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A fuzzy expert system for predicting the mortality of COVID’19

Monika MANGLA[1*], **Nonita SHARMA**[2], **Poonam MITTAL**[3]
[1]CSED, Lokmanya Tilak College of Engineering, Navi Mumbai, India
[2]Dr. B.R. Ambedkar National Institute of Technology, Jalandhar, India
[3]JC Bose University of Science and Technology, YMCA, Faridabad, Haryana, India

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Abstract: The COVID-19 pandemic has had a widespread impact on health and economy across the globe. It is leading to a huge number of deaths per day. Few researchers have been attracted to analyzing the mortality rate of COVID-19 from various perspectives. During the research, it has become evident that these fatalities are not only caused by COVID-19, but they are also affected by some other factors. The authors of this paper aim to encompass three important types of factors viz. risk factors, clinical factors, and miscellaneous factors that influence the mortality of COVID-19. This manuscript presents a rule-based model under the Mamdani-based fuzzy expert system (FES) to analyze the mortality rate of the highly contagious COVID-19. The proposed model creates three FESs and thereafter generates the final FES which aggregates these three FESs. The FES for risk value considers 5 aggregate factors viz. immunity, temperature, ventilation, population density, and pollution. The second FES is to model the clinical facilities based on ICU count, quarantine centers, and tests performed. The third FES is created to model the miscellaneous factors. Finally, the concluding FES combines three base FESs to evaluate the mortality value. The results obtained by the suggested model are promising and hence advocate the efficacy of the proposed model.

Key words: COVID-19, clinical facilities, miscellaneous factors, Mamdani-fuzzy inference model, mortality

1. Introduction

During the past few months, COVID-19 has emerged as a highly contagious disease caused by a novel corona virus. Apart from higher risk of contamination, another concerning issue is unavailability of any medication or immunizations to date. Hence, the best possible way to avert its transmission is to be cautious about the spread of the COVID-19 infection. Nonetheless, there are numerous progressing clinical investigations assessing potential medicines. However, the infection has a low casualty rate, still it is declared to be a pandemic considering the massive scale of its spread. As of 29 May 2020, there are 359,791 deaths reported worldwide, while more than 2.3 million patients have recovered. Unfortunately, these numbers tend to underreport the actual number of deaths that this pandemic has caused. In numerous places, the reported figures exclude those who were not tested positive or was not admitted to hospital. This can be attributed to the fact that the reason of death takes quite a few days to get reported, thereby causing a lag in the data. Moreover, even the most accurate COVID-19 data will not tally individuals who died due to insinuating circumstances that may ordinarily have been dealt with, had medical clinics not been overpowered by a flood of patients requiring escalated care.

Epidemiological studies of the recovered cases and deaths have identified several risk factors arising from

*Correspondence: manglamona@gmail.com

COVID-19. Current studies have revealed that T cells were reduced in COVID-19 patients, and the immune system was weakened due to the infection thus causing tissue injury. Consequently, immune dysfunction is highly probable to be a risk factor for modelling the mortality of COVID-19 disease, and immunological profiling may aid the forecast of organ injury in COVID-19 patients. Furthermore, environmental studies related to COVID-19 consider air pollution as the most significant risk factor in the spread and mortality rate of the infection. A research related to corona virus uncovered that higher number of deaths occurred in the regions which are highly polluted. In a recent work, researchers found the relevance of ventilation to improve indoor air quality to curb the spread of COVID-19 infection. Indoor air quality has substantial impact on human health and is affected by several factors such as cleanliness and hygiene. Ventilation unquestionably improves the air quality but in case of COVID-19, it can be viewed as a way of exposure and thus a source of contamination. Furthermore, population density is also one of the key factors to determine the vulnerability of a location due to corona virus. The data revealed that the places with higher population density are hit harder as compared to the smaller communities. Furthermore, meteorological factors play an important role in modelling infectious diseases. Temperature and humidity substantially reduce the transmission of virus. To model the mortality of COVID-19, the factors discussed above play a dominant role as risk factors.

Clinical facilities are an indispensable part of primary care, and three essential services, specifically intensive care unit (ICU) centers, number of quarantine centers, and tests performed are important factors in modelling mortality rate of COVID-19. If medical systems are overwhelmed, both direct casualty from the pandemic and indirect deaths from treatable diseases upsurge considerably. Governments will need to make difficult choices to balance the immediate demand of COVID-19 patients and corresponding the essential health services. The mortality rate of COVID-19 is dependent on consolidated set of immediate steps taken by governments at national as well as local levels to maintain essential medical services for all. Miscellaneous factors, for example the patients delaying the treatment of other health conditions so as to avoid the contraction of corona virus in hospital, medical systems giving priority to COVID-19 patients, prioritization of COVID-19 patients by health services, anxiety of medical professionals, and other domestic factors introduced due to lock-down also have a considerable impact on the mortality of COVID-19.

In the medical domain, most of the concepts are fuzzy, which makes it hard to model and objectify them. Thus, fuzzy modelling is deemed to be an appropriate technique for modelling the uncertainty in the medical domain [1]. Fuzzy approach is the most suitable technique for modelling in an inaccurate, uncertain, and incomplete environment. The concept of fuzzy logic was introduced in 1965 and the medical domain was the first to apply the same. The manuscript presents a rule-based model under Mamdani-based FES to model the mortality of COVID-19. Three FESs, namely risk factor, clinical facilities, and miscellaneous factors are created to model the final FES to determine the mortality index. The FES for risk factors considers 5 aggregate factors viz. immunity, temperature, ventilation, population density, and pollution, where each factor is a combination of several other related factors; for example, immunity is taken as an aggregate of current health condition, age, and other related factors. The second FES is to model the clinical facilities based on ICU count, quarantine centers, and tests performed. The third FES is created to model the miscellaneous factors. The final FES which presents the final mortality model is derived from these three rule-based FESs.

The manuscript has been organized in various sections. Section 1 briefly introduces the motive of study. Related work is presented in Section 2. The various factors that have been considered during the study have been discussed in Section 3. Fuzzy-based model to evaluate mortality is presented in Section 4. The results are discussed in Section 5; and finally, Section 6 presents the conclusion of the manuscript.

2. Related work

The pandemic has been spreading exponentially despite best possible efforts of various governing bodies. Hence, it becomes absolutely necessary to understand the unmatched and unprecedented spread of this epidemic which is further obscured by its small time span. As a result, researchers and health professionals have been attempting various approaches to curb the spread of this virus. Apart from the spread of this virus, rigorous research is also taking place to understand the mortality rate of COVID-19. An effective understanding of mortality rate due to COVID-19 may be helpful for a nation for prioritizing treatment of COVID-19 patients if situation grows beyond control. The authors in this paper attempt to develop a mathematical model for mortality due to COVID-19. This model is based on studies by various researchers in the related field. This section briefly presents the work related to mortality rate presented by various researchers.

The authors in [2] attempted to investigate various factors that influence death of COVID-19 patients. They prospectively collected all laboratory and clinical parameters from COVID-19 patients and attempted to derive the logistic regression equations to investigate the association among these parameters and risk of death of patients. This study included a total of 179 patients of which 21 died. The study revealed that age more than 65 years, existing cardiovascular diseases, and cardiac troponin are a few major factors which strongly contribute to higher mortality of the disease. The authors in [3] also assessed the occurrence of comorbidities in the COVID-19 patients and concluded that current health issues (if any) put the life of COVID-19 patients at risk.

The authors in [4] attempted to evaluate the death rate in the United States and envisaged it to be in the range of 100,000 and 240,000. This study also claims that minimal surge in exposure to particulate matter (PM) leads to substantial rise in COVID-19 mortality of up to 20 times. The authors in [4] also observed that an increase of mere 1 g/m3 in PM leads to 15% increase in mortality rate. This result is based on statistical analysis and is robust to sensitivity and secondary analyses. Hence, pollution level is proven to be the most critical parameter that governs the mortality due to COVID-19. As a result, the study strongly advocates the importance of maintaining stringent air pollution guidelines even after COVID-19.

A retrospective study of clinical characteristics and mortal causes of the pandemic was also carried out by researchers in [5]. The authors collected data related to dead patients in China. The study included 159 dead patients from 24 provinces. The median age of these patients who died during treatment is 71 years, which indicates that elderly COVID-19 patients are more prone to death. Another conclusion from this study is that mortality rate of COVID-19 patients is highly subjective to hypertension and preexisting respiratory disorders. Additionally, heart disease is also observed to be an important risk factor affecting mortality of COVID-19 patients. Hence, based on this experiment, it becomes evident that old patients with preexisting health conditions (like hypertension, respiratory disorder, and heart disease) need utmost medical attention.

While significant research is going on to analyze mortality due to COVID-19 patients, the authors in [6] attempted to analyze the mortality of non-COVID-19 patients. It is quite evident that COVID-19 is claiming many lives across the world but it has also resulted in an increase in the mortality of non-COVID-19. This may be due to an attitude to avoid hospital visits, prolonged lock-down, and economic slowdown, etc. Based on the research in [6], it is claimed that there is an increase of 867 deaths of non-COVID-19 patients per week in Wales and England since the start of this pandemic. This study establishes a quite concerning finding and thus urges the need to understand and analyze death of non-COVID-19 patients. This understanding enables a nation to formulate appropriate policies to save lives of population.

The authors in [7] also attempted to assess the death rate of the infected patients with respect to age in

Italy. The authors employed a surveillance system to gather information regarding COVID-19 patients across the country. The mortality rate of the infected patients in Italian population is 7.2% on March 17, 2020 (1625 deaths for 22,512 positive cases) [8]. While the overall mortality rate of Italy is 7.2%, this rate is 22.7% among patients above 90 years old. During this investigation, it is clear that COVID-19 is more lethal for older patients. When mortality rate (stratified by age groups) of Italy is compared with that of China, it is revealed that the mortality rate is similar in both countries for age groups 0 to 69 years. However, mortality rate among patients above 70 years of age is higher in Italy in comparison to China. This difference in mortality rate among two leading countries is still unexplained; research is still taking place to uncover the reason behind.

Another research was carried out in [9] to have an enhanced understanding of the mortality. The authors in [9] suggest different scenarios that impact mortality rate of COVID-19. The first scenario considers the death despite full intensive care support. Although such deaths cannot be predicted, they are assumed to be infrequent. Another scenario considers limitations of medical facilities and poor predictive outcome due to old age and existing health conditions. The authors suggest a third scenario that focuses on COVID-19 patients admitted to ICU hospitals whose death is not directly related to COVID-19. Although these deaths may be due to severe trauma, brain injury or ICU stay, it will also be attributed to statistics of COVID-19. The authors in this paper attempted to propose a mathematical model that aims to analyze and evaluate the mortality of COVID-19 with respect to various factors discussed in following section.

3. Related factors

The proposed fuzzy model is based upon three factors viz. risk factors, clinical factors, and miscellaneous factors. The factors are selected, and the various values are associated with them based on the literature reviewed and public data available. A brief description of all the factors is given below:

3.1. Risk factors

COVID-19 is still in its nascent stages in terms of any vaccine or cure available to treat the infection. Although the medical facilities available to the patients are keeping the mortality rate low as compared to the actual spread of the disease, there are still inadequacies related to the evaluation and estimation of the involved risk factors [10]. In this research work, the following risk factors involved to diagnose the COVID-19 infection are determined to model the mortality of the disease.

3.1.1. Immunity

The literature related to COVID-19 mortality cases indicates that a weakened immune system renders individuals more prone to infection [11]. The T cells and NK cells are vital for developing effective immunity to fight against infections; their absence leads to disease progression. Patients exposed to COVID-19 infection have poor innate immunity and thus the chances of succumbing to the disease are higher, thereby affecting the mortality rate of the disease. Furthermore, age is an important factor to model the mortality of the disease. Although the corona virus has impacted the young and middle-aged adults, the severity of the disease is the highest for those aged above 60 years and fatal for those above 80 years [12]. However, this has been attributed to the underlying health complications already present in aged populations. Underlying health conditions can lead to more severe symptoms and higher mortality rates of the disease [9]. Moreover, as people age, they are prone to chronic illnesses, thereby losing their immunity, making all these factors are interlinked. Immunity, the first risk factor considered here, depends on two related factors namely age and underlying health conditions.

3.1.2. Atmospheric temperature and population density

Along with the epidemiological factors, meteorological factors are important to be considered while modelling the mortality of the pandemic. A study conducted in Wuhan, China revealed the association of COVID-19 with environmental factors and demonstrated a positive correlation with diurnal temperature range and negative correlation with humidity. The findings suggested temperature and humidity as important risk factors for modelling COVID-19 mortality and further suggested to maintain a cool environment for COVID-19 patients [13]. The major strategy to curb the spread of the infection has been contact tracing. Higher population density areas are regarded as a catalyst in the spread of COVID-19. By reducing contact rates, the spread of the outbreak can be controlled substantially. Controlling contact rates is the key to outbreak control, and such a strategy depends on population densities. It would be difficult to control the contact rates in highly populated areas. To control the contact rates in highly populated areas would be a difficult option; hence, population density poses a challenge to the administration trying to control the infection.

3.1.3. Ventilation

The worldwide accepted solution to avert the COVID-19 infection is social distancing and countries worldwide have implemented lock-down for containing the disease. Prolonged lock-down enforces the population to stay home for months. This has led to deterioration of air quality inside homes. Moreover, the population rarely gets exposed to natural environment fearing the pandemic virus. The quality of air that we breathe in has a huge impact on health. However, there may be several biological, chemical, and physical contaminants further deteriorating the indoor air quality. The only solution to this is proper air ventilation that guarantees to improve air quality [14]. Numerous researchers have been working to understand viruses and affected air quality [15–17]. The isolation apparatus, implemented in several nations, for both diseased and healthy individuals may be a viable solution; however, it may induce other medical issues if not implemented properly. Hence, ventilation is considered a vital risk factor in modelling COVID-19 mortality.

3.1.4. Pollution level

As the COVID-19 pandemic affects a large number of people around the world and brings economies to a standstill, pollution level seems to be another significant risk factor in the spread of the infection. The impact of pollution level on COVID-19 is further strengthened as COVID-19 is an infection that severely hits respiratory system of the patient. Moreover, it has been proven by various researchers that the air is the most prominent carrier of the virus itself. Hence, after social distancing, reduction in the level of airborne-particle can be considered to be the next most effective approach to stop the virus from spreading.

3.2. Clinical factors

In the present study, the authors consider various clinical factors that influence the mortality rate of COVID-19. There are numerous clinical factors which can be considered for the study. However, the authors of this paper consider three major clinical factors viz. ICU count, quarantine centers, and tests performed. The motive behind inclusion of these factors is discussed as follows.

3.2.1. ICU count

As COVID-19 impacts the respiratory system of the patient, it is observed that about 33% of patients require ICU admission [18]. Considering the spread of this pandemic, each nation is continuously striving hard to improve its medical facilities specifically in terms of ICU. Moreover, the authors in [18] presented guidelines for preparation of ICU based on its early experience. The study makes a profound basis that ICUs are the most dominating parameter that influences mortality rate of COVID-19. The authors in [19] proposed a model that estimates the ICU and inpatient bed needs for COVID-19 patients in the US cities based on the data obtained from China if the outbreak reaches the level of Wuhan, China.

3.2.2. Quarantine centers

Quarantining a person in order to contain the virus imposes several restrictions of activities. Moreover, considering the severity of spread, not only COVID-19 patients are quarantined but the ones who could have possibly been exposed to infection are also quarantined. This is done in order to enable close monitoring of the asymptotic individuals and thus ensures early detection of cases. However, if not implemented properly, quarantine may also act as sources of contamination and dissemination of the disease. According to the global containment guidelines[1], laboratory-confirmed cases are rapidly identified and immediately quarantined at either a medical facility or at home.

3.2.3. Tests performed

As per report by weforum[2], the likelihood of identifying infected patients is primarily associated to the number of tests performed. A high test rate for COVID19 has emerged as a proven method to control the impact of the pandemic across the world. For instance, within India, Kerala performed a very high rate of tests by maximizing contact tracing and local surveillance in relation to its population. This early and rigorous testing strategy helped the state to control the number of infected patients in minimum time. By the Kerala model, it has been proven that spread of this pandemic is highly dependent upon intensity of tests performed.

3.3. Miscellaneous factors

Apart from risk and clinical factors, some other factors have also emerged during the study that have been contributing to mortality rate due to COVID-19. In this subsection, we present some of these major factors as follows.

3.3.1. Postponed treatment rate

As per a report[3], European Mortality Monitoring Project (Euro MOMO) states that there has been a substantial increase in the overall mortality coinciding with COVID-19 pandemic. This increase in non-COVID mortality is primarily due to an attitude of patients to postpone treatment that enhances the severity of their disease.

3.3.2. Priority of hospitals

Similar to non-COVID patients of postponing their treatment, hospitals are also prioritizing the treatment of COVID patients. Hospitals are more inclined towards treatment of COVID patients. Many of the hospitals have even been transformed to COVID-only hospitals due to the epidemic nature of COVID-19.

[1] https://apps.who.int
[2] https://www.weforum.org
[3] https://www.thehindu.com

3.3.3. Psychological issues

This unprecedented and unmatched epidemic is spreading like wild fire. In order to control the spread of this virus, national authorities have been forced to announce nation-wide lock-down. This pandemic has impacted the psychological health of population at large in terms of anxiety, stress, emotional breakdown etc. These psychological states are results of lack of physical activity, social distancing, and economy slowdown to name a few.

4. Proposed model

The authors in this paper classify these influencing factors into risk factors, clinical factors, and miscellaneous factors. The authors of this manuscript aim to propose a fuzzy inference model to evaluate the mortality rate of COVID-19.

4.1. Objective

In order to assess the influence of the discussed factors on the mortality rate of COVID-19, an integrated and analytical approach is required. The proposed model is an effort in this direction that efficiently models the impact of various factors on COVID-19 mortality.

4.2. Proposed fuzzy expert model

The proposed FES is based on Mamdani-fuzzy inference [20]. The proposed model predicts the mortality of COVID-19 based on various factors viz. risk, clinical, and miscellaneous factors. The motive for selecting fuzzy logic is its competence to predict unknown issues. The various components of a generic FES are demonstrated in Figure 1. The readers can refer to [20] to have a detailed understanding for function of each block.

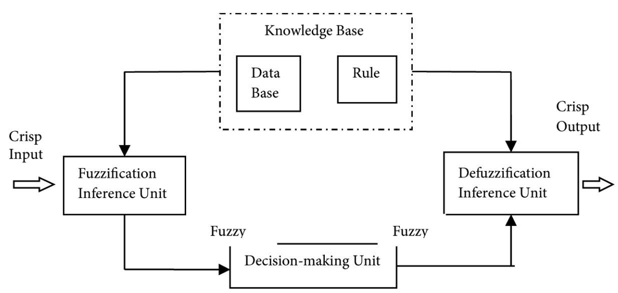

Figure 1. Block diagram of a fuzzy expert system.

4.3. Proposed Mamdani-based FES

The proposed fuzzy model for mortality prediction employs a hierarchy of 4 FESs. Among these four FESs, FES1, FES2, and FES3 (the base FESs) analyze the risk factors, clinical factors, and miscellaneous factors, respectively, as shown in Figure 2. Each of these FESs considers the factors as discussed in the previous section. Furthermore, the output of these 3 FESs is fed as input to FES4. The proposed model is implemented in MATLAB-R2013b.

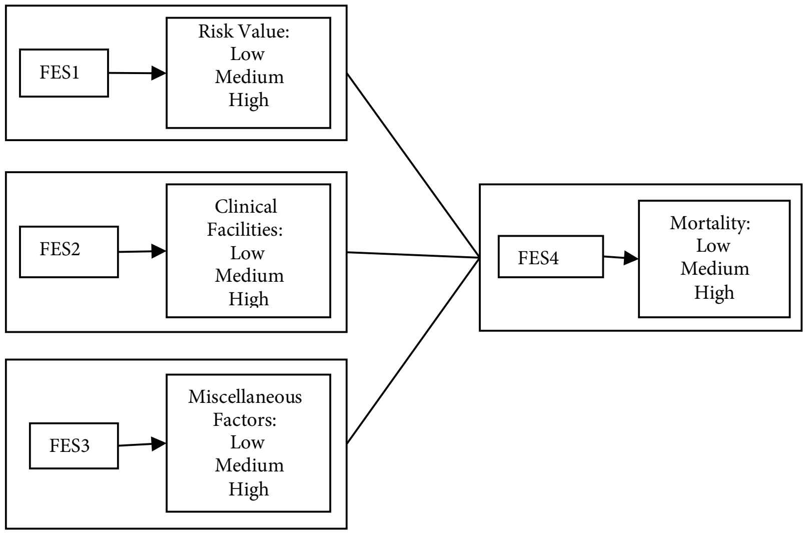

Figure 2. Hierarchy of FESs in the proposed model.

4.3.1. FES implementation for risk factors

To calculate risk factors, the proposed FES uses 5 inputs representing 5 major risk factors and produces an output value that indicates the risk value. The proposed FES is illustrated in Figure 3. The considered risk factors that contribute to risk value are immunity, atmosphere temperature, population density, ventilation, and pollution level. Each input parameter uses a different range. For instance, immunity and temperature is considered to be in the range of (0-10) and (0-45)^{0}C, respectively. The entire range of each parameter is further classified into multiple subcategories (a linguistic variable denotes each subcategory) as shown in Table 1. The number written along with parameter represents the number of subcategories for that parameter. Hence, it becomes evident from Table 1 that a total of 162 rules are formed for FES1.

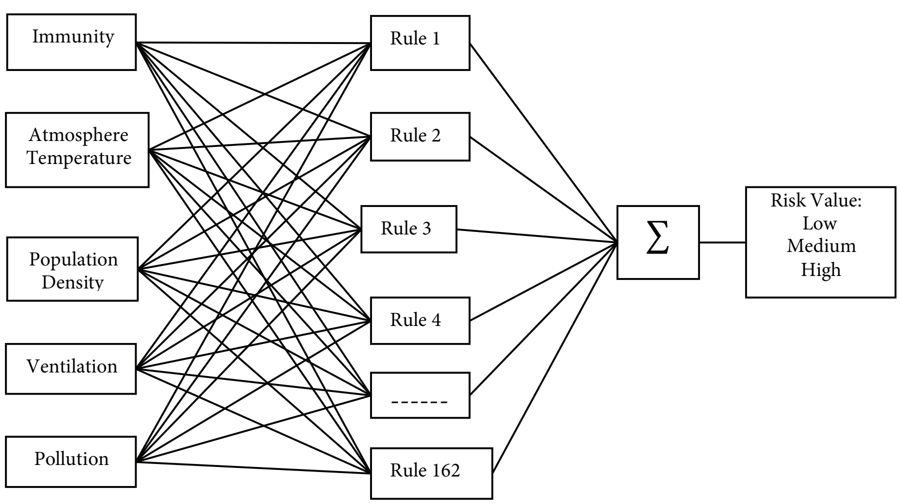

Figure 3. Fuzzy pattern to calculate risk value.

Table 1 represents the membership functions and the input range for each input parameter. From Table 1, it is evident that there are 162 rules in the rule base. Few of these rules are illustrated in Table 2.

Table 1. Fuzzy classification of I/O parameters in FES1.

–	Parameters	Membership functions		
Input	Immunity (2)	Adaptive [0 0 6]	Innate [5 10 10]	–
Input	Temperature (3)	Cold [0 0 20]	Mild [15 22 30]	Hot [22 45 45]
Input	Population density (3)	Sparse [0 0 300]	Moderate [200 350 600]	Dense [450 1000 1000]
Input	Ventilation (3)	Suffocated [0 0 25]	Moderate [18 28 40]	Airy [30 50 50]
Input	Pollution (3) (particulate matter)	Small [0 0 3]	Medium [2 4 6]	Large [5 10 10]
Output	Risk value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Table 2. Rule base for FES1.

Inputs					Output
Immunity	Temperature	Population density	Ventilation	Pollution	Risk value
Adaptive	Cold	Sparse	Suffocated	Large	Low
Adaptive	Cold	Sparse	Airy	Small	Medium
Adaptive	Cold	Sparse	Airy	Medium	Medium
Adaptive	Cold	Sparse	Airy	Large	Low
:	:	:	:	:	:
:	:	:	:	:	:
Innate	Hot	Dense	Airy	Large	Low

4.3.2. FES implementation for clinical facilities

The fuzzy pattern that evaluates the clinical facilities takes 3 input parameters (ICU count, quarantine center, and number of tests performed) and generates 1 output parameter as shown in Figure 4. This output parameter indicates the level of clinical facilities and thus has a strong influence on mortality. Here, all three input parameters and one output parameter have been taken on a Likert scale (0–10). In FES2, there exist 3 input parameters each having 3 subcategories, thus giving 27 rules.

The fuzzy classification of all I/O variables of FES2 that evaluates clinical facilities is represented in Table 3.

4.3.3. FES implementation for miscellaneous factors

Similar to FES1 and FES2, this subsection discusses the FES3 which evaluates the various miscellaneous factors involved in the study of mortality analysis. The fuzzy pattern to evaluate the miscellaneous factors is shown in Figure 5. This model takes 3 input parameters (postponed treatment, priority of hospitals, and psychological issues) and gives 1 output parameter. In this FES3, all input and output parameters have been taken in the range of 0 to 10. Moreover, each I/O parameter is categorized into three classes viz. low, medium, and high as represented in Table 5.

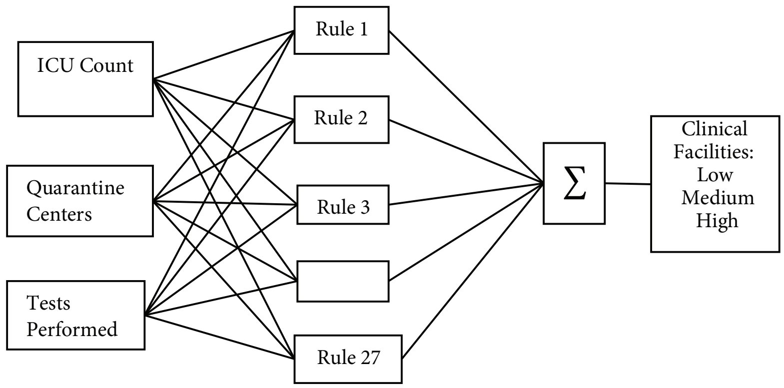

Figure 4. Fuzzy pattern to calculate clinical facilities value.

Table 3. Fuzzy classification of I/O parameters in FES2.

–	Parameters	Membership functions		
Input	ICU count (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Input	Quarantine center (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Input	Tests performed (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Output	Clinical facilities	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Table 4. Rule base for FES2.

Inputs			Output
ICU count	Quarantine centers	Test performed	Clinical facilities
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Low
Low	High	High	Medium
:	:	:	:
:	:	:	:
High	High	High	High

The range of I/O parameters for this fuzzy pattern is shown below in Table 5.

The rule base for FES3 is also demonstrated in Table 6.

4.3.4. Fuzzy model implementation for mortality index

Figure 6 illustrates the fuzzy pattern to evaluate mortality rate using the 3 FESs that evaluate risk factors, clinical factors, and miscellaneous factors. This FES gives one output parameter that represents the mortality index.

In this FES, we get 3 input ranges for each input variables (risk factors, clinical factors, and miscellaneous factors). Hence, a total of 27 rule bases are generated as shown in Table 7 for final FES, i.e. FES4.

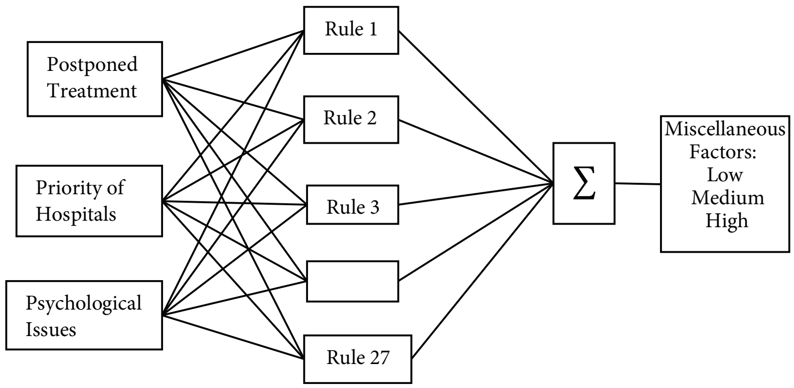

Figure 5. Fuzzy pattern to calculate miscellaneous factors.

Table 5. Fuzzy classification of I/O variables for miscellaneous factors.

–	Parameters	Membership functions		
Input	Postponed treatment rate (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Input	Priority of hospitals rate (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Input	Psychological issues (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Output	Miscellaneous factors (3)	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Table 6. Rule base for FES3.

Inputs			Output
Postponed treatment rate	Priority of hospitals	Psychological issues	Miscellaneous factors
Low	Low	Low	Low
Low	Low	Medium	Medium
Low	Low	High	High
Low	High	High	Medium
:	:	:	:
:	:	:	:
High	High	High	High

5. Results and discussion

This section discusses the results that are obtained from the proposed FES to evaluate mortality index. As discussed previously, the mortality index is evaluated based on the evaluation of risk factors, clinical factors, and miscellaneous factors. The following subsections discuss the impact of each of contributing factors on the mortality index.

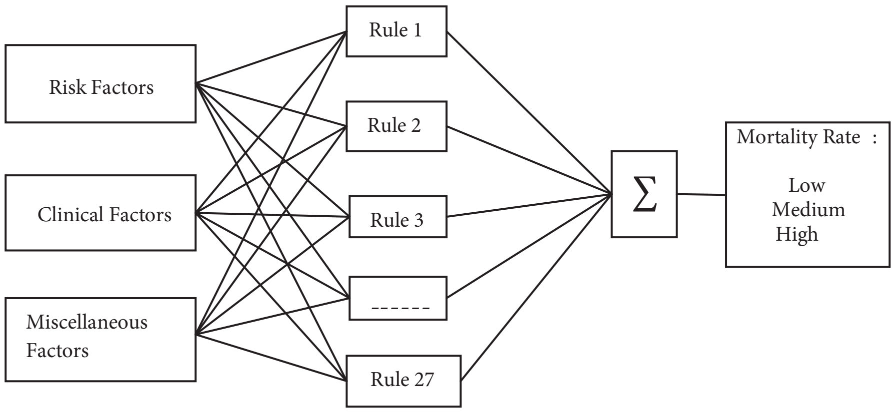

Figure 6. Snapshot of FES3 to calculate mortality index.

Table 7. Rule base for FES4.

Inputs			Output
Risk factors	Clinical facilities	Miscellaneous factors	Mortality index
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Medium
Low	High	High	Medium
:	:	:	:
:	:	:	:
High	High	High	High

5.1. Impact of risk factors on mortality index

The mortality index observes a strong influence of risk factors (immunity, atmospheric temperature, population density, ventilation, and pollution). The intensity of impact of these input factors in mortality index is illustrated in Figure 7 that shows the 3-D surface view of FES1. It enables to have a better understanding of contributing parameters on risk evaluation. As can be observed from Figure 7, lower atmospheric temperature and higher population density result in the highest risk value.

5.2. Impact of clinical facilities on mortality index

The output of FES2, i.e. clinical value, is also converted to Crisp value by Fuzzifier and mapped on Likert scale (0-10) as in Figure 8. It considers different values of ICU count, quarantine centers, and tests performed.

The 3-D surface view of FES2 is illustrated in Figure 8 that represents the impact of contributing variables in the evaluation of clinical facilities.

5.3. Impact of miscellaneous factors on mortality index

Similar to risk and clinical factors, miscellaneous factor is also evaluated based on input parameters viz. treatment postponement, priority of hospital, and psychological issues. The output of FES3 i.e. miscellaneous value (low, medium, and high) is converted to Crisp value by Fuzzifier and mapped on Likert scale (0–10) as shown in Figure 9.

The 3-D surface view of FES3 is illustrated in Figure 9 that represents the impact of contributing variables in the evaluation of miscellaneous factors.

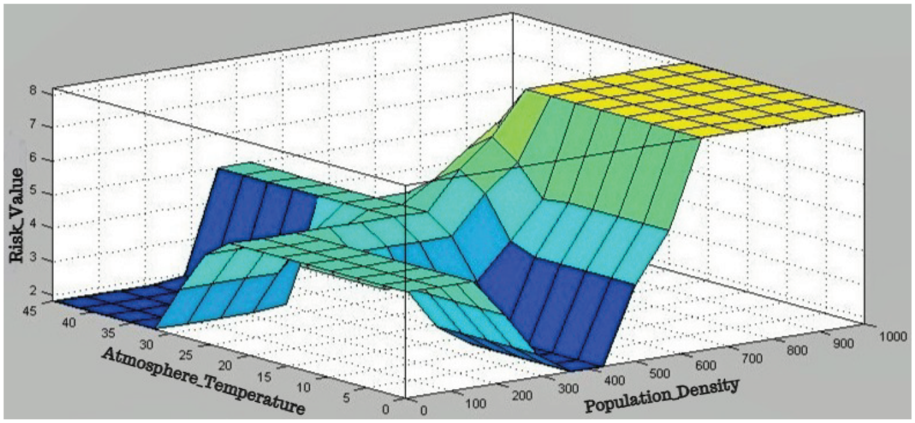

Figure 7. 3-D surface view of the FES1 for risk value.

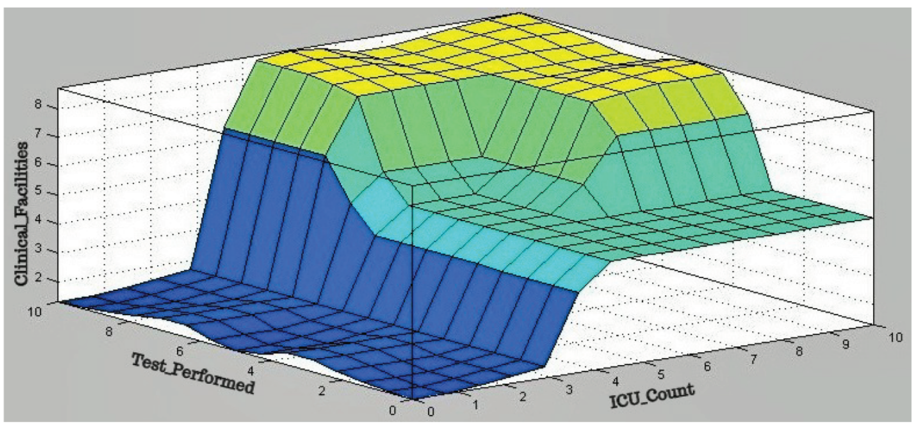

Figure 8. 3-D surface view of the FES2 for clinical factors.

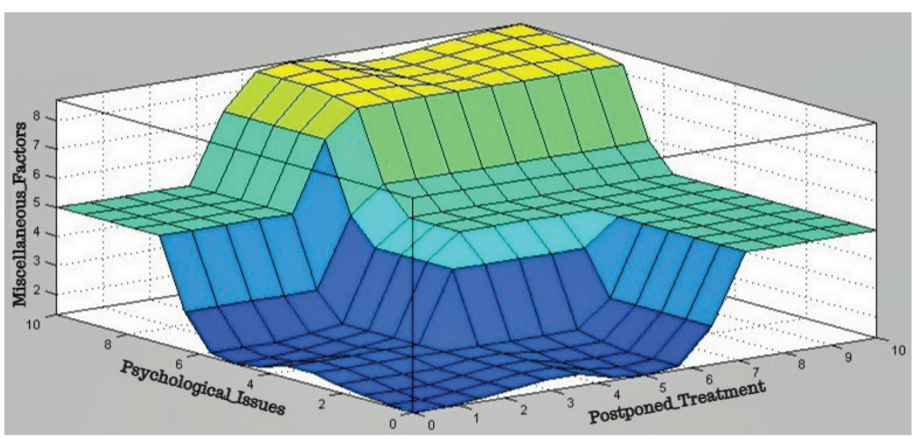

Figure 9. 3-D surface view of the FES3 for miscellaneous factors.

5.4. Outcome as mortality index

As represented in Figure 2, the final FES4 takes output of FES1, FES2 and FES3 as input and evaluates the mortality index based on risk factors, clinical factors, and some miscellaneous factors.

The 3-D surface view of FES4 is illustrated in Figure 10 that represents the impact of risk factors, clinical factors, and other miscellaneous factors in the evaluation of the mortality index. From Figure 10, it is evident that when miscellaneous factors and risk factors become high, the mortality reaches its peak. Thus, 3-D surface view enables to have a clear understanding about impact of each factor on mortality index. This understanding helps in devising efficient strategies to curb the mortality rate of COVID-19.

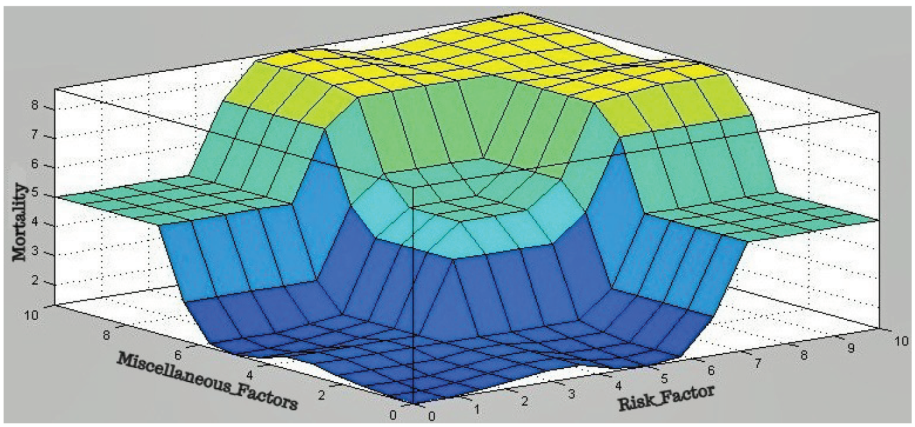

Figure 10. 3-D surface view of the FES4 for mortaility index.

6. Conclusion

In this manuscript, the authors propose a Mamdani-based fuzzy inference model that aims to analyze the impact of various risk, clinical, and miscellaneous factors on the mortality rate of COVID-19. The proposed model further considers various input parameters in risk factors viz. virulency, immunity, temperature, population density, and ventilation. The considered clinical factors are ICU beds, quarantine centers, and the number of tests performed. Similarly, miscellaneous factors (Non-COVID) include the study of factors like attitude of patients to postpone treatment to avoid hospital visits, hospitals' prioritization towards treating COVID-19, and associated psychological issues (anxiety, stress, depression due to lack of physical activity). The proposed model efficiently demonstrates the impact of each factor on the mortality and hence can be successfully implemented to control mortality. The proposed model can be further extended to incorporate additional stochastic factors.

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