, everyone needs healthcare. Hospital resource allocations should weaves their accepted ethical principle into every level of decision-making for optimal health care.

- The main objective of this research article is to find a priority allocation model for COVID-19 patients.
- However, as the number of people receiving treatment for COVID-19 increases, scarcity of resources can put victims at a greater disadvantage and increase mortality.
- When providing medical assistance in this complex situation, we need to consider not only the degree of disease impact, but also other important factors that researchers are aware of.
- However, no method has yet been proposed to treat patients by taking into account all the factors and calculating the priority. In this research article, we provide a solution for this process.
- Using the method we have introduced, it is very easy to rank high-risk individuals to low-risk individuals and help provide timely medical care to COVID-19 patients. This algorithm will make it easier to deal with problems that arise when the number of hospitalized patients continues to increase.
- This will reduce the mortality rate by providing timely treatment to COVID-19 patients. It can be very useful for medical professionals to make the best decisions.

In this research article, Section 2 describes the review of literature. The Section 3 and Section 4 discuss the prominent features of CBR method and FCBR method in medical diagnosis decision-making. In Section 5, described the factors and corresponding fuzzy sigmoid functions. The proposed method and algorithm are given in Section 6. In the Section 7, case studies of COVID-19 patients are conducted. Finally, article concluded with the Section 8.

2. Literature Review

In this section, we analyze various aspects of the risk of death caused by the corona virus. Various researchers have studied the causes of death caused by the corona virus in various aspects. Goddek (2020) states that the people infected by COVID-19, those with adequate vitamin D blood serum levels are less likely to have severe symptoms caused by the corona virus. Sun, Hu, and Xie (2021) have studied the COVID-19 mortality rate based on spatial variations across the UK. Both factors such as hospital accessibility and humidity have been negatively correlated with the COVID-19 mortality rate. Unemployment status is positively correlated. The COVID-19 mortality rate due to spatial imbalance is higher than that of non-COVID-19 patients. Due to urban air pollution, especially nitrous oxide, the mortality rate of COVID-19 patients has increased (Liang et al., 2020). The number of people infected with corona in the early stages of the disease is much higher than the official figures. It maximizes the number of deaths caused by infection (Liang et al., 2020). Assaad et al. (2020) point out that among people affected by COVID-19, people with cancer have a higher mortality rate. Ozkan, Ozkean, Yalaman, and Yildiz (2021) exploring the impact of transnational variations such as climate risk, preparedness, and culture on the mortality of people infected with the corona virus. Zhang, Yao, Wang, Long, and Fu (2020) analyzed the causes of COVID-19 mortality in Wuhan and Hubei provinces and found that timely

Table 1
Analysis of COVID-19 people among different factors.

Authors	Title	Factor
Goddek (2020)	"Vitamin D3 and K2 and their potential contribution to reducing the COVID-19 mortality rate"	Vitamin D blood serum levels
Liang et al. (2020)	"Urban air pollution may enhance COVID-19 case fatality and mortality rate in the United States"	Urban air pollution
Assaad et al. (2020)	"High mortality rate in cancer patients with symptoms of COVID-19 with or without detectable SARS-COV-2 on RTPCR"	Cancer patients mortality risk (comorbidity)
Zhang et al. (2020)	"Wuhan and Hubei COVID-19 mortality analysis reveals the critical role of timely supply of medical resources"	Demand for timely supply of medical resources
Shang et al. (2020)	"Diabetes mellitus is associated with severe infection and mortality in patients with COVID-19: A systematic review and meta-analysis"	Diabetes Mellitus mortality risk (comorbidity)
Padhi et al. (2020)	"ABO blood group system is associated with COVID-19 mortality: An epidemiological investigation in the Indian population"	Mortality of ABO blood group system in COVID-19
Davies et al. (2020)	"Age-dependent effects in the transmission and control of COVID-19 epidemics"	Age-dependent effects
Sun et al. (2021)	"Spatial inequalities of COVID-19 mortality rate in relation to socioeconomic and environmental factors across England"	Spatial variation, hospital accessibility, unemployment, relative humidity
Odane et al. (2021)	"Doubled mortality rate during the COVID-19 pandemic in Italy: quantifying that is not captured by surveillance"	Lack of surveillance in the data of COVID-19 patients
Ozkan et al. (2021)	"Climate risk, culture and the COVID-19 mortality: A crosscountry analysis"	Climate risk, preparedness, culture

provision of medical resources plays an important role in patient mortality. Shang et al. (2020) pointed out that diabetic patients are more likely to be severely infected by the corona virus and cause a decrease in mortality. When examining the mortality rate of individuals with COVID-19, Padhi et al. (2020) suggested that the prevalence of blood group O is negatively related to COVID-19 death and that the prevalence of blood group B is positively correlated with COVID-19 death, such that blood type B is a detrimental factor for COVID-19 infections. Davies, Klepac, Liu, Prem, and Jit (2020) clearly pointed out that children between 10 and 19 years old are prone to asymptomatic infections, and the risk is about half that of children over 20 years old. It has been reported that in individuals affected by the disease, the severity and symptoms of the disease vary with age. (See Table 1).

2.1. Motivation and contributions

As can be seen from the literature review, many researchers have studied various factors that have led to the increase in the number of deaths from COVID-19 disease. The researchers considered many factors when conducting research, such as spatial changes, climate risks, preparedness, blood type, age, comorbidities, and the need for timely provision of drug resources. There is a research gap in analyzing the reason behind the mortality risk of the COVID-19 patients. Many of the above factors may increase the mortality rate of people infected with COVID-19. At the same time, the mortality rate is likely to increase even though COVID-19 patients do not receive proper medical care in a timely manner. Even some of the most developed countries, such as the United States, Italy, Spain, and the United Kingdom, have failed to reduce the number of deaths caused by COVID-19. The unavailability of

timely medical care for a growing number of COVID-19 patients will increase the number of deaths. Some researchers describe the results as an increase in mortality due to the lack of timely access to medical services. However, no method or algorithm is proposed to prioritize and allocate medical resources and facilities for COVID-19 patients. In this research article, we propose an algorithm to find the priority of COVID-19 patients to provide medical resources and reduce mortality.

The main contribution of this research article is proposed an algorithm to find the priority of the COVID-19 patients to allocate hospital resources and facilities during a period of resource shortage. If we make a mistake in allocating hospital resources or in an inappropriate way, it will cause many deaths in all countries. Therefore, we are in an emerging situation, looking for a model to allocate hospital facilities and beds to COVID-19 patients. Through proper distribution, we will be able to reduce the global mortality rate. Therefore, in this research paper, we introduce an algorithm that can find the priority of COVID-19 patients with eight important factors.

3. Case-Based Reasoning Approach

In recent days, medical domains experiences more knowledge on diseases, treatments and changes in types of diseases and its symptoms which leads to complex in diagnosing the disease. Case-Based Reasoning (CBR) system is a valuable method on diagnosing the disease with knowledge-based technique and to solve the problems by searching and reusing the solutions of similar cases from the past. CBR has learning capability to solve new cases and self-adaptability. CBR performs vital role in complex decision making, especially in medicinal domains with uncertainty in knowledge. Problems may occurs in diagnosis process or about optimization. Multi-agent systems can make decision by combining the ontology, knowledge-base, database to the clinical approach and the final decision with the help of CBR. This will improves the acquisition of accessible knowledge and reduces the abundance quotation of existing databases in the clinical approach (Ying, Jodl, Armella, & Kai, 2015). CBR developed from the field of cognitive science and now performs abundantly in artificial intelligence. Lamy, Sekar, Guezennec, Bouaud, and STroussi (2019) proposed a CBR system which can be automatically executed both in algorithm and in visual reasoning. A novel CBR framework with gradient accurately with the reduced set of cases (Ramos-González, López-Sánchez, Castellanos-Garzón, Paz, & Corchado, 2017). In medical domain, intensive care unit (ICU) is the most data maintain center for a single patient. Decision-making in ICU's also complex because of the large data with uncertainties. Alizadeh et al. (2019); Jia et al. (2020) cross-validation error model is more accurate for our proposed hospital allocation problem in the current epidemic situation, but the computational time is high (Wan, Li, Gao, & Li, 2019). Feng and Xiang-Yang (2018) CBR responses rapidly in all emergency situations, especially in cascading disasters (Alizadeh, Beiragh, Soltanisehat, Soltanzadeh, & Lund, 2020).

The basic experts system method depends completely on knowledge-based and it takes longer to build a single domain. To overcome this, experts system combines with CBR system which can be easily extends to different domains and free from maintaining knowledge-base for each domain (Kumar, Singh, & Sanyal, 2009). A static and non-evaluative case base can hind the accuracy of the system while solving problems. Bentaiba-Lagrid, Bouzar-Benlabiod, Rubin, Bouabana-Tebibel, and Hanini (2020) proposed a randomized CBR system with amplification technique to the strutted CBR which speeds up case retrieval supports case retention. In recent years, there are various genetically modified viruses, bacteria and other germs spreads various diseases in human community. Natural immune system requires supports from outside of the body called artificial immune system (AIS) for recover, adaptation and retention of cases. A hybrid CBR model along with AIS to identify the high density areas, alternative way of clustering cases and to improve search efficiency and to find similarities (Silva, Carvalho, & Caminhas, 2020; Alizadeh, Lund, & Soltanisehat, 2020; Zhong, Chen,

Table 2
Common symptoms among people with COVID-19.

Fever	Fatigue	Dry cough
Sore throat	Lack of appetite	Aches and pains
Difficulty breathing	Mucus/phlegm	Diarrhea

Zhou, & Hu, 2018). This will leads to the detection and diagnose of current sensation, novel coronavirus as much as earlier. An improved CBR system allows for the utilization of case-base knowledge was previously experienced for solving new cases. Case similarities can be found from a semantic-based mathematical model (Oyelade & Ezugwu, 2020).

4. Fuzzy Case-Based Reasoning Approach

A computerized decision support system gathers and analyzes data to produce comprehensive information reports rapidly. Decision support system becomes popular in the medical field for their efficacy while making decisions and it allows for timely problem-solving and more informed decision-making. A valuable method exists on diagnosing the disease with knowledge-based technique called CBR system, it can solve the diagnosed problems by searching and reusing the solutions of similar cases from the past. CBR identified and developed from the field of cognitive science, now it performs abundantly in artificial intelligence (Alizadeh & Soltanisehat, 2019, 2020; Wang, Qin, Yang, & Yuan, 2020). A CBR decision support system can enhances the diagnosis of disease rapidly, which results better solutions for the complicated problems (Sarkheyli-Hgele & Söffker, 2020). The greater implementation is the fuzzy approach integrate with CBR process is to ease the handling of imprecise and uncertain knowledge and to mimic humans for better decision making. The basic fuzzy-based CBR model was developed by Plaza, Esteva, Garcia, Godo, and Mántaras (1998) called precedent-based plausible reasoning technique to accessing the similarities between a current problem and a precedent one and to develop a relation between a precedent and the solutions. So, Tahmasebian, Langarizadeh, Ghazisaeidi, and Mahdavi-Mazdeh (2016) implemented a fuzzy-based CBR system on android platform to summarize the diseased patients. Data mining method extracts the summary of the disease and fuzzy approach measures the similarities and compares with the previously solved cases using known methods of CBR system (Satapathy, Bhateja, Udgata, & Pattnaik, 2016). A unique attempt not yet made to develop decision support system can be made by integrating FCBR, can learn from the past, and Discrete-Event Simulation (DES) can be analyzed to predict future situations in a simulated environment with proposed solutions (Kasie & Bright, 2019; Soltanisehat, Alizadeh, Hao, & Choo, 2020; Sharma, Kaushal, & Khehra, 2017).

5. Theory Basis for Prominent Factors

By clear understanding the pathway to deaths of COVID-19 patients, the true causes of death include existing treatment limitations and general commitments from patient variables such as age and comorbidities or environmental factors, such as lack of facilities, bed, staff, or equipment. Hence, at the time of shortage of hospital resources, we need to consider some important facts of COVID-19 patients like age and comorbidities, cardiovascular diseases etc (Davies et al., 2020; Rousan, Elobeid, Karrar, & Khader, 2020; Sanyaolu et al., 2020; Chandra, Verma, Singh, Jain, & Netam, 2021).

5.1. Symptoms

The seriousness of COVID-19 indications can go from extremely gentle to serious. A few people may have only a two or three manifestation, and a few people may have no manifestation at all. About a week after symptoms begin, some people may experience symptoms such as shortness of breath and worsening pneumonia. These manifestations are
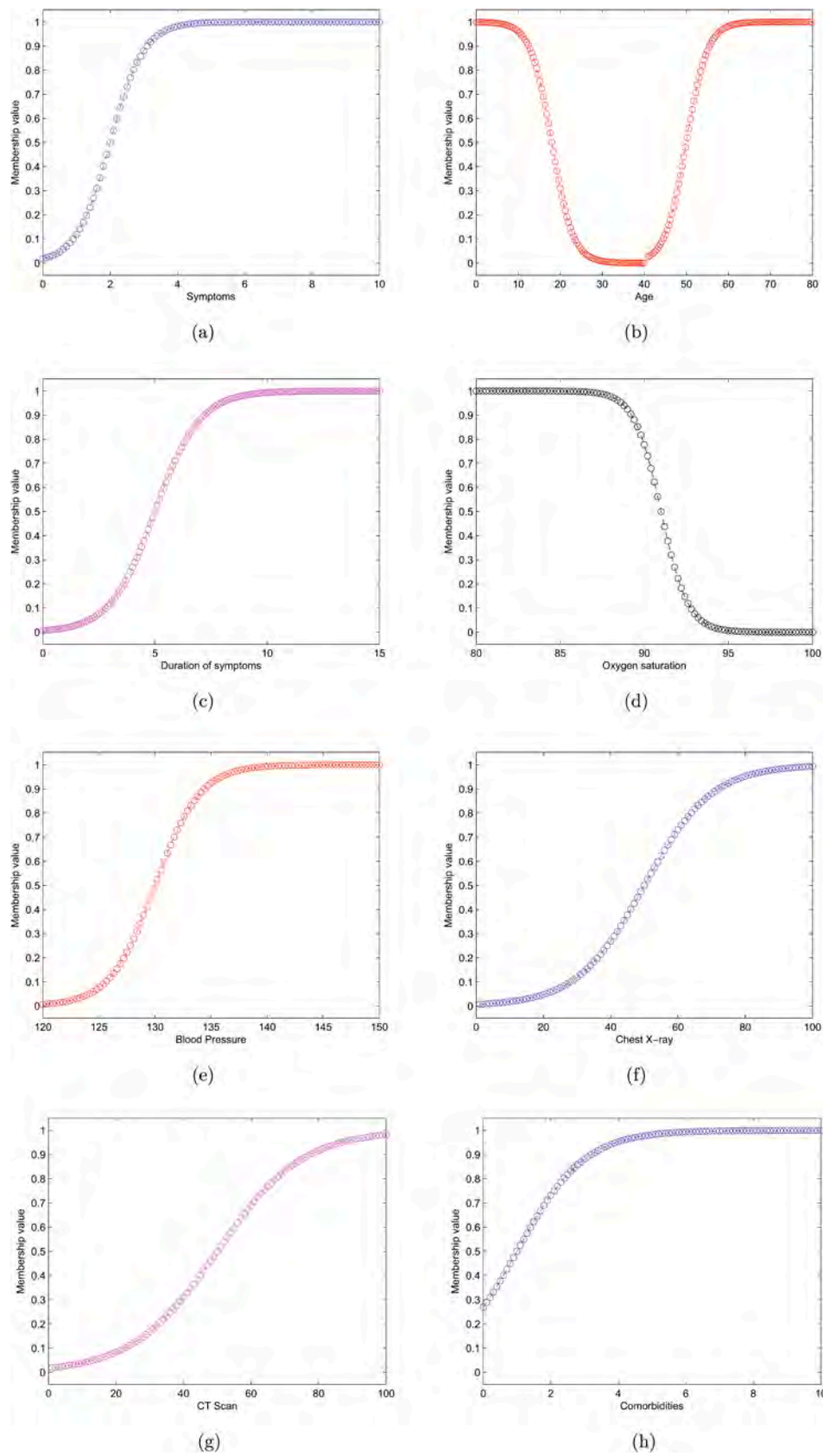
Fig. 1. Graphical view of fuzzy sigmoid function values of factors.

Table 3
Age and preference of COVID-19 patients.

Age	Preference
1–8	High
9–25	Moderate
26–40	Low
41–58	Moderate
greater than 58	High

Table 4
Duration of symptoms and preference of COVID-19 patients.

Duration of symptoms	Preference
2 days	Very Low
4 days	Low
6 days	Moderate
8 days	High
10 days	Very High
12 days	Extremely High
greater than 12 days	Extremely High

Table 5
Oxygen saturation and preference of COVID-19 patients.

Oxygen saturation SpO2		
Arterial oxygen	Level	Preference
Normal	75%-100%	Low
Below-normal	60%	Medium
Pulse ox meter readings		
Normal	95%-100%	Low
Below-normal	91%-94%	Medium
Severe	<90%	High

Table 6
Blood pressure and preference of COVID-19 patients.

Blood pressure	Level	Preference
Normal	less than (120/80)	Low
Elevated	(120–129/ <80)	Medium
Stage 1	(130–139/80–89)	High
Stage 2	(140 or >140/90 or >90)	Very High

normally mellow and start continuously. The following symptoms (Table 2) are the most common symptoms among people with COVID-19.

Mathematically, we are considering the symptoms of COVID-19 as one of the main factors in evaluating patient priority. The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1a).

X={Fever, Fatigue, Dry cough, Sore throat, Lack of appetite, Aches and pains, Difficulty breathing, Mucus/phlegm, Diarrhea}

$$\mu_{(x)} = \begin{cases} \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } x \in X \\ 0 & \text{if } x \notin X \end{cases}$$

5.2. Age

COVID-19 can prompt young and middle-aged adults to be hospitalized and even die. COVID-19 has caused the most extreme medical problems for grown-ups beyond 60 years old – with especially lethal outcomes for those 80 years and more established. We are considering age as one of factor in the evaluation of priorities of the patients (Table 3). The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1b).

$$\mu_{(x)} = \begin{cases} \dfrac{1}{1 + e^{\beta(x-\alpha)}} & \text{if } 0 < x < 40 \\ \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } 41 < x < 80 \\ 1 & \text{if } x > 80 \end{cases}$$

5.3. Duration of symptoms

The infection can cause a range of indications, extending from gentle sickness to pneumonia. Two to fourteen days after the appearance, the signs and manifestations of COVID-19 may appear. This time after presentation and before having manifestations is known as the brooding period.

Mathematically, we are considering duration of symptoms of COVID-19 in days (Table 4). The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1c).

$$\mu_{(x)} = \begin{cases} 0 & \text{if } x < 2 \\ \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } 2 < x < 14 \\ 1 & \text{if } x > 14 \end{cases}$$

5.4. Oxygen saturation

Oxygen deficiency may occur at different stages of COVID-19. Not every person affected by COVID-19 will have low oxygen issues. Generally, people who are more likely to have oxygen problems are people with lung and heart disease, obesity, as well as people who actively smoke.

Basically, the breathing rate is regularly guided by counting the rising or falling events of the chest every second. The oxygen in ordinary blood vessels is about 75–100%. Masses below 60% usually prove the need for supplemental oxygen. A normal heartbeat oximeter reading is usually 95–100% and below 90% is considered inferior (Table 5).

Mathematically, we are considering oxygen saturation as one of important factor in the evaluation of priority of the patients. The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1d).

$$\mu_{(x)} = \begin{cases} \dfrac{1}{1 + e^{\beta(x-\alpha)}} & \text{if } 95 < x < 100 \\ 1 & \text{if } x < 90 \end{cases}$$

5.5. Blood pressure

More and more data show that patients with high blood pressure are at higher risk of contracting COVID-19 and have difficulties. A survey of early information from China and the United States shows that hypertension is the most prevalent pre-existing condition between hospitalized patients, affecting 30–50% of patients (Table 6). Mathematically, we are considering blood pressure in the evaluation of priorities of the patients. The following fuzzy sigmoid function represents the membership values of the factor blood pressure (Fig. 1e).

$$\mu_{(x)} = \begin{cases} \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } (120/80) < x < (130 - 139/80 - 89) \\ 1 & \text{if } x > (140 \ or > 140/90 \ or > 90) \end{cases}$$

5.6. Findings at chest X-ray

The radiological point of view utilized for ailment evaluation and development is extremely useful. It allows us to quickly understand the psychopathology of the disease cycle. From the third day of symptom, chest X-ray (CXR) examination is usually performed. In the many case, the score of ground glass opacity helps determine the extent of infection

Table 7
Findings at chest X-ray and preference.

Finding chest X-ray	Severity score	Preference
No involvement	0%	Very Low
Mild	1–25%	Low
Moderate	26–49%	Medium
Severe	50–75%	High
Critical	> 75%	Very High

Table 8
Finding at CT scan and preference.

Findings at CT scan	Severity score	Preference
No involvement	0%	Very Low
Mild	1–25%	Low
Moderate	26–49%	Medium
Severe	50–75%	High
Critical	> 75%	Very High

Table 9
Comorbidities among people with COVID-19.

Hypertension	Cardiovascular diseases	Diabetes
Obesity	Asthma	Liver diseases
Renal diseases	Malignancy	Chronic obstructive pulmonary disease

in each lung. As the days go by, consolidation helps to track the involvement of each lung. The last seriousness score of patients, evaluated by adding the score of each lung. The severity score range from 0 to 4 (0 = no involvement; 1 = <25% Mild; 2 = 25–50% Moderate; 3 = 50–75% Severe; 4 = >75% Critical).

Mathematically, we are considering finding chest X-ray (Table 7) as one of important factor in the evaluation of priority of the patients. The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1f).

$$\mu_{(x)} = \begin{cases} 0 & \text{if } x = 0 \\ \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } 1 < x < 75 \\ 1 & \text{if } x > 75 \end{cases}$$

5.7. Findings at CT scan

The seriousness of the lung inclusion on the CT relates with the seriousness of the infection. The seriousness on CT can be assessed by visual evaluation. This idea is the most straightforward approach to score the seriousness. Ground glass opacity (GGO) design is the most widely recognized finding in COVID-19 diseases. They are normally multifocal, bilateral and marginal, but at the beginning of the disease, GGO may appear as a single focal injury, most commonly in the second isokinetic projection of the right lung. The severity score range from 0 to 4 (0 = no involvement; 1 = <25% Mild; 2 = 26–49% Moderate; 3 = 50–75% Severe; 4 = >75% Critical).

Mathematically, we are considering finding at CT scan (Table 8) as one of important factor in the evaluation of priority of the patients. The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1g).

$$\mu_{(x)} = \begin{cases} 0 & \text{if } x = 0 \\ \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } 1 < x < 75 \\ 1 & \text{if } x > 75 \end{cases}$$
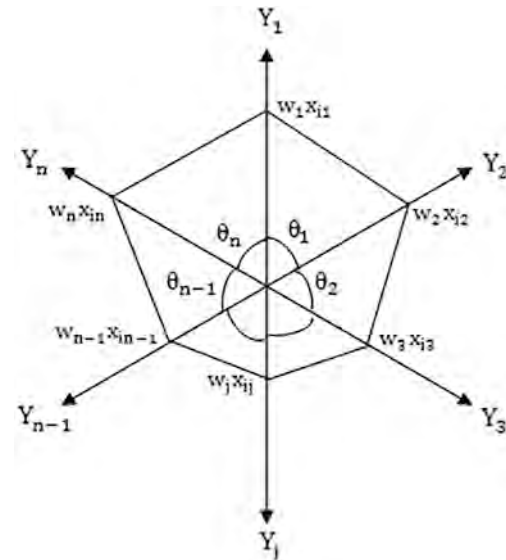

Fig. 2. Cobweb solution model.

5.8. Comorbidities

The other health conditions like hypertension, cancer, diabetes and lung disease, etc are also included the priority evaluation. The following Table 9 lists the comorbidities of the COVID-19 patients.

Mathematically, we are considering comorbidities of COVID-19 as one of major factor in the evaluation of priority of the patients. The following fuzzy sigmoid function represents the membership value of the factor (Fig. 1h).

X={Hypertension, cardiovascular diseases, diabetes, obesity, asthma, liver diseases, chronic obstructive pulmonary disease, malignancy, renal diseases}

$$\mu_{(x)} = \begin{cases} \dfrac{1}{1 + e^{-\beta(x-\alpha)}} & \text{if } x \in X \\ 0 & \text{if } x \notin X \end{cases}$$

6. Fuzzy CBR approach with Cobweb Model

Many diseases have separate methods to diagnose like MRI, ultrasound etc., but the similarities of the resulted data can be identified by using some techniques as CBR, artificial neural network, Bayesian network and decision tree. Sharaf-El-Deen, Moawad, and Khalifa (2014) presents a hybrid CBR approach for medical diagnosis to improve the accuracy of CBR technique and some methods are implemented with CBR systems. In future, android platforms will be the leading tool at the point of medical care for the humans. A fuzzy-based CBR approach with the knowledge management and sharing with experts' frame-work enhances the point of care. Here we introduced a decision model to allocate priority of the patients and enhance the care of patients. As mentioned in Section 5, we need to consider some important factors in the model. At the same time, we need to reduce the influence of a particular factor in decision-making. For example, common determinant comorbidities have a great influence on other factors. But we need to address the high impact of comorbidities on other factors, such as age and duration of symptoms, blood pressure, oxygen saturation, etc. We use the cobweb model (Agliari, Naimzada, & Pecora, 2017; Lin, Heo, & Hong, 2018; Lundberg, Jonson, Lindgren, Bryngelsson, & Verendel, 2015) to overcome the high influence of one factor on other factors. The cobweb model effectively provides a solution by avoiding the high influence of a specific factor (Fig. 2). The proposed model proposes a solution in which all factors in the result are considered.

Here, $\{y_1, y_2, ..., y_n\}$ - set of factors, $\{w_1, w_2, ..., w_n\}$ - weights or
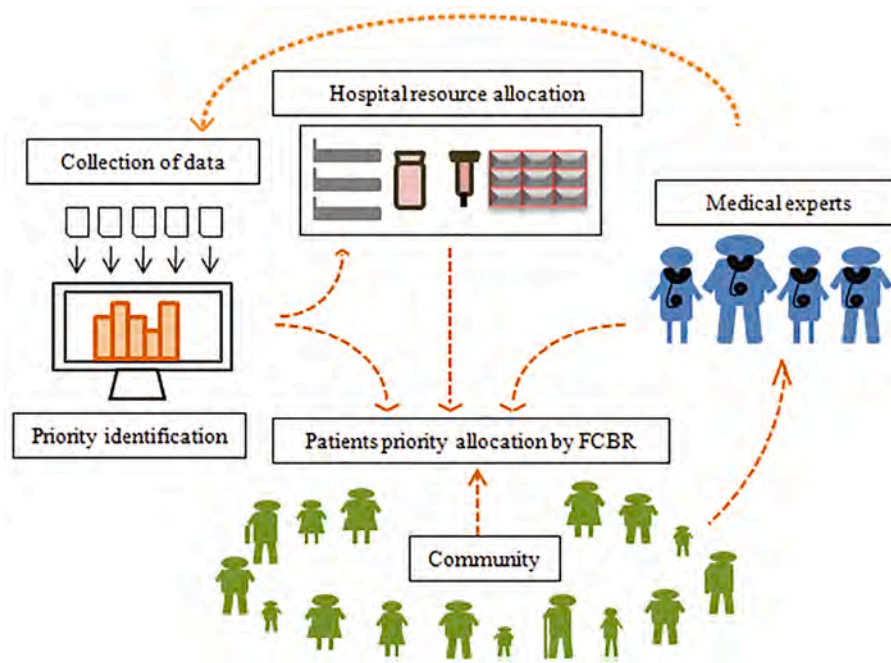
Fig. 3. Priority allocation model by fuzzy CBR.

importance degree of factors, $\{P_1, P_2, \ldots, P_m\}$ - list of patients involved in the evaluation, $\{\theta_1, \theta_2, \ldots, \theta_n\}$ - angle between adjacent factors. Here, all θ_n are considered as equal angle.

6.1. Proposed Method

Steps:

1. Consider P_i- the finite set of cases $\{P_1, P_2, \ldots, P_m\}$, where $i = \{1, 2, \ldots, m\}$ and m is the number of COVID-19 cases.
2. Consider y_j- the finite set of factors $\{y_1, y_2, \ldots, y_n\}$ for evaluate the preference of COVID-19 patients. Here, $j = \{1, 2, \ldots, n\}$ and n is the total number of factors.
3. Define the membership values by fuzzy sigmoid function

$$f(x_{ij}) = sigmf(y, [\alpha \quad \beta]). \tag{1}$$

   Where x_{ij} - fuzzy sigmoid membership value of P_i under y_j
4. Determine all the factors value of each COVID-19 patients.
5. Determine cobweb area model solution of each COVID-19 patients.

$$Ca(x_{ij}) = \frac{1}{2}w_1 x_{i1} \ w_2 x_{i1} sin\frac{2\pi}{n} + \frac{1}{2}w_1 x_{i2} \ w_2 x_{i2} sin\frac{2\pi}{n} + \ldots + \frac{1}{2}w_1 x_{in} \ w_2 x_{i1} sin\frac{2\pi}{n} \tag{2}$$

6. Find normalized values of $Ca(x_{ij})$.

$$NCa(P_i) = \frac{Ca(x_{ij})}{\underset{j \in nCa(x_{ij})}{Max}} \tag{3}$$

7. Sort $NCa(P_i)$ values.

6.2. Algorithm

Algorithm of the proposed Fuzzy CBR approach.

Setting parameters α and β based on experts opinion

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if $\alpha = a$
$\beta = b$
a and b are random real number $\in [-10, 10]$
for $1 < i < m$
for $1 < j < n$
i = number of COVID-19 patients
j = number of factors in the analysis
m and n are random number $\in [1, \infty]$
$f(x_{ij}) = \dfrac{1}{1 + exp^{-\beta(y_j - \alpha)}}$ right shoulder sigmoid function
$f(x_{ij}) = \dfrac{1}{1 + exp^{\beta(y_j - \alpha)}}$ left shoulder sigmoid function

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Cobweb area model solution of each patient

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find $f(x_{ij}) \leftarrow d_{ij}$
determine $Ca(P_i)$
$NCa(P_i) \leftarrow$ normalize $Ca(P_i)$
for all i
sort $NCa(P_i)$ by ascending order
$max\{(NCa(P_i))\} \leftarrow$ sort $NCa(P_i)$

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7. Case Study

The quality of CBR can be enhanced when it combines with other

Table 10
Sigmoid functions of factors and value of variables.

Factors	Sigmoid function	Variables β and α
Symptoms (Y1)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 5$ and $\alpha = 5$
Age (Y2)	$\dfrac{1}{1 + e^{\beta(x-\alpha)}}$	$\beta = -0.4$ and $\alpha = 18$
	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 0.4$ and $\alpha = 55$
Duration of symptoms (Y3)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 1$ and $\alpha = 5$
Oxygen saturation (Y4)	$\dfrac{1}{1 + e^{\beta(x-\alpha)}}$	$\beta = -1.25$ and $\alpha = 91$
Blood pressure (Y5)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 0.08$ and $\alpha = 50$
Findings at chest X-ray (Y6)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 0.1$ and $\alpha = 50$
Findings at CT scan (Y7)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 0.08$ and $\alpha = 50$
Comorbidities (Y8)	$\dfrac{1}{1 + e^{-\beta(x-\alpha)}}$	$\beta = 1$ and $\alpha = 1$

Table 11
Factor values of the COVID-19 patients.

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8
P1	3	63	4	84	130/80	Severe	Severe	Nil
P2	2	8	3	98	100/60	Mild	Mild	Nil
P3	3	52	2	96	150/100	Mild	Mild	Diabetes,
P4	4	52	5	92	160/110	Moderate	Moderate	Diabetes
P5	4	60	4	98	130/90	Mild	Mild	Nil
P6	3	24	3	97	90/70	Mild	Mild	Nil

artificial intelligence techniques. The inclusion of fuzzy logic with CBR was one of such great approach to ease the handling of uncertain knowledge and to imitate humans for the best decision making. Diagnosing disease using fuzzy CBR decision support system is more effective and with the knowledge management and sharing with experts' framework enhances the point of care. First the effective parameters were extracted using data mining method from the previously prepared structured discharge summary for patients, then by sharing with experts' frame-work and data mining method for the weights of the proposed parameters. At last, fuzzy approach measures the similarities of the disease and compares it with the past cases using known methods of CBR system to extracts the summary of the disease.

Here, we considering eight factors in the allocation of hospital resource allocation (Fig. 3). The proposed fuzzy CBR approach, determined the membership value of each factor by sigmoid function. The Table 10 described the type of sigmoid functions of factors and value of

variables. The original factor values of the COVID-19 patients is given in Table 11.

The COVID-19 shows an increase in the number of cases, and the risk of extreme infections becomes more serious with age. We found that people under the age of 20 are generally half as vulnerable as those over the age of 20. After clearly understanding the susceptibility of the age group to individual infections reported by Davies et al. (2020), we set the parameter level as (1–8) and (58 and above) with high priority, (9–25) and (41–58) with moderate priority, (25–40) with low priority level. The clinical society recommends using CXR as a first-line imaging device and storing other parts in chest CT as a proof of the difference between the common bright spots of COVID-19 pneumonia in some cases (Cozzi et al., 2020). In our proposed model, priority of the CXR like gradually increased from (0–100). Various studies have shown that CXR may not have the indicative strength of CT, but in fact it has the function of responding to the pandemic (Majidi & Niksolat, 2020). We set the priority of the CT based on the severity score, gradually increased from (0–100). The other factors oxygen saturation and blood pressure priority level also set by experts knowledge.

7.1. Results

The following Table 12 given the fuzzy sigmoid values of patients.
The cobweb area model solution of COVID-19 patients is given in Table 13.
The cobweb area model solution of COVID-19 patients is given as
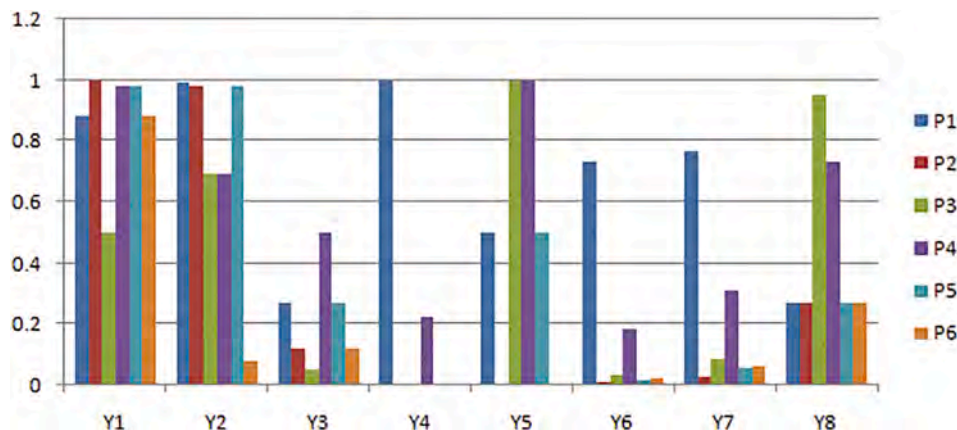
Table 12
Fuzzy sigmoid values x_{ij} of the COVID-19 patients.

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8
P1	0.8808	0.9945	0.2689	0.9998	0.5000	0.7311	0.7685	0.2689
P2	0.9997	0.9820	0.1192	0.0002	0.0000	0.0110	0.0287	0.2689
P3	0.5000	0.6900	0.0474	0.0019	1.0000	0.0293	0.0832	0.9526
P4	0.9820	0.6900	0.5000	0.2227	1.0000	0.1824	0.3100	0.7311
P5	0.9820	0.9820	0.2689	0.0002	0.5000	0.0180	0.0573	0.2689
P6	0.8808	0.0832	0.1192	0.0006	0.0000	0.0219	0.0666	0.2689

Table 13
Cobweb area model solution of the COVID-19 patients.

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8
P1	0.0389	0.0440	0.0119	0.0442	0.0221	0.0323	0.0340	0.0119
P2	0.0442	0.0434	0.0053	0.0000	0.0000	0.0005	0.0013	0.0119
P3	0.0221	0.0305	0.0021	0.0001	0.0442	0.0013	0.0037	0.0421
P4	0.0434	0.0305	0.0221	0.0098	0.0442	0.0081	0.0137	0.0323
P5	0.0434	0.0434	0.0119	0.0000	0.0221	0.0021	0.0053	0.0119
P6	0.0389	0.0037	0.0053	0.0000	0.0000	0.0010	0.0029	0.0119

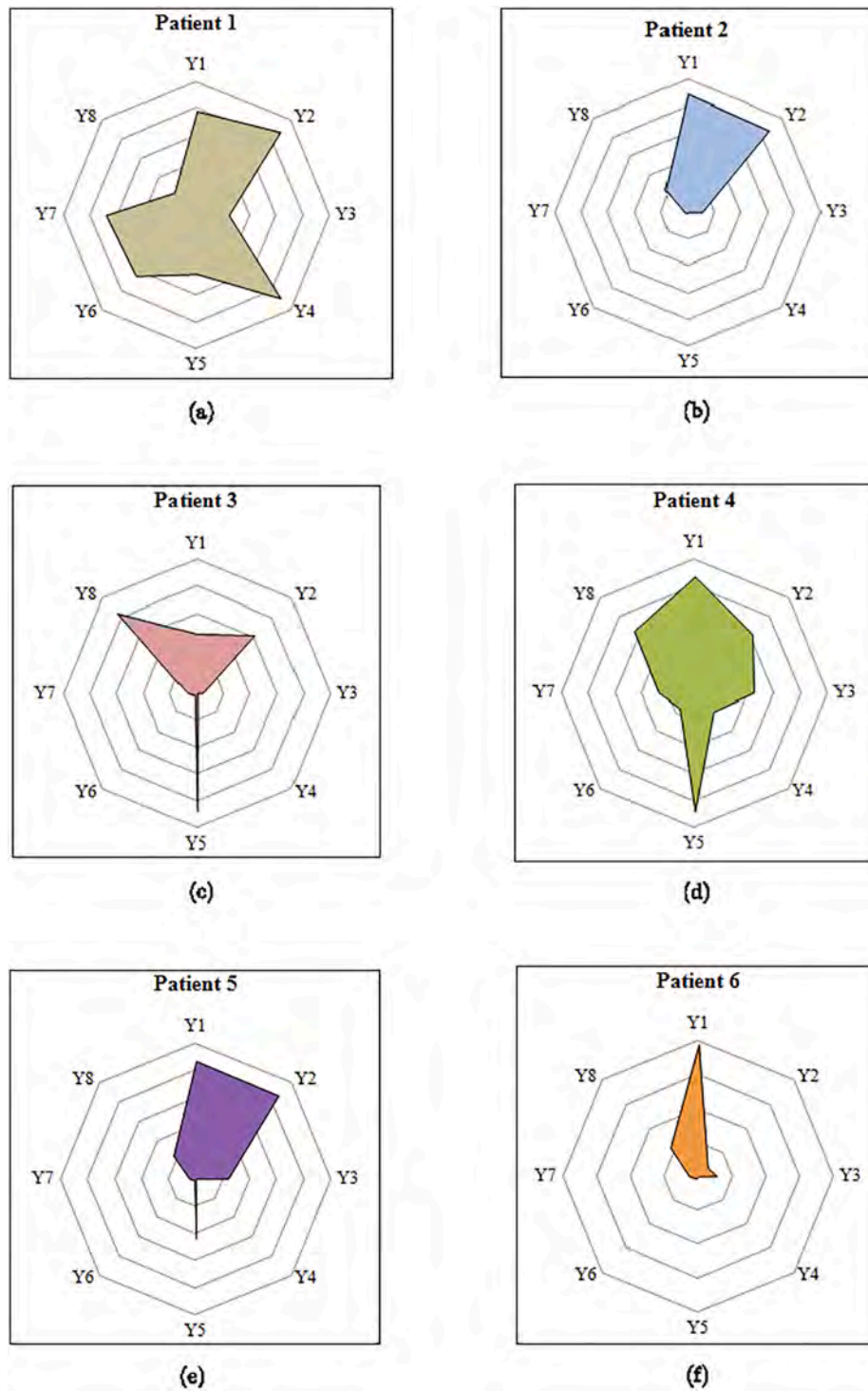**Fig. 4.** Fuzzy sigmoid values.

Fig. 5. Cobweb model solution of COVID-19 patients.

follows:

$$Ca(x_{ij}) = \{0.2392, 0.1065, 0.1460, 0.2041, 0.1360, 0.0637\} \tag{4}$$

$$\underset{j \in nCa(x_{ij})}{Max} = 0.2392 \tag{5}$$

The normalized cobweb area model solution of COVID-19 patients is given as follows:

$$NCa(P_i) = \{1.0000, 0.4452, 0.6105, 0.8532, 0.5686, 0.2663\} \tag{6}$$

Sort $NCa(P_i)$ values in descending order.

$$\begin{aligned} Sort\ (NCa(P_i)) = \{&1.0000 - P1, 0.8532 - P4, 0.6105 - P3, 0.5686 \\ &- P5, 0.4452 - P2, 0.2663 - P6\} \end{aligned} \tag{7}$$

7.2. Discussion

The fuzzy sigmoid values of each factor is given in Fig. 4. The Fig. 5a–f shows the individual cobweb area solution of all COVID-19 patients. The Fig. 6 shows that the combined cobweb area solution of
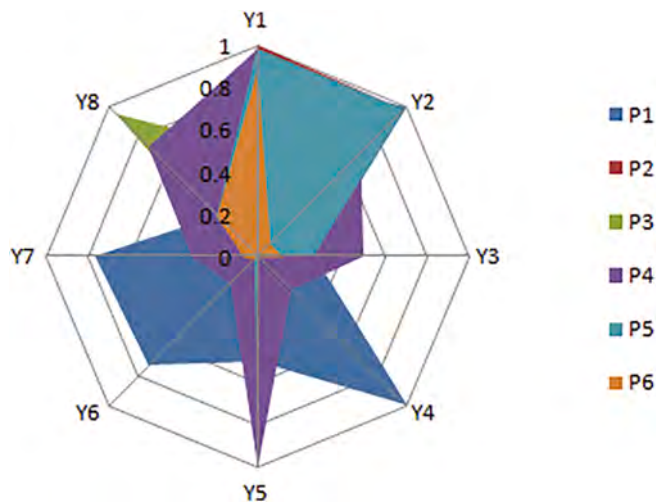
Fig. 6. Combined Cobweb model solution.

Table 14
Final priority list of patients.

Patient list	priority	Significant factor
P1	1	symptoms, age, oxygen saturation, chest X-ray, chest CT
P4	2	symptoms, blood pressure, diabetes, hypertension
P3	3	age, blood pressure, hypertension
P5	4	symptoms, age, blood pressure
P2	5	symptoms, age
P6	6	symptoms

all COVID-19 patients. As shown in Fig. 5, patients 1 having high score in five factors symptoms, age, oxygen saturation, chest X-ray, chest CT (Fig. 5a). Patient 2 having high score in two factors symptoms, age (Fig. 5b). The patient 3 having high score in factor age, blood pressure, comorbiditites (Fig. 5c). Patient 4 having high score in three factors symptoms, blood pressure, comorbidities (Fig. 5d). Patient 5 having high score in symptoms, age (Fig. 5e). Patient 6 having high score only in symptoms (Fig. 5f). Final priority list of patients is given in Table 14.

8. Conclusion

Fuzzy case-based reasoning approach not only for diagnosis, to know the patient's vulnerability and use it to prioritize treatment is a new endeavor. Through the methods we introduced, we can understand the status of the patient severity and help them immediately. Thus, we can prevent patient mortality by treating them first with the level of the patient severity. For a patient with COVID-19, if the priority to the patient's in treatment given only with the degree of impact of the disease, the condition of many patients will become worse and more repetitive. The reason is that if one patient has a prevalence rate of 35% and another patient has a prevalence rate of 30%, and has high blood pressure or diabetes, then the second person does need priority treatment. Therefore, it is not correct to prioritize treatment based only on the degree of impact of the disease. The method we introducing will help to prioritize treatment considering the patient's age, severity, and comorbidities. And this method can help improve the decision-making ability of medical professionals. For medical professionals, it can be very useful in the critical moment of making complex decisions.

Previously, many research results were published based on specific factors (spatial change, climate risk, disaster preparedness, blood type, age, comorbidities and timely provision of medical resources) and published potential factors that increase the number of deaths. If medical experts try to make a decision that does not involve any of these

factors, patients with higher mortality due to other factors may be at greater risk. An effective algorithm is needed to consider all these factors to make medical decisions. Hence, we have introduced a method to cover all these factors.

In the priority assignment, we considered eight important factors, such as symptoms, age, duration of symptoms, blood oxygen saturation, blood pressure, chest X-ray results, CT scan results, comorbidities. At the same time, don't overemphasize any particular factor or give different degrees of importance to each factor. Hence, we have used the cobweb solution method. In this way, all factors can be given equal importance, and the extent of their influence can be clearly seen. In addition, by using the sigmoid function to calculate the values of these factors, we can classify and manipulate the metrics of these factors very clearly. In the future, this approach will be expanded to help the healthcare system operate effectively when other diseases or epidemics occur.

CRediT authorship contribution statement

Selvaraj Geetha: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Samayan Narayanamoorthy:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Supervision, Validation, Visualization, Writing - review & editing. **Thangaraj Manirathinam:** Writing - original draft, Writing - review & editing. **Daekook Kang:** Funding acquisition, Investigation, Resources, Supervision, Validation, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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