

Fuzzy Expert Systems for Prediction of ICU Admission in Patients with COVID-19

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Abstract

The pandemic COVID-19 disease has had a dramatic impact on almost all countries around the world so that many hospitals have been overwhelmed with Covid-19 cases. As medical resources are limited, deciding on the proper allocation of these resources is a very crucial issue. Besides, uncertainty is a major factor that can affect decisions, especially in medical fields. To cope with this issue, we use fuzzy logic (FL) as one of the most suitable methods in modeling systems with high uncertainty and complexity. We intend to make use of the advantages of FL in decisions on cases that need to treat in ICU. In this study, an interval type-2 fuzzy expert system is proposed for prediction of ICU admission in COVID-19 patients. For this prediction task, we also developed an adaptive neuro-fuzzy inference system (ANFIS). Finally, the results of these fuzzy systems are compared to some well-known classification methods such as Naive Bayes (NB), Case-Based Reasoning (CBR), Decision Tree (DT), and K Nearest Neighbor (KNN). The results show that the type-2 fuzzy expert system and ANFIS models perform competitively in terms of accuracy and F-measure compared to the other system modeling techniques.

Keywords: Fuzzy Logic, Expert System, COVID-19

1. Introduction

COVID-19 or Coronavirus has affected the public health and economics of many countries in the world due to its contagious nature and lack of effective medicine or vaccine [1]. It has spread to over 50 million people worldwide by the end of September 2020. According to medical reports, the mortality rate associated with this virus is low. However, the long duration of the disease and the disability of patients for a long time cause further spread of the disease and thus increase the mortality associated with this disease. It has killed over 1200000 people by the end of September 2020 [2].

It is noteworthy that many COVID-19 patients will develop mild to moderate illness and recover without hospitalization. Fever, dry cough, and tiredness are the most common symptoms of COVID-19. These patients are advised to manage their symptoms at home. On the other hand, serious symptoms such as difficulty breathing and chest pain have appeared in some patients during the disease [3]. This condition can quickly get worse so that an emergency situation occurs. These critical situations can increase human decision-making errors leading to more financial and non-financial losses.

Besides, predicting the situation of patients is useful for hospitals and health centers due to the spread of this virus. It can help to design targeted tests of people, predict the number of required resources in hospitals and health centers, and inform medical plans for prioritizing the level of care, design-related policy about vaccination, and so on. [4, 5]. In this way, health centers and hospitals can

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prediction of chronic kidney disease was determined [26]. In another study, Hussain et al. presented a multi-layered fuzzy Mamdani inference system to analyze the prevailing thyroid disease. In their study, the proposed expert system is based on two layers. In layer 1, the presence or absence of thyroid disease is diagnosed. If layer 1 indicates the presence of thyroid disease, then layer 2 is activated by which the type of thyroid disease is determined [27].

Khalil et al. developed a new fuzzy soft expert system to predict lung cancer disease by using weight loss, shortness of breath, chest pain, persistent cough, blood in sputum, and age of patients. In their work, a prediction of the fuzzy soft expert system is composed of four main steps: 1) Transforming real-valued inputs into fuzzy numbers. 2) Converting fuzzy numbers into fuzzy soft sets. 3) Reducing the family of fuzzy soft sets obtained to a new family of fuzzy soft sets. 4) Using the proposed method to get the output data [28]. Mahanta and Panda developed a fuzzy expert system for the prediction of prostate cancer. In their study, age, prostate-specific antigen (PSA), prostate volume (PV), and Free PSA (FPSA) are fed as inputs into the system, and prostate cancer risk (PCR) is obtained as the output [29].

Mirmozaffari et al. presented an expert system for diagnosing the type of gastrointestinal disease and determining the type of tests needed to diagnose the disease [30]. Mojriari et al. presented a method based on a multilayer fuzzy expert system for the detection of breast cancer using an extreme learning machine (ELM) classification model integrated with radial basis function (RBF) kernel called ELM-RBF. In this study, they showed that their proposed method outperforms the linear-SVM model [31].

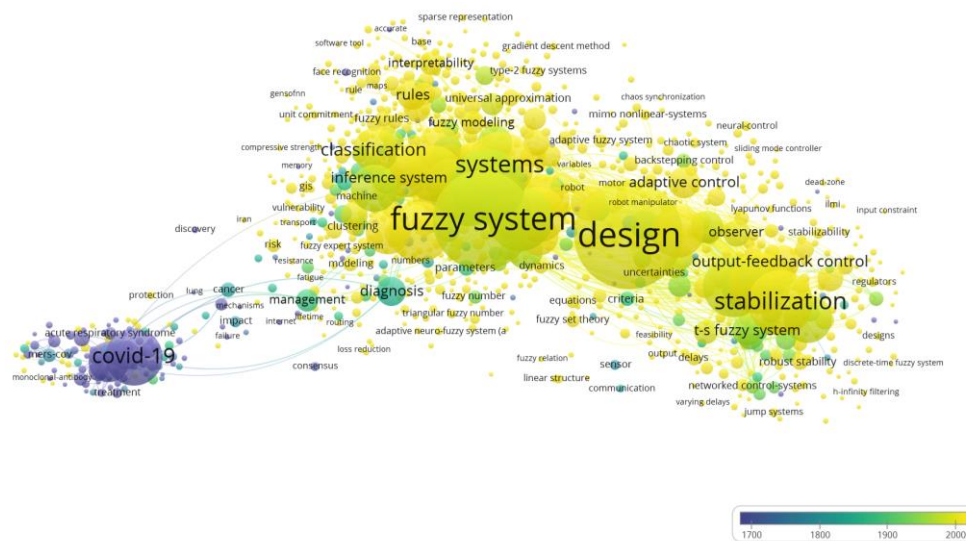


Figure 2. The year of published articles about COVID-19 and expert systems

In another study, Naseer et al. proposed a fuzzy expert system for the diagnosis of heart disease. In their proposed system, the input variables comprised of age, chest pain, electrocardiography, blood pressure systolic, diabetes, and cholesterol are transmitted with the help of fuzzy rules which are framed in the light of low, normal, high, and very high intensity and the output is obtained using the Mamdani Inference method diagnosing the heart disease [32]. Siddiqui et al. developed an adaptive hierarchical Mamdani fuzzy expert system for the detection of arthritis. In their research, the expert system is comprised of two layers. In the first layer, the input variables are rest pain, morning stiffness, body pain, joint infection, swelling, redness, past injury and age that detects output condition of arthritis to be normal, infection and/or other problem, and in the second layer, the type of arthritis is diagnosed [33]. Table 1 summarizes the fuzzy expert systems proposed for the diagnosis of various types of diseases.

Table 1. A review on the application of fuzzy expert systems in medical fields

Author [year]	Disease	Technique
Sotudian et al. (2016) [7]	Hepatitis	Indirect approach for fuzzy system modeling
Guzmán et al. (2017) [8]	Blood pressure	Neuro-fuzzy hybrid model
Meza-Palacios et al. (2017) [9]	Type-2 diabetes mellitus	Fuzzy expert system based on experts' guidelines
Sadat Asl & Zarandi (2017) [10]	Leukemia	Type-2 fuzzy expert system with Mamdani-style inference
Zarandi et al. (2017) [11]	Heart disease	Expert system based on fuzzy bayesian network
Motlagh et al. (2018) [12]	Depressive disorder	Web-based fuzzy expert system
Caliwag et al. (2018) [13]	Venereal diseases	Mobile expert system based on fuzzy logic
Muhammad et al. (2018) [14]	Coronary artery disease	Expert system with developed knowledge acquisition
Nazari et al. (2018) [15]	Heart diseases	Fuzzy inference-fuzzy analytic hierarchy process-based
Soltani et al. (2018) [16]	Glaucoma	Expert fuzzy logic & image processing methods
Tuan et al. (2018) [17]	Dental disorders	Fuzzy computing & image processing methods
Terrada et al. (2018) [18]	Cardiovascular diseases	Fuzzy medical system using risk factors based on data
Ahmad et al. (2019) [19]	Hepatitis B	Multilayer Mamdani fuzzy inference system
Raza et al. (2019) [20]	Erythematous squamous	Expert system based on fuzzy rules
Arji et al. (2019) [21]	Infectious & communicable disease	Fuzzy inference & rule-based fuzzy logic, ANFIS
Kaur & Kakkar (2019) [22]	Neurodevelopmental disorders	Fuzzy based-systems based on co-morbid factors
Sadat Asl (2019) [23]	Leukemia	Two-stage expert system based on type-2 fuzzy logic
Mirmozaffari (2019) [24]	Liver diseases	Expert system based on the VP-Expert shell
Mujawar & Jadhav (2019) [25]	Diabetes	Web-based fuzzy expert system
Mutawa and Alzuwawi (2019) [26]	Uveitis	Multilayered rule-based expert system
Sajadi et al. (2019) [27]	Hypothyroidism	Fuzzy rule-based expert system
Hamedan et al. (2020) [28]	Chronic kidney disease	Fuzzy expert system with Mamdani inference system
Hussain et al. (2020) [29]	Thyroid disease	Multi-layered fuzzy Mamdani inference system
Khalil et al. (2020) [30]	Lung cancer	Fuzzy soft expert system
Mahanta & Panda (2020) [31]	Prostate cancer	Fuzzy expert system with Mamdani inference system
Mirmozaffari (2020) [32]	Gastrointestinal diseases	Fuzzy expert system based on VP-Expert shell
Mojrrian et al. (2020) [33]	Breast cancer	Multilayer fuzzy expert system based on RBF
Naseer et al. (2020) [34]	Heart disease	Mamdani fuzzy inference expert system
Siddiqui et al. (2020) [35]	Arthritis	Adaptive hierarchical Mamdani fuzzy expert system

3. Designing the type-2 fuzzy expert system

As mentioned earlier, the main objective of this paper is to design an expert system to predict ICU needs for COVID-19 patients based on type-2 FL. To this end, there are two common approaches for the selection of the parameters of a type-2 FL system. The first one is the partially dependent approach. In this approach, first, the best possible type-1 FL system is designed. Then, it is used to initialize the parameters of a type-2 FL system. The second one is the totally independent approach where all of the parameters of the type-2 FL system are tuned without using an existing type-1 design [36]. In this paper, we use the partially dependent approach because of its advantages compared with the totally dependent approach. After designing type 1 fuzzy system, a type-2 rule based fuzzy system with uncertain standard deviation and interval-valued membership function is implemented. The same rules of the type-1 fuzzy system are used by this system and the only difference is that if-part and then-part are type-2. The designed system is comprised of the following steps:

- Data preprocessing and determining the inputs and output of the system;
- Clustering the output space and determination of the number of rules;
- Projection of membership functions of the output onto the inputs to obtain the membership values of the inputs;
- Tuning the parameters of type-1 membership functions of inputs and output variables;
- Transforming type-1 to interval type-2 membership functions;
- Tuning the parameters of type-2 membership functions.

3.1. Data Preprocessing

We use a publicly available dataset, containing information of about 566602 patients. The data contains some information about pregnancy, diabetes, chronic obstructive pulmonary disease (COPD), asthma, cardiovascular, obesity, tobacco, etc. and determines whether a patient needs an ICU or not [6]. In this dataset, there are 444814 missing data for ICU. Therefore, the final number of patients used in fuzzy expert systems and other classification techniques is 121788. Besides, a few outliers (e.g., male patient's pregnancy) were detected and removed from the dataset.

Most precondition features of this dataset are categorical, each of which takes the value yes, no, and unspecified. These categorical features were converted to numerical by ‘one-hot’ encoding. By creating auxiliary variables that help differentiate between various categories of a feature, one-hot encoding transforms the categorical feature to multiple binary variables. Finally, highly correlated variables were eliminated as they provide similar information. Specifically, we calculated pairwise correlations among the variables and one among any two highly correlated variables with an absolute correlation coefficient higher than 0.85 was removed. After the preparation of the dataset, we reached 27 features, with one output determines whether a patient need to the ICU or not.

3.2. Clustering the output space and determination of the number of rules

To determine the number of rules, we use Fukuyama cluster validity index which can be defined as follows [37]: (1)

$$\min_{2 \leq c \leq C_{max}} V_{FS}(U, V, X) = \sum_{i=1}^c \sum_{j=1}^N u_{ij}^m \|x_j - v_i\|^2 - \sum_{i=1}^c \sum_{j=1}^N u_{ij}^m \|v_i - \bar{v}\|^2, \quad (1)$$

where $X = \{x_1, x_2, \dots, x_N\} \subseteq \mathbb{R}^d$ is the dataset in d-dimensional vector space, u_{ij} is the degree of belonging of the j^{th} data to the i^{th} cluster, $V = \{v_1, v_2, \dots, v_c\}$ is the prototypes of clusters, c is the number of clusters, $\bar{v} = \frac{\sum v_i}{c}$, m is the degree of fuzziness, U is fuzzy partition matrix, and N is the number of samples. By solving $\min_{2 \leq c \leq C_{max}} V_{FS}$, the optimal cluster number is obtained. In this study, this cluster validity index was implemented and the optimal value for the number of clusters is obtained five clusters. Therefore, we have five rules in our system. In the proposed system, Mamdani inference system is used where the antecedents and consequents of the rule-based system are fuzzy sets. We clustered the output data and then obtained the output clusters' primary membership grades using Sugeno and Yasukawa method [38]. First, we partition the output space, and then, get the input space clusters by projecting the output space partition to each input variable space.

3.3. Projection of membership functions of the output onto the inputs

For the input variables, the appropriate membership grades should be calculated after clustering the output space. One way is to set each input's membership grade equal to its corresponding output membership grade obtained by the procedure of output data clustering. In this way, for each output data,

all the related input variables would then have a similar membership grade. The issue with this approach is that the membership functions are not convex and a further approximation is required to form the convex membership functions. Furthermore the output membership grade is not always the same as the input membership grades at each sample point [39]. For these reasons, in this paper, Zarandi's approach is used. According to this approach, first, the ranges in which the membership functions of the input variable adopt value 1 are determined. The data points are then classified using GK method, by given m and c determined in the preceding step (obtained from output variable clustering stage) and analyzing the objective function of classification algorithm (for more details please refer to [39]).

3.4. Tuning the parameters of type-1 membership functions

There are several parameters in type-1 FL systems that can either be pre-specified or can be tuned during a training phase. An impeccable FL system should have $f(x) = d$, where d is the desired output. However, there are typically errors between the desired and actual output. Therefore, in order to produce better results, tuning the parameters of the fuzzy model is important. In this paper, the suggested tuning algorithm by Liang and Mendel is used. Based on this approach, all of the parameters related to a Gaussian type-1 are tuned using the steepest-descent method. Given an input-output training pair $(x^{(i)}, y^{(i)})$, $x^{(i)} \in R^G$ and $y^{(i)} \in R$, a type-1 fuzzy is designed by minimizing the following error function [40]:

$$e(t) = \frac{1}{2} [f(x^{(i)}) - y^{(i)}]^2, \quad i = 1, \dots, N. \quad (2)$$

3.5. Transforming type-1 to interval type-2 membership functions

To transform type-1 to an interval type-2 fuzzy set with uncertain standard deviation, the case of a Gaussian primary membership function with a fixed mean m_f^S and uncertain standard deviation that takes on values in $[\sigma_{f_1}^S, \sigma_{f_2}^S]$ is considered [40]:

$$u_f^S(x_f) = \exp \left[-\frac{1}{2} \left(\frac{x_f - m_f^S}{\sigma_f^S} \right)^2 \right], \quad \sigma_f^S \in [\sigma_{f_1}^S, \sigma_{f_2}^S], \quad (3)$$

where $f = 1, \dots, G$; G is number of antecedent; $S = 1, \dots, D$; and D is number of rules. We can obtain the upper and lower membership functions by replacing $\sigma_{f_2}^S$ and $\sigma_{f_1}^S$ with σ_f^S in the above expression.

3.6. Tuning the parameters of type-2 membership functions

For tuning the parameters of the interval type-2 FL system, we use the proposed tuning algorithm by Liang and Mendel. In interval type-2 system, $f(x)$ is determined by upper and lower membership functions and centroids of interval type-2 fuzzy sets, and therefore, we want to tune these parameters. Since an interval type-2 FL system can be identified by two fuzzy basis function expansions, we can focus on tuning the parameters of just these two type-1 FL systems [41].

4. Proposed interval type-2 fuzzy expert system

In this paper, we use Mamdani inference system in which the antecedents and consequent are type-2 fuzzy sets which have a fixed mean and an uncertain standard deviation that takes values in an interval.

The interval type-2 FL system is created from the type-1 FL system. The proposed system uses singleton fuzzification, product t-norm, product inference, and center-of-sets type-reduction, with the same number of fuzzy sets and rules as the type-1 FL system. Several defuzzification methods have been used, such as centroid, bisector, and Yager. The best results of this system is obtained by Yager defuzzification method. Figure 3 demonstrates the rule based and inference mechanism for the proposed interval type-2 fuzzy system.

5. Performance Evaluation and Analysis

In this paper, in addition to developing a type-2 fuzzy expert system for prediction of ICU admission, we develop the ANFIS model for this prediction task using MATLAB toolbox. Then, we compare the performance of the developed fuzzy expert systems to several well-known classification methods such as NB, CBR, DT, and KNN in terms of accuracy and F-measure. To evaluate the performance of each system, the dataset is divided into training and test sets. In this way, for each system modeling technique, 70% of the dataset has been used for training. Table 2 shows the accuracy and F-measure of different system modeling techniques implemented in this study.

Classification accuracy is the total number of accurate predictions divided by the total number of predictions made for a dataset. As a performance measure, accuracy is not sufficient for imbalanced classification problems. The key explanation is that the vast number of examples from the dominant class or classes would overwhelm the number of minority class examples. Using precision and recall metrics is an alternative to using classification accuracy. F-Measure integrates both precision and recall into a single measure and captures both properties [42]. As can be seen in Table 2, the developed fuzzy expert systems could achieve an accuracy of 91.6% and an F-measure of 95.6%. Comparing to the CBR and KNN methods, the fuzzy expert systems can improve the accuracy and F-measure by about 1.5% to 5% and 1% to 3%, respectively. Furthermore, the developed fuzzy models performed competitively compared to the other classification methods. Overall, the results show that both type-2 fuzzy system and ANFIS model could outperform the well-known classification methods.

Type-2 FL systems usually give better results than their type-1 counterparts as the type-2 fuzzy sets and systems generalize type-1 fuzzy sets and systems so that more uncertainty can be handled. However, in our case, as can be seen, the results of the type-2 fuzzy expert system are very close to the ANFIS model. In the dataset, as most input variables are categorical, the type-2 fuzzy sets lost its efficiency. Therefore, in this specific problem, type-2 FL has lost its superiority over the developed ANFIS model.

Table 2. Accuracy and F-measure of different system modeling techniques

Methods	Accuracy %	F-measure %
Type-2 fuzzy system	91.64	95.64
ANFIS	91.66	95.66
NB	90.79	95.15
CBR	86.26	92.54
DT	90.63	95.06
KNN	90.04	94.73

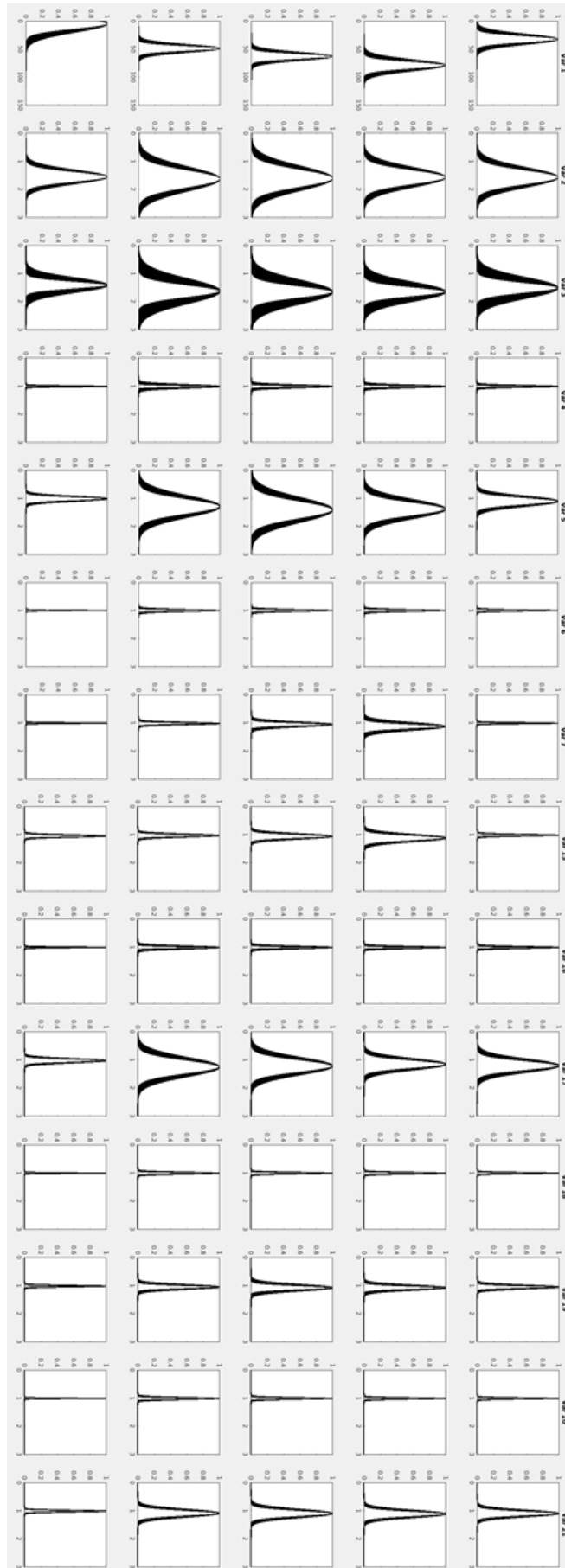


Figure 3. Interval type-2 fuzzy rule base

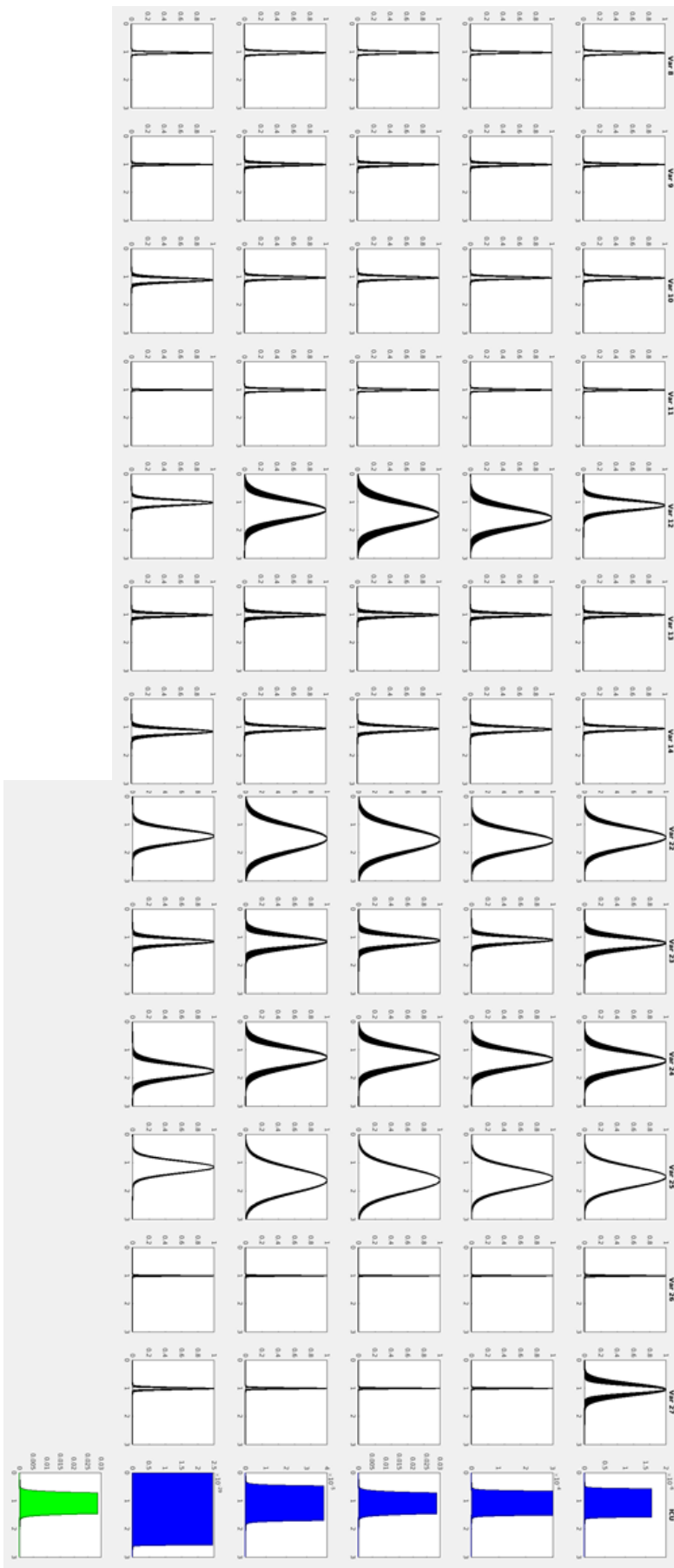


Figure 3. (continued) Interval type-2 fuzzy rule base

6. Conclusion

In this study, a type-2 fuzzy expert system and an adaptive neuro-fuzzy inference system are developed for the prediction of ICU admission. Furthermore, to evaluate the performance of these fuzzy systems, several classification methods such as NB, CBR, DT, and KNN are also implemented. All these methods are tested on a publicly available dataset. The results demonstrate the efficacy of the proposed fuzzy expert systems, with an accuracy of 91.6% and an F-measure of 95.6%, which outperform the other conventional classification techniques. When comparing the two developed fuzzy expert systems, we can notice that the results of the type-2 fuzzy expert system are very close to the ANFIS model since, in our problem, most input variables are categorical.

Over time, more datasets will be published related to the COVID-19 disease because more and more tests are performed every day for this disease. Therefore, for future studies, the proposed fuzzy expert systems can be evaluated over some other datasets. As mentioned earlier, in this study, the type-2 FL has lost its superiority over the type-1 fuzzy model as most of the input variables are categorical. If the number of continuous input variables in new datasets is higher, the type-2 fuzzy expert system may provide better results due to its higher generalizability.

References

- [1] Silva PC, Batista PV, Lima HS, Alves MA, Guimarães FG, Silva RC. COVID-ABS: An agent-based model of COVID-19 epidemic to simulate health and economic effects of social distancing interventions. *Chaos, Solitons & Fractals*. 2020 Oct 1;139:110088.
- [2] World Health Organization. Coronavirus disease 2019 (COVID-19): situation report, 72.
- [3] Menni C, Valdes AM, Freidin MB, Sudre CH, Nguyen LH, Drew DA, Ganesh S, Varsavsky T, Cardoso MJ, Moustafa JS, Visconti A. Real-time tracking of self-reported symptoms to predict potential COVID-19. *Nature medicine*. 2020 May 11:1-4.
- [4] Fischer GS, da Rosa Righi R, de Oliveira Ramos G, da Costa CA, Rodrigues JJ. EIHealth: Using Internet of Things and data prediction for elastic management of human resources in smart hospitals. *Engineering Applications of Artificial Intelligence*. 2020 Jan 1;87:103285.
- [5] Horvitz E. From data to predictions and decisions: Enabling evidence-based healthcare. *Computing Community Consortium*. 2010 Sep 18;6.
- [6] <https://www.kaggle.com/tanmoyx/covid19-patient-precondition-dataset?select=covid.csv>.
- [7] Sotudian, Shahabeddin, MH Fazel Zarandi, and I. B. Turksen. "From Type-I to Type-II fuzzy system modeling for diagnosis of hepatitis." *International Journal of Computer and Information Engineering* 10.7 (2016): 1280-1288.
- [8] Guzmán JC, Melin P, Prado-Arechiga G. Neuro-fuzzy hybrid model for the diagnosis of blood pressure. In *Nature-Inspired Design of Hybrid Intelligent Systems 2017* (pp. 573-582). Springer, Cham.
- [9] Meza-Palacios R, Aguilar-Lasserre AA, Ureña-Bogarín EL, Vázquez-Rodríguez CF, Posada-Gómez R, Trujillo-Mata A. Development of a fuzzy expert system for the nephropathy control

- assessment in patients with type 2 diabetes mellitus. *Expert Systems with Applications*. 2017 Apr 15;72:335-43.
- [10] Asl, Ali Akbar Sadat, and Mohammad Hossein Fazel Zarandi. "A type-2 fuzzy expert system for diagnosis of leukemia." *North American Fuzzy Information Processing Society Annual Conference*. Springer, Cham, 2017.
- [11] Zarandi, MH Fazel, et al. "An expert system based on fuzzy bayesian network for heart disease diagnosis." *North American Fuzzy Information Processing Society Annual Conference*. Springer, Cham, 2017.
- [12] Motlagh HA, Bidgoli BM, Fard AA. Design and implementation of a web-based fuzzy expert system for diagnosing depressive disorder. *Applied Intelligence*. 2018 May 1;48(5):1302-13.
- [13] Caliwag JA, Reyes FC, Castro PJ, Castillo RE. A mobile expert system utilizing fuzzy logic for venereal and sexually transmitted diseases. *Journal of Advances in Information Technology*. 2018 Aug;9(3).
- [14] Muhammad LJ, Garba EJ, Oye ND, Wajiga GM. On the Problems of Knowledge Acquisition and Representation of Expert System for Diagnosis of Coronary Artery Disease (CAD). *International Journal of u-and e-Service, Science and Technology*. 2018;11(30):49-58.
- [15] Nazari S, Fallah M, Kazemipoor H, Salehipour A. A fuzzy inference-fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. *Expert Systems with Applications*. 2018 Apr 1;95:261-71.
- [16] Soltani A, Battikh T, Jabri I, Lakhoua N. A new expert system based on fuzzy logic and image processing algorithms for early glaucoma diagnosis. *Biomedical Signal Processing and Control*. 2018 Feb 1;40:366-77.
- [17] Tuan TM, Fujita H, Dey N, Ashour AS, Ngoc VT, Chu DT. Dental diagnosis from X-ray images: an expert system based on fuzzy computing. *Biomedical Signal Processing and Control*. 2018 Jan 1;39:64-73.
- [18] Terrada O, Cherradi B, Raihani A, Bouattane O. A fuzzy medical diagnostic support system for cardiovascular diseases diagnosis using risk factors. In *2018 International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS) 2018 Dec 5* (pp. 1-6). IEEE.
- [19] Ahmad G, Khan MA, Abbas S, Athar A, Khan BS, Aslam MS. Automated diagnosis of hepatitis b using multilayer mamdani fuzzy inference system. *Journal of healthcare engineering*. 2019 Jan 1;2019.
- [20] Raza MA, Liaqat MS, Shoaib M. A Fuzzy Expert System Design for Diagnosis of Skin Diseases. In *2019 2nd International Conference on Advancements in Computational Sciences (ICACS) 2019 Feb 18* (pp. 1-7). IEEE.

- [21] Arji G, Ahmadi H, Nilashi M, Rashid TA, Ahmed OH, Aljojo N, Zainol A. Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature and classification. *Biocybernetics and Biomedical Engineering*. 2019 Oct 1;39(4):937-55.
- [22] Kaur G, Kakkar D. Fuzzy Based Integrated Diagnostic System for Neurodevelopmental Disorders. In 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN) 2019 Mar 7 (pp. 132-136). IEEE.
- [23] Asl, Ali Akbar Sadat. "A Two-Stage Expert System for Diagnosis of Leukemia Based on Type-2 Fuzzy Logic." *International Journal of Computer and Information Engineering* 13.2 (2019): 34-41.
- [24] Mirmozaffari M. Developing an expert system for diagnosing liver diseases. *European Journal of Engineering Research and Science*. 2019 Mar 2;4(3):1-5.
- [25] Mujawar IK, Jadhav BT. Web-based Fuzzy Expert System for Diabetes Diagnosis. *International Journal of Computer Sciences and Engineering*. 2019;7.
- [26] Mutawa AM, Alzuwawi MA. Multilayered rule-based expert system for diagnosing uveitis. *Artificial intelligence in medicine*. 2019 Aug 1;99:101691.
- [27] Sajadi NA, Borzouei S, Mahjub H, Farhadian M. Diagnosis of hypothyroidism using a fuzzy rule-based expert system. *Clinical Epidemiology and Global Health*. 2019 Dec 1;7(4):519-24.
- [28] Hamedan F, Orooji A, Sanadgol H, Sheikhtaheri A. Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach. *International Journal of Medical Informatics*. 2020 Mar 30:104134.
- [29] Hussain A, Hussnain SA, Fatima A, Siddiqui SY, Saeed A, af Saeed Y, Ahmed A, Khan MA. A Novel Approach for Thyroid Disease Identification Empowered with Fuzzy Logic. *IJCSNS*. 2020 Jan;20(1):173.
- [30] Khalil AM, Li SG, Lin Y, Li HX, Ma SG. A new expert system in prediction of lung cancer disease based on fuzzy soft sets. *Soft Computing*. 2020 Mar 2:1-29.
- [31] Mahanta J, Panda S. Fuzzy expert system for prediction of prostate cancer. *New Mathematics and Natural Computation*. 2020 Mar;16(01):163-76.
- [32] Mirmozaffari M. Presenting an expert system for early diagnosis of gastrointestinal diseases. *International Journal of Gastroenterology Sciences*. 2020;1(1):21-7.
- [33] Mojriani S, Pinter G, Joloudari JH, Felde I, Szabo-Gali A, Nadai L, Mosavi A. Hybrid Machine Learning Model of Extreme Learning Machine Radial basis function for Breast Cancer Detection and Diagnosis; a Multilayer Fuzzy Expert System. In 2020 RIVF International Conference on Computing and Communication Technologies (RIVF) 2020 Oct 14 (pp. 1-7). IEEE.
- [34] Naseer I, Khan BS, Saqib S, Tahir SN, Tariq S, Akhter MS. Diagnosis Heart Disease Using Mamdani Fuzzy Inference Expert System. *EAI Endorsed Transactions on Scalable Information Systems*. 2020;7(26).

- [35] Siddiqui SY, Hussnain SA, Siddiqui AH, Ghufraan R, Khan MS, Irshad MS, Khan AH. Diagnosis of arthritis using adaptive hierarchical Mamdani fuzzy type-1 expert system. EAI Endorsed Transactions on Scalable Information Systems. 2020;7(26).
- [36] Wu, Dongrui, and Woei Wan Tan. "A type-2 fuzzy logic controller for the liquid-level process." 2004 IEEE International Conference on Fuzzy Systems (IEEE Cat. No. 04CH37542). Vol. 2. IEEE, 2004.
- [37] Zarandi, Mohammad Hossein Fazel, Shahabeddin Sotudian, and Oscar Castillo. "A New Validity Index for Fuzzy-Possibilistic C-Means Clustering." arXiv preprint arXiv:2005.09162 (2020).
- [38] Sugeno, M., & Yasukawa, T. (1993). A fuzzy logic based approach to qualitative modeling. IEEE Transactions on Fuzzy Systems, 1, 7–31.
- [39] Zarandi, MH Fazel, et al. "A type-2 fuzzy rule-based expert system model for stock price analysis." Expert Systems with Applications 36.1 (2009): 139-154.
- [40] Mendel, Jerry M. "Uncertainty, fuzzy logic, and signal processing." Signal Processing 80.6 (2000): 913-933.
- [41] Liang, Qilian, and Jerry M. Mendel. "Interval type-2 fuzzy logic systems: theory and design." IEEE Transactions on Fuzzy systems 8.5 (2000): 535-550.
- [42] Brownlee, Jason. "How to Calculate Precision, Recall, and F-Measure for Imbalanced Classification." URL: <https://machinelearningmastery.com/precisionrecall-and-f-measure-for-imbalanced-classification> (2020).