Coronavirus risk factor by Sugeno fuzzy logic

Saba Qasim Hasan[1], Raid Rafi Omar Al-Nima[2], Sahar Esmail Mahmmod[1]
[1]Department of Computer Systems Technologies, Mosul Technical Institute, Northern Technical University, Mosul, Iraq
[2]Department of Medical Instrumentation Techniques Engineering, Technical Engineering College of Mosul, Northern Technical University, Mosul, Iraq

Article Info

Article history:

Received May 25, 2023
Revised Jul 30, 2023
Accepted Sep 29, 2023

Keywords:

Coronavirus
Fuzzy logic
Membership functions
Risk factor
Sugeno

ABSTRACT

World recently faced big challenges with the pandemic of coronavirus disease 2019 (COVID-19). Governments suffer from the problem of appropriately identifying the risk factor of this virus and establishing their safety procedures accordingly. This paper concentrates on designing a coronavirus risk factor (CRF) by the power of Sugeno fuzzy logic (SFL). The main advantage of the CRF is that it can provides a quick and suitable risk evaluation. According to the degree of severity, three essential parameters are considered: number of infected cases, number of people in intensive care units (ICU) and number of deaths. All of these parameters are provided per population. Such interesting and promising outcomes are attained, where the total effect is found equal to 95.3%.

Corresponding Author:

Saba Qasim Hasan
Department of Computer Systems Technologies, Mosul Technical Institute, Northern Technical University
Mosul, Iraq
Email: saba.qassim73@gmail.com

1. INTRODUCTION

World faced a severe virus during a long period of time, it is called a novel coronavirus in the global pandemic crisis (GPC). First infection of this virus was reported on December 2019 in Wuhan, China. Then, number of infected cases has rapidly been increased [1]. This virus has widely spread and broadcasted from Wuhan to other world regions causing serious risks. It has been given the name coronavirus disease 2019 (COVID-19). The disease affects people differently, where the symptoms appear in some cases mildly and in many cases severe and dangerous [2].

Numerous studies have explored different approaches to address medical challenges and decision-making. There is a great deal of uncertainty in the decision-making process, and ambiguous information. In March 2020, due of COVID-19's rapid spread, the World Health Organization (WHO) issued a state of emergency [3]. The fields of artificial intelligence, big data, mathematical modelling, and processing have made significant contributions to the comprehension and justification of the virus's epidemiological behaviour [4]. For literature, there are recent studies that work on in different aspects or point of views.

Užga-Rebrovs and Kuļešova [5] described the basic concepts of fuzzy inference system (FIS) operations. It translated real values to fuzzy values according to Mamdani method. The intelligent steam valve (ISV) technology was introduced by Al-Ridha *et al.* [6]. Their approach involved creating a fuzzy logic system that utilized two inputs (pressure and temperature) and one output (valve opening). Once the was established, the strategy was implemented using the adaptive neuron-fuzzy inference (ANFIS). So, the ISV was built, trained and tested. For real-time systems, this technology can intelligently operate a steam valve. Al Mahmoud *et al.* [7] introduced artificial intelligence method to predict the risks and impacts of COVID-19. Such predictions may help to control the disease and prevent its spreading. Selection correlation coefficient of characteristics, information gain and gain ratio were used. Adwibowo [8] presented COVID-19 safety assessment of dental care with fuzzy logic assistance, this work set out to develop a fuzzy-assist system, the fuzzy method allowed for evaluation. Ashraf *et al.* [3] presented the control of spreading COVID-19 for emergency situations. A spherical intelligent fuzzy decision model was proposed in this study as a means of managing and diagnosing COVID-19. A mathematical model based on data from fuzzy decision-making approach was utilized. For sensitive and comparative analyses, the results showed feasibility and reliability. A new diagnostic strategy, known as the hybrid diagnose strategy (HDS), was proposed by Shaban *et al.* [9]. The approach involved projecting features into a hypothetical patient space (PS) and ranking them using a novel method. A feature connectivity graph (FCG) was created to illustrate the weight of each feature and its degree of association with other features. To classify the features, the authors utilized a combination of two classifiers: a fuzzy inference engine and a deep neural network (DNN). The genetic neuro-fuzzy (GNF) network is a artificial intelligence that was proposed by Al-Nima *et al.* [10]. This approach combined fuzzy logic with a neural network and a genetic algorithm. Sharma *et al.* [4] utilized the mediative fuzzy logic evaluation to formulate the alpha-beta cutting technique based on mathematical models. It was demonstrated that the correlation technique was permitted when linking the increments of COVID-19 patients because the first upper and lower limits of the median fuzzy correlation coefficient were determined in this manner. Alsahlani and Popa [11] presented ideas with the internet of things (IoT). The authors provided COVID-19 health measurements to control the virus spreading. This study suggested reducing direct human contacts. Integrating IoT and cloud-based technologies can help to mitigate COVID-19's effects by allowing people to remotely handle their important activities with minimal efforts. In order to aid in the early infection risk assessment, Ejodamen and Ekong [12] proposed a fuzzy expert system diagnostic strategy using significant clinical characteristics, personality features, and symptoms. Relevant study results were used to choose fuzzy membership criteria for the handling of imprecision is noticeable in this area, as some symptoms are indicators of other illnesses. Ly [13] suggested ANFIS for forecasting the number of COVID-19 cases. As a case study the country of United Kingdom (UK) was considered. The work examined different ANFIS factors. As a result, this leaded to obtain a prediction model with effective time series. Abdulraheem *et al.* [14] introduced a work for predicting the risk of confirmed and death incidents. The machine learning of byesian regularization backpropagation (BRB) was employed. The BRB could predict numbers of incidents from applied population date and density. Shafiekhani *et al.* [15] approached COVID-19 forecasting system by utilizing the ANFIS and long short term memory (LSTM). The aim here was to investigate a suitable machine learning algorithm that could confirm hospital admissions for COVID-19 with high performance. Graphical user interface (GUI) was constructed. Şimşek and Yangın [16] proposed an alternative method in order to determine individual's risk of COVID-19. Fuzzy logic was employed in this study. The aim here was to construct a support system to help professionals in detecting the risk of COVID-19 infection in an accurate and timely manner. An output value on symptoms was attained for the virus from each human. The proposed system consists of a main system and three fuzzy logics, these were for the personal information, rare symptoms and common serious symptoms. Then, the outputs of the three fuzzy logics were fused in the main system. Type Mamdani was concentrated in this work. Şahin *et al.* [17] developed a fuzzy logic of type-2 to diagnose COVID-19. This study was to provide a decision support system, which consisted of blood test results and clinical examination. The work was presented for health professionals that can use with existing COVID-19 diagnoses methods. The developed system involved of three fuzzy logics. The first one was for generating a percentage of COVID-19 positivity. The second one was for achieving a blood tests result. The third one was for evaluating the outputs of the first and second fuzzy logics to attain the result.

This paper is aiming to produced the novel method of coronavirus risk factor (CRF) which is the main contribution here. This is considered by using the power of Sugeno fuzzy logic (SFL). The reason beyond using the Sugeno is that it has the capability to well adapt the outputs by exploiting the linear or first-order functions. The rest sections will be represented as follows: section 3 illustrates the theory of this work, section 4 provides the findings and discussions and section 5 highlights the conclusion.

2. METHODOLOGY

2.1. Overview

Zadeh was the first to establish fuzzy logic in the middle of the previous century. It is focused on fuzzy analysis' ambiguous linguistics. It contains functional elements like membership functions and rules [7]. They created a mathematical model to capture the ambiguity and uncertainty of linguistic issues [18]. The fuzzy logic is used in a variety of disciplines such as engineering, medicine and industry [10]. Fuzzy subset is a classical set with no sharp boundary. So, let A is a fuzzy subset of X and $\mu_A(x)$ is the x grade membership in A. Thus, the (1) represents the completed characterized A [19].

$$A = \{(x, \mu_A(x)), x \in X\} \tag{1}$$

2.2. Membership functions

In addition to simplifying system design and ensuring that the system can be readily maintained throughout time, membership function makes it simple to create fuzzy systems [20]. A membership function is a transfer fuction that describes how each point in the input space transfers to a membership value (or degree of participation) ranging from 0 to 1. Each point in the input space is described by a membership function as transferring to a value (degree of participation) which rangs from 0 to 1. A membership functyion can mathematically be represented as (2) [21].

$$\mu A(x) = \begin{cases} 1 & \text{if } x \text{ is totally in } A \\ 0 & \text{if } x \text{ is not in } A \\ > 0 \ \& < 1 & \text{if } x \text{ is partly in } A \end{cases} \quad (2)$$

2.3. Fuzzy rules

Fuzzy rules are a specific type of conditional statement that solves the challenge of connecting the input variables to the output variables I n fuzzy logic systems. They are expressed in the form of "if-then" statements, where the "if" part represents the input variables, and the "then" part represents the output variables. Fuzzy rules are useful for handling ambiguous or imprecise information because they use linguistic variables and fuzzy sets to express the inputs and outputs. Many applications, including control systems, decision-making, and pattern recognition, frequently use fuzzy rules.

2.4. Fuzzification and defuzzification processes

The fuzzy system analyzes values between 0 and 1. The fuzzy system works in two main processes called the fuzzification and defuzzification. Fuzzification process converts actual data into fuzzy data between 0 and 1 in order to analyze them in the fuzzy logic environment. On the other hand, defuzzification process converts fuzzy data into actual data in order to provide the actual output values.

2.5. Mamdani versus Sugeno

The method used to obtain the output from the fuzzy inputs is the main distinction between Mamdani type FIS and Sugeno type FIS [20]. Mamdani FIS uses the method of defuzzification of a fuzzy output, whereas Sugeno FIS uses a weighted average to compute the crisp output. Crisp data is processed at the input and produced at the output of a fuzzy logic system. To do this, the system's front end uses a fuzzifier to turn crisp data into fuzzy data, while the system's back end uses a defuzzifier to do the opposite.

The key difference between Mamdani and Sugeno FIS is in the method used to produce the crisp output from the fuzzy inputs [22], [23]. Mamdani FIS employs the defuzzification technique, whereas Sugeno FIS skips this step and computes the crisp output using a weighted average [18], [20]. Popular techniques in fuzzy logic systems include Mamdani and Sugeno. The Mamdani and Sugeno approaches have a number of important distinctions that are listed below,

- Rule format: Mamdani method uses a rule format where the output is a fuzzy set. In contrast, Sugeno method uses a rule format where the output is a crisp value.
- Output calculation: in the Mamdani method, the output is determined by computing the weighted average of the output fuzzy sets obtained from each rule. In the Sugeno method, by adding the weighted sum of the outputs from each rule, the output is computed.
- Linguistic variables: The Mamdani method uses linguistic variables for both inputs and outputs, which can be difficult to define and work with. The Sugeno method, on the other hand, uses numerical variables for the inputs and linguistic variables for the outputs, which can make the system easier to design and implement.
- Rule base: the rule base in the Mamdani method is typically larger and more complex than that of the Sugeno method, since it involves defining fuzzy sets for each input and output variable. The Sugeno method, in contrast, uses a simpler rule base with fewer rules.
- Applications: the Mamdani method is often used in control and decision-making applications, while the Sugeno method is more commonly used in function approximation and modeling applications.

Overall, the two approaches depends on the particular requirements of the current application, as each has advantages and disadvantages of its own [24].

2.6. Proposed method

First of all, SFL commonly referred to as the Takagi-Sugeno-Kang (TSK) technique, is an instance of fuzzy logic utilizing if-then statements to describe a system's behavior. The output of a system is determined by a set of rules in SFL which explain the relationship between the input variables and the output variable. General fuzzy processes for our proposed method are given in Figure 1.

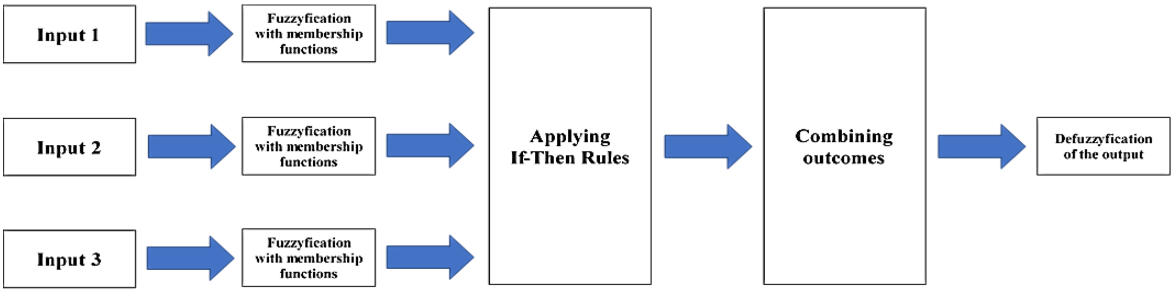


Figure 1. General fuzzy processes for our proposed method

So, from this figure it can be seen that 3 inputs are employed. Each one of them will be fuzzified with its assigned membership function in order to be re-mapped for the fuzzy range from 0 to 1. Then, if-then rules will be considered in the structure to analyze the relationships between the fuzzified inputs and implicate their outputs. Consequently, the outcomes are combined or aggregated. Subsequently, the output value will defuzzyfficated and provided. There are two methods for output defuzzification in Sugeno namely: the weighted average of all rule outputs and weighted sum of all rule outputs [25]. The first method is used in this work.

SFL is often used in decision-making applications, such as risk assessment, where there are multiple variables to consider. When the relationships between the input variables and the output variable are nonlinear or challenging to mathematically express, it is especially helpful. In the context of CRF assessment, SFL can be used to combine multiple risk factors (such as age, comorbidities, and exposure history) into a single risk score. The method involves the following steps,

- Define the input variables: the risk factors are defined as input variables, each with a range of possible values (e.g., age 0-100 years and comorbidity score 0-10).
- Define the output variable: the output variable is the risk score, which can also be expressed as a probability or a degree of membership in a high-risk group.
- Define the rules: the rules describe the relationship between the input variables and the output variable. Each rule takes the form "if [input variable *A* is *X*] and [input variable *B* is *Y*] and ... then [output variable is *Z*]". For example, "if age is over 60 and comorbidity score is over 5, then risk score is high".
- Determine the rule weights: the weights of the rules are determined based on their importance in predicting the output variable. This can be done using statistical methods, expert judgment, or a combination of both.

The output variable is calculated as a weighted average of the outputs of each rule, where the weights are determined by the rule weights. Overall, SFL is a powerful method for combining multiple risk factors into a single risk score, which can be used to assess the likelihood of coronavirus infection or severe disease. However, it requires careful consideration of the input variables, rules, and weights to ensure accurate and reliable predictions [26]–[29].

Here, we have considered the SFL to provide the CRF. The proposed method consists of a set of inputs in which the severity of coronavirus in any region is recognized. Actually, three inputs are employed, these are the: number of infected cases per population, number of people in intensive care units (ICU) per population and number of deaths per population. They are represented by the following equations,

$$\frac{Number\ of\ infected\ cases}{Population} \tag{3}$$

$$\frac{Number\ of\ people\ in\ ICU}{Population} \tag{4}$$

$$\frac{Number\ of\ deaths}{Population} \tag{5}$$

These inputs represent the most severity factors that have to be considered for coronavirus as these are related to humans' health and lives. Such inputs are highly related to the output of CRF, which is required to be specified as it can affect decision makers. Accordingly, the decision makers would take appropriate steps about providing suitable help to reduce the effects of the employed inputs.

Figure 2 displays the membership functions of the inputs. That is, Figure 2(a) shows the membership functions of the first input, Figure 2(b) provides the membership functions of the second input and Figure 2(c) demonstrates the membership functions of the third input. Connection of OR function is applied to provide the relationships between the employed inputs.

On the other hand, the primary output of CRF is used in the output. It has linear membership functions, each is provided by specific values for its parameters. Such parameter values are used by the SFL to produce the exact CRF output value. Table 1 shows the parameter values of output linear membership functions.

CRF output value is ranged from 30 to 300. That is, its lowest value of 30 refers to the minimum requirements of considering the coronavirus and its highest value of 300 refers to a very high risk which even being out of control in the local infected coronavirus area. Blockdiagram of our proposed CRF system, it is based on the SFL is provided in Figure 3.

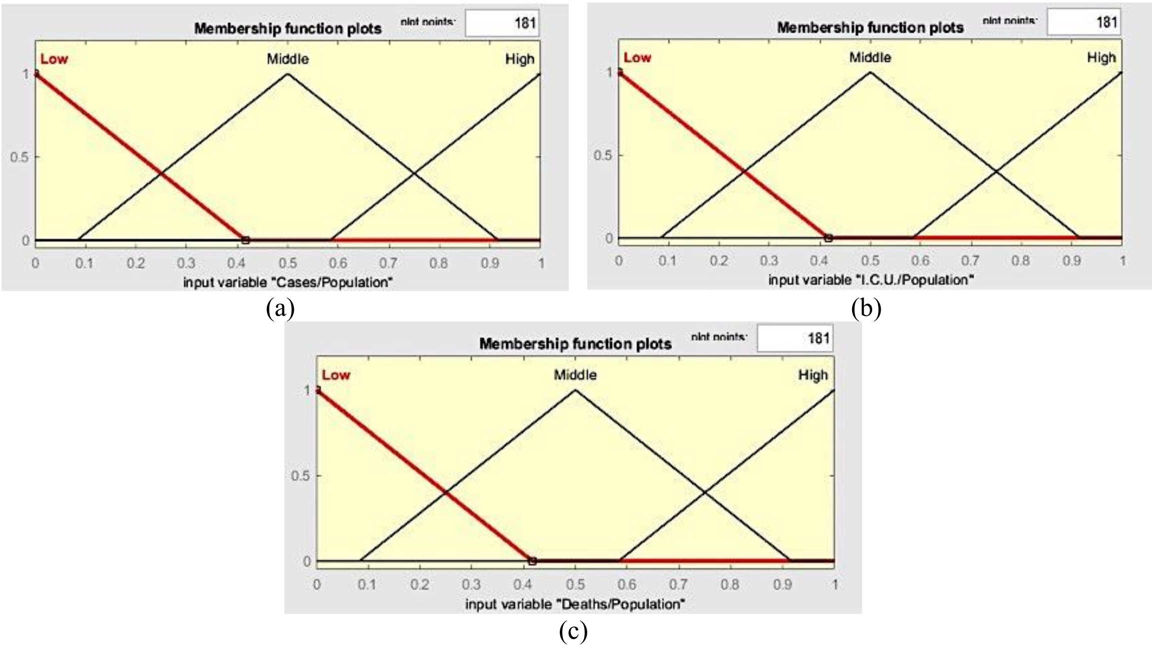


Figure 2. Membership functions for the inputs: (a) number of infected cases/population, (b) number of people in ICU/population, and (c) number of deaths/population

Table 1. The parameter values of output linear membership functions

Membership label	Parameter values
Low	[0 10 20 30]
Middle	[30 40 50 60]
High	[60 70 80 90]

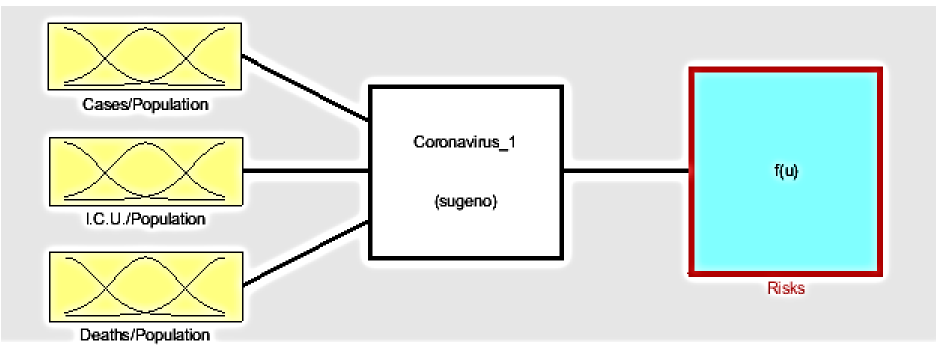


Figure 3. Blockdiagram of our proposed CRF system, it is based on the SFL

3. RESULTS AND DISCUSSION

According to the degree of severity, three essential parameters are considered in the input of the proposed CRF. These are the number of infected cases, number of persons in the ICU and number of deaths. As mentioned, each of these parameters is considered per population.

In the regression analysis, the data to be analyzed must be retrieved so as to have Normal distribution property. There for the normality of the data were assessed by the "Kolmogorov-Simonov method". By using this method, it has been found that the inputs of the proposed CRF conform to the normal distribution of linear regression for dataset which was derived through multiple regressions [29]. One multiple linear regressions (MLR) model is derivative among risk factor and variables that affect it, see Table 2. We have found that the derivative through multiple regression model is statistically strong, evaluating the precision of multiple regression model the result of this model equated with the data of (number of infected cases per population, number of persons in ICU per population and number of deaths per population). According to the result of Table 2 the value of beta (the effect of essential input parameters) on risk factor have reach comparable percentages. This percentage can be reported as 35.37%, 31.75% and 28.18% for each of number of deaths per population, number of persons in ICU per population, number of infected cases per population, respectively. So that, the outcomes of the fuzzy logic study show the impact of the combined number of infected cases and ICU patients, as well as, the number of deaths that occurred as a result of sever coronavirus infections. The value of the total effects of these essential factors has attained the rate of 95.3%, as shown in Table 3 which represents the regression analysis of employed variable. The adjusted R square of 95.3% provides the value of total influence of input variable on the risk factor value for the proposed model.

Table 2. Regression analyses for the risk factor results of the proposed CRF

Considerations	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
Constant	-6.751	.862		-7.831	.000	-8.443	-5.060
Rates of deaths	98.371	.935	.625	105.192	.000	96.536	100.205
Rates in the ICU	88.371	.935	.561	94.499	.000	86.536	90.205
Rates of infected cases	78.371	.935	.498	83.805	.000	76.536	80.205

Coefficients= dependent variable

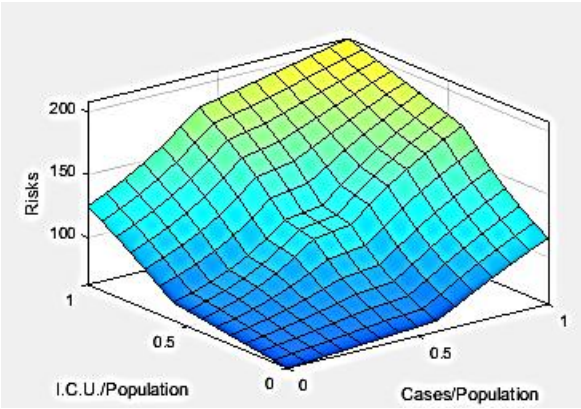
According to Table 2, the results indicate that the values of beta (the effect of input essential parameters) on the risk factor have reached comparable percentages. These percentages can be reported as 35.37%, 31.75% and 28.18% for each of the number of deaths per population, the number of people in the ICU per population and the number of infected cases per population, respectively. The total effect is benchmarked to 95.3% as in Table 3 which represent the regression analyses of the employed variables. It provides the value of the total influence of the input variables (Adjusted R Square) on the risk factor values for the proposed model summary. This makes sense according to the way of providing good treatments and efforts that lead to reducing the severity of coronavirus infections. Starting from a good care measure, followed by considering the number of patients in the ICU, and finally, raising the attentions toward the number of deaths. Such efficient preventive measure can be valuable for reducing the cases of coronavirus infections and seeking help from others, determined by decision-makers especially at the beginning of raising deaths which is the strongest indication of risk. Additional relationships have been collected between the employed variable inputs and output. Figure 4(a) shows triple relationships between the number of infected cases per population, number of people in the ICU per population and risk factor of the proposed CRF. Figure 4(b) provides triple relationships between the number of infected cases per population, number of deaths per population and risk factor of the proposed CRF. Figure 4(c) demonstrates triple relationships between the number of people in the ICU per population, number of deaths per population and risk factor of the proposed CRF.

Table 3. Total summary for the risk factor[d] results of the proposed CRF

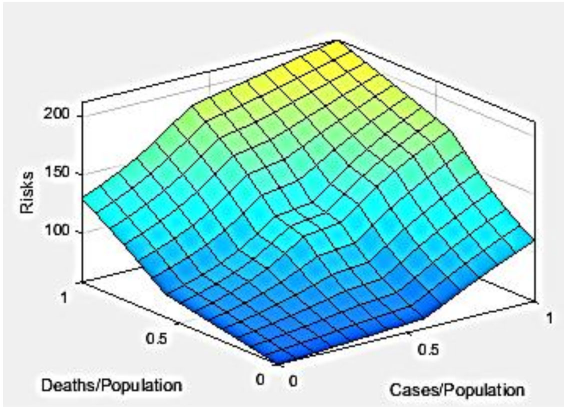
R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.976[c]	.953	.953	10.788709450	.248	7023.356	1	1327	.000	.557

[c] Predictors for the considerations in Table 2
[d] Dependent variable

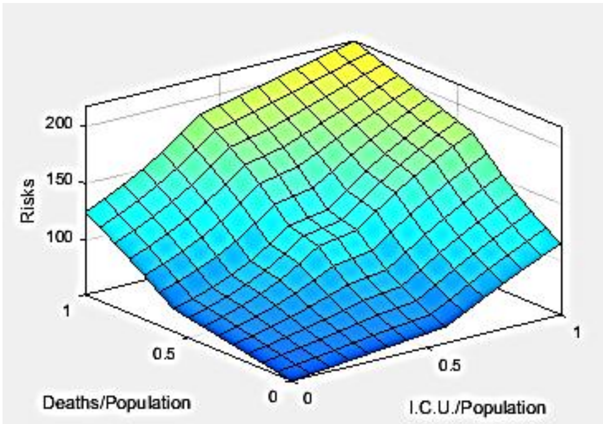
All of these figures are indicated that the proposed CRF based on the SFL can successfully provide fuzzy relationships between different employed variables. That is, the non-fuzzy relationships would demonstrate pure plains and this is not the case in Figure 4. This is a strong evidence about the successfulness of the SFL calculations for obtaining the CRF output values.



(a)



(b)

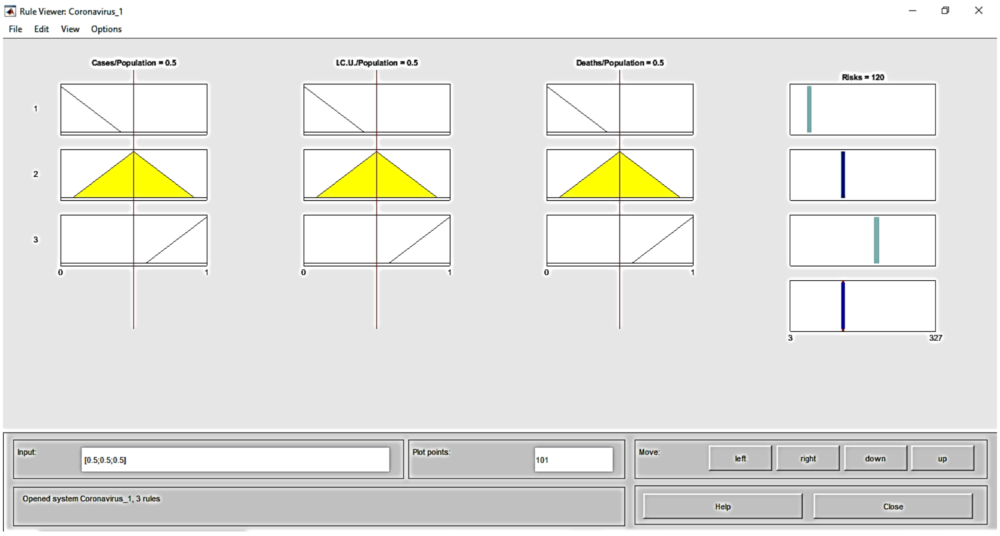


(c)

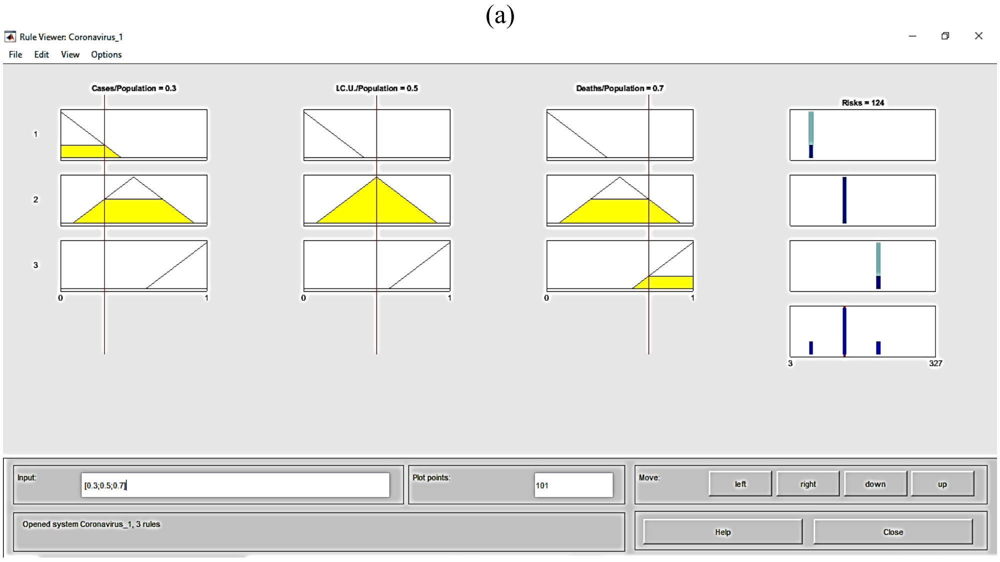
Figure 4. Triple relationships between: (a) the number of infected cases per population, number of people in the ICU per population and risk factor of the proposed CRF; (b) the number of infected cases per population, number of deaths per population and risk factor of the proposed CRF; and (c) the number of people in the ICU per population, number of deaths per population and risk factor of the proposed CRF

As mentioned, the CRF output uses the first-order functions. Its values are ranged between a very low risk of 30, where the coronavirus still requires observation, to a very high risk of 300, where it represents 3 times of risks for the three inputs (100 for each input). Examples of the proposed CRF based on the SFL are simulated in Figure 5. These examples have simulation implementations for various values. Figure 5(a) shows a moderate outcome of Risk= 120 for the moderate input values of 0.5 each. Figure 5(b) shows a bit high outcome of Risk= 124 for the number of infected cases/population = 0.3, number of people in ICU/population = 0.5 and number of deaths/population= 0.7. Here, the number of infected cases/population is more than the number of deaths/population and because death cases are more risky than infection cases, the output risk factor is increased. Figure 5(c) shows a bit low outcome of Risk= 116 for the number of infected cases/population = 0.7, number of people in ICU/population= 0.5 and number of deaths/population = 0.3. Here, the number of infected cases/population is less than the number of deaths/population and because infection cases are less risky than death cases, the output risk factor is decreased.

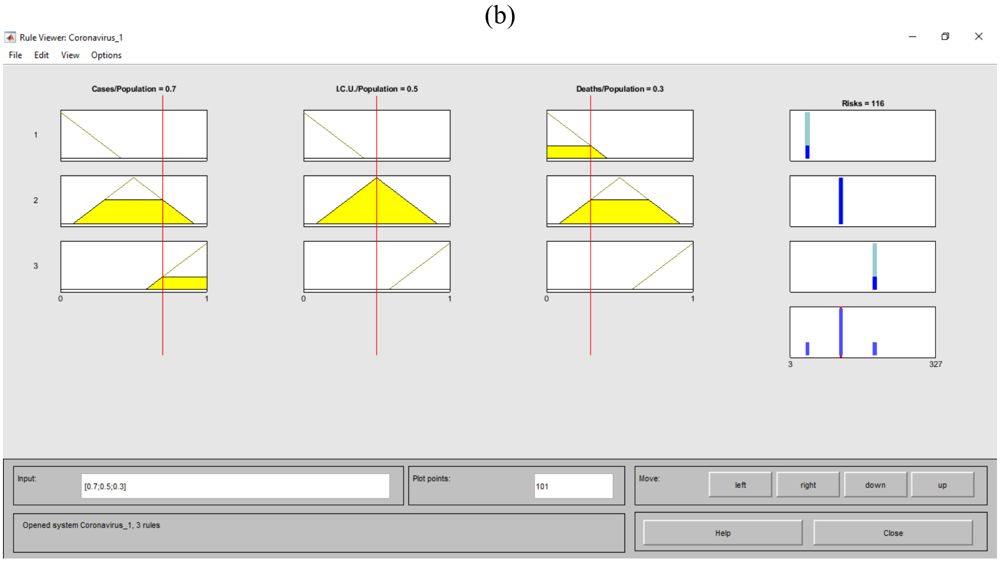
For the case of comparisons with other existing studies, it has been invistigated that other studies of risks have achieved various performances. That is, the work in 29] has reported the performance of 80%. Furthermore, the work in [17] has recorded the performance of 86.6%. Hence, it can be seen that our method has benchmarked the highest performance of 95.3%.



(a)



(b)



(c)

Figure 5. Examples of the proposed CRF based on the SFL: (a) moderate values to all inputs, (b) number of infected cases/population more than number of deaths/population, and (c) number of deaths/population than number of infected cases/population more

4. CONCLUSION

Soft computing technologies, such as fuzzy logic, are valuable tools for preventing infection sources, helping patients, and preventing disease progression. These technologies can also support decision-making by providing information to declare a state of emergency in a country and indicating when assistance is needed from other countries. The coronavirus pandemic has highlighted the need for effective techniques and models for identifying and analyzing risk factors associated with the spread of the disease. It seems like fuzzy logic is a good tool for assessing and detecting risk factors so that other nations can be informed and asked for help. This paper focuses on using SFL to determine the CRF based on three inputs: the number of deaths per population, the number of people in the ICU per population, and the number of infected cases per population. The aim is to prevent exacerbation of the epidemic by reducing the severity of injuries and providing intensive care as necessary. Death is the last stage, and the goal is to lessen the epidemic's impact on society. The study found that the total effect of these essential factors is 95.3%. This work of this study has the limitation of real-time implementation as it currently uses simulations. However, this can be sorted out by exporting the SFL of the CRF to an appropriate program. For possible future work directions, the following contributions can be considered: providing real-time implementation, delivering risk outcomes to decision makers and considering machine learning techniques.

REFERENCES

[1] B. Hu *et al.*, "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus-infected pneumonia in Wuhan, China," *JAMA-Journal of the American Medical Association*, vol. 323, no. 11, pp. 1061–1069, Mar. 2020, doi: 10.1001/jama.2020.1585.

[2] U. H. Issa, A. Balabel, M. Abdelhakeem, and M. M. A. Osman, "Developing a risk model for assessment and control of the spread of COVID-19," *Risks*, vol. 9, no. 2, p. 38, Feb. 2021, doi: 10.3390/risks9020038.

[3] S. Ashraf, S. Abdullah, and A. O. Almagrabi, "A new emergency response of spherical intelligent fuzzy decision process to diagnose of COVID19," *Soft Computing*, vol. 27, no. 3, pp. 1809–1825, Feb. 2023, doi: 10.1007/s00500-020-05287-8.

[4] M. K. Sharma, N. Dhiman, Vandana, and V. N. Mishra, "Mediative fuzzy logic mathematical model: A contradictory management prediction in COVID-19 pandemic," *Applied Soft Computing*, vol. 105, no. 10, p. 107285, Jul. 2021, doi: 10.1016/j.asoc.2021.107285.

[5] O. Užga-Rebrovs and G. Kuļešova, "Comparative analysis of fuzzy set defuzzification methods in the context of ecological risk assessment," *Information Technology and Management Science*, vol. 20, no. 1, pp. 25–29, 2018, doi: 10.1515/itms-2017-0004.

[6] M. Y. Al-Ridha, R. R. O. Al-Nima, and A. S. Anaz, "Adaptive neuro-fuzzy inference system for controlling a steam valve," in *2019 IEEE 9th International Conference on System Engineering and Technology (ICSET)*, Oct. 2019, vol. 6, no. 1, pp. 156–161, doi: 10.1109/ICSEngT.2019.8906307.

[7] R. H. Al Mahmoud, E. Omar, K. Taha, M. Al-Sharif, and A. Aref, "Covid-19 global spread analyzer: An ML-based attempt," *Journal of Computer Science*, vol. 16, no. 9, pp. 1291–1305, 2020, doi: 10.3844/jcssp.2020.1291.1305.

[8] A. Adwibowo, "Fuzzy logic assisted COVID 19 safety assessment of dental care," *medRxiv*, 2020, doi: 10.1101/2020.06.18.20134841.

[9] W. M. Shaban, A. H. Rabie, A. I. Saleh, and M. A. Abo-Elsoud, "Detecting COVID-19 patients based on fuzzy inference engine and Deep Neural Network," *Applied Soft Computing*, vol. 99, p. 106906, Feb. 2021, doi: 10.1016/j.asoc.2020.106906.

[10] R. R. Al-Nima, F. S. Abdullah, and A. N. Hamoodi, "Design a technology based on the fusion of genetic algorithm, neural network and fuzzy logic," *arXiv:2102.08035*, 2021.

[11] A. Y. F. Alsahlani and A. Popa, "LMAAS-IoT: Lightweight multi-factor authentication and authorization scheme for real-time data access in IoT cloud-based environment," *Journal of Network and Computer Applications*, vol. 192, p. 103177, Oct. 2021, doi: 10.1016/j.jnca.2021.103177.

[12] P. U. Ejodamen and V. E. Ekong, "A fuzzy expert system model for the determination of coronavirus disease risk," *International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)*, vol. 11, no. 39, pp. 4825–4831, 2021.

[13] K. T. Ly, "A COVID-19 forecasting system using adaptive neuro-fuzzy inference," *Finance Research Letters*, vol. 41, p. 101844, Jul. 2021, doi: 10.1016/j.frl.2020.101844.

[14] F. H. Abdulraheem, M. Y. Al-Ridha, and R. R. O. Al-Nima, "Predicting death and confirmed cases of coronavirus," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 1, pp. 380–385, 2022, doi: 10.11591/eei.v11i1.3133.

[15] S. Shafiekhani, P. Namdar, and S. Rafiei, "A COVID-19 forecasting system for hospital needs using ANFIS and LSTM models: A graphical user interface unit," *Digital health*, vol. 8, p. 20552076221085056, Jan. 2022, doi: 10.1177/20552076221085057.

[16] H. Şimşek and E. Yangın, "An alternative approach to determination of Covid-19 personal risk index by using fuzzy logic," *Health and Technology*, vol. 12, no. 2, pp. 569–582, Mar. 2022, doi: 10.1007/s12553-021-00624-9.

[17] İ. Şahin, E. Akdogan, and M. E. Aktan, "A type-2 fuzzy rule-based model for diagnosis of COVID-19," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 31, no. 1, pp. 39–52, Jan. 2023, doi: 10.55730/1300-0632.3970.

[18] O. Castillo, P. Melin, J. Kacprzyk, and W. Pedrycz, "Type-2 Fuzzy logic: theory and applications," in *2007 IEEE International Conference on Granular Computing (GRC 2007)*, Nov. 2007, pp. 145–145, doi: 10.1109/GrC.2007.118.

[19] D. J. Dubois and H. M. Prade, *Fuzzy sets and systems: theory and applications*, vol. 144. New York, US: Academic Press, 1980.

[20] I. B. Turksen, "Measurement of membership functions and their acquisition," *Fuzzy Sets and Systems*, vol. 40, no. 1, pp. 5–38, 1991, doi: 10.1016/0165-0114(91)90045-R.

[21] Y. Wang and Y. Chen, "A comparison of mamdani and sugeno fuzzy inference systems for traffic flow prediction," *Journal of Computers*, vol. 9, no. 1, pp. 12–21, 2014, doi: 10.4304/jcp.9.1.12-21.

[22] A. Hamam and N. D. Georganas, "A comparison of Mamdani and Sugeno fuzzy inference systems for evaluating the quality of experience of Hapto-audio-visual applications," in *2008 IEEE International Workshop on Haptic Audio visual Environments and Games*, Oct. 2008, pp. 87–92, doi: 10.1109/HAVE.2008.4685304.

[23] M. Dhimish, V. Holmes, B. Mehrdadi, and M. Dales, "Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection," vol. 117, pp. 257–274, 2018, doi: 10.1016/j.renene.2017.10.066.

[24] N. Walia, H. Singh, and A. Sharma, "ANFIS: Adaptive neuro-fuzzy inference system- a survey," *International Journal of Computer Applications*, vol. 123, no. 13, pp. 32–38, 2015, doi: 10.5120/ijca2015905635.
[25] MathWorks, "Fuzzy logic toolbox," *The MathWorks, Inc.*, 2020. https://www.mathworks.com/products/fuzzy-logic.html.
[26] X. Zhang, Z. Yin, Y. Jiang, Y. Jiang, D. Sun, and Y. Liu, "Fuzzy Knowledge Distillation from High-Order TSK to Low-Order TSK," *arXiv:2302.08038*, pp. 1–10, 2023.
[27] O. I. Alsaif, S. Q. Hasan, and A. H. Maray, "Using skeleton model to recognize human gait gender," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 2, pp. 974–983, Jun. 2023, doi: 10.11591/ijai.v12.i2.pp974-983.
[28] C. Iwendi, K. Mahboob, Z. Khalid, A. R. Javed, M. Rizwan, and U. Ghosh, "Classification of COVID-19 individuals using adaptive neuro-fuzzy inference system," *Multimedia Systems*, vol. 28, no. 4, pp. 1223–1237, Aug. 2022, doi: 10.1007/s00530-021-00774-w.
[29] S. I. M. Alobyde, F. S. Hamid, and I. K. S. Albayati, "Comparison of Artificial neural network and regression pedotransfer function for prediction of soil cation exchange capacity at Iraq, Ray AL Jazeera, Mosul region," *Journal of Engineering Sciences and Information Technology*, vol. 4, no. 2, pp. 90–109, Jun. 2020, doi: 10.26389/AJSRP.P161219.

BIOGRAPHIES OF AUTHORS

Saba Qasim Hasan received her B.Sc. in Computer Science Department Mosul University, Mosul, Iraq at 1996 and the M.Sc. in Image Security Processing from Computer Science Department Mosul University at 2003. She is currently working as lecturer in Mosul Technical Institute Northern Technical University in Mosul Iraq. Her research interests image security and objects detection. She can be contacted at email: saba.qassim73@ntu.edu.iq.

Raid Rafi Omar Al-Nima received the B.Sc. and M.Sc. degrees in Technical Computer Engineering in 2000 and 2006, respectively. During 2006, he worked as an Assistant Lecturer in the Technical College of Mosul, Iraq. In 2011, he obtained the Lecturer scientific title in the same college. In 2017, he accomplished his Ph.D. in the School of Electrical and Electronic Engineering at Newcastle University, UK. In 2020, he achieved the title of Assistant Professor in the Northern Technical University. His research interests are in the fields of pattern recognition, security, artificial intelligence, and image processing. He can be contacted at email: raidrafi3@ntu.edu.iq.

Sahar Esmail Mahmmod is a graduate of a master's degree in computer science, specializing in artificial intelligence, from the University of Mosul, with a scientific title as a teacher. Lecturer at the Northern Technical University, Mosul Technical Institute, Department of Computer Systems Technologies. She have a collection of research mostly in the field of artificial intelligence. She can be contacted at email: sahar_esmaiel@ntu.edu.iq.