Fuzzy Logic: An Application To Detect Chronic Kidney Disease And Failure

*Ain Nazirah Binti Mohd Adnan[1], *Nur Idrina Binti Zakaria[2], Nur Solihah Khadhiah Binti Abdullah[3], Suraya Ya'acob[4]

[1,2,3] Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA Terengganu Branch
Kuala Terengganu Campus
21080 Kuala Terengganu, Terengganu, Malaysia

[4]*Razak Faculty of Technology and Informatics,*
Universiti Teknologi Malaysia
Jalan Sultan Yahya Petra, 54100 Kuala Lumpur
Malaysia
ainnazirahmohdadnan@yahoo.com[1],
idrinazakaria97@gmail.com[2],
suraya.yaacob@utm.my[4]

Article history

Received:
9 Sept 2019

Received in revised form:
31 Oct 2019

Accepted:
20 Dec 2019

Published online:
30 Dec 2019

*Corresponding author
ainnazirahmohdadnan@yahoo.com

Abstract

In the Malaysian Dialysis and Transplant Registry 24th Report 2016, it was stated that for over the past 10 years, Malaysia has seen 100% increment in the number of new dialysis patients that suffer from chronic kidney disease (CKD). One of the identified factors that has contributed to this increment is the late detection of the CKD status among the patients. In fact, in the effort to reduce CKD patients, detecting the presence of CKD at an early stage is very crucial. Accordingly, the purpose of this study is to apply the predictive model in detecting CKD using MATLAB software (fuzzy logic toolbox). There are five steps involved in developing the model. First, the variables used as input data were identified which were blood urea nitrogen test, eGFR (estimated glomerular filtration rate) and serum creatinine test. Second, fuzzification of inputs and output was applied by using min-max normalization processing. Next, inference engine was constructed followed by rule aggregation. Lastly, the status of CKD for every patient was analysed by defuzzification of the outputs from the predictive model. In this study, 70 patients' clinical tests were used as a set of data. The result shows that 47 out of 70 patients were detected as CKD patients. As a conclusion, early detection of CKD is very important to treat the disease at an early stage. This will allow patients to take an early action and follow up treatments or consultations with nephrologist to avoid any serious complications.

* *Corresponding author. ainnazirahmohdadnan@yahoo.com*

Keywords: chronic kidney disease (CKD), fuzzy logic, membership function

1. Introduction

Chronic kidney disease (CKD) is described as a gradual loss of kidney function over time. The main function of kidneys is to filter wastes and excess fluids from the blood, which are then excreted in urine. Fuzzy logic is an extension of boolean logic that was introduced by Lotfi Zadeh (1988) based on mathematical theory of fuzzy sets, which is a generalization of the classical set theory. Fuzzy logic is introduced in the verification of a condition, hence enabling the condition to be in a different state from true or false. It provides a valuable flexibility for reasoning, which makes it possible to consider inaccuracies and uncertainties.

The use of fuzzy logic in medical-base cases has been explored by many researchers. Balanica, Dumitrache, Caramihai, Rae & Herbst (2011) focused on the evaluation of breast cancer risk by using fuzzy logic. The purpose of this research was to describe an intelligent method based on fuzzy techniques that could be used for the evaluation of breast cancer risk. This paper discussed the basic principles of the application of fuzzy logic with two input variables and one output variable. The diagnosis required the definition of a set of cautiously chosen for estimation of breast cancer risks by using 55 fuzzy rules related to personal patient data. The data of 60 patients was taken including their age, the extracted tumour segmentation result from the processed mammograms and the experts' clinical and pathological truth determination for each case. Kowsigan. M, Saravanan, Jebamalar, & Roshini (2017) highlighted the prediction of heart disease by analysing various parameters using fuzzy logic. This research emphasized on the early state of the patient, even before they had a sign of angina pectoris or commonly known as chest pain. Five parameters were chosen in this research in order to predict the heart disease. The algorithm used in this research was fuzzy logic. MATLAB was used as the modelling tool to represent the concept of fuzzy logic graphically. The simulated fuzzy logic system contains five input variables and three output variables. In this research, 17 rules were designed to figure the mapping from a given input to an output. In the context of CKD, Micheal & Olayinka (2018) proposed a predictive model for the likelihood of detecting chronic kidney failure and disease using fuzzy logic. They developed a fuzzy-logic-based model using the MATLAB software to overcome the complication involved in detecting CKD. Four variables were chosen including blood urea test, urea clearance test, creatinine clearance test and estimated glomerular filtrate rate (eGFR). The model is hoped to carefully ascertain the likelihood of CKD detection among patients, hence provide a necessary treatment.

Other than fuzzy logic, several researchers suggested different methods on the prediction of CKD. A group of researchers worked on prediction of CKD using data mining technique (Gharibdousti, Azimi, Hathikal, & Won, 2017). This paper focused on applying different machine learning classification algorithm to a dataset with 400 observations and 24 attributes for diagnosis of CKD. Classification methods that were used in this research were decision tree, linear regressing, super vector machine, naïve Bayesian and neural network. The measurements of different methods were calculated and compared before and after applying the feature selection to each of the methods. The performance measurement used criteria like sensitivity, specificity, accuracy and area under cover. Chimwayi, Haris, Caytiles, & Iyenger (2017) reported the risk level prediction of CKD using neuro-fuzzy and hierarchical clustering algorithm. They aimed to build a model for risk level prediction in CKD considering all the symptoms and reasons contributing to it. The symptoms were the attributes that would define different stages of kidney diseases. The data under consideration initially had 25 attributes. Based on the different stages, one could classify a set of patient records to identify to which class of kidney disease a patient may belong to.

There are many factors that contribute to CKD such as diabetes, high blood pressure, family history, age, ethnicity and others. A good condition of kidney is necessary to maintain a stable balance of body chemicals. It is important to keep a healthy kidney since kidney damage can cause other diseases such as anaemia, bone disease, heart disease, fluid build-up and others. Locatelli, Vecchio & Pozzoni (2002) stated that early and regular nephrology specialist care in the predialytic phase of CKD was associated with decreased morbidity, decreased short-term mortality, improved long-term survival on dialysis, and decreased costs. However, most people with CKD especially those in early stages may be unaware of their disease. In population based-study by Hooi, et al., (2013) among 876 respondents, only 35 of them (4%) were aware that they had CKD while 96% being unaware. The lack of awareness about this disease was due to the fact that people were not exposed to the symptoms of the disease.

Therefore, the predictive model in detecting chronic kidney failure and disease using fuzzy logic was applied in this study. According to the National Kidney Foundation (2018), there are several indicators to test the presence of CKD which are blood pressure, blood creatinine, blood urea test, urinalysis, urea clearance test, creatinine test, estimated glomerular filtration rate (eGFR) and renal ultrasound test. Based on the previous findings, blood urea nitrogen test, eGFR and serum creatinine test were chosen as the input data in this study. The objectives of this study were to conduct a review on the factors of CKD and identify the relationship between the variables using fuzzy logic. Hence, the model used can produce the status of CKD for every patient. Five steps were conducted throughout the study, starting with the data identification as an input value and completing the steps with the defuzzified of output in terms of “yes” or “no”.

2. Methodology

The method used in this research was fuzzy logic. The fuzzy logic system is available in the Fuzzy Logic Toolbox of the MATLAB R2017b. Five steps used were data identification, fuzzification of inputs and outputs, construction of the inference engine, rule aggregation and analyzed result by defuzzified of output.

2.1 Data identification

The variables that were used as an input data were identified. Three most significant variables used were blood urea nitrogen test, eGFR (estimated glomerular filtration rate) and serum creatinine test.

2.2 Fuzzification of inputs and outputs

Fuzzification is the process of transformation the crisp value (normal value) into fuzzy value (between 0 to1). Min-max normalization method was used, where the interval for each variable was set up by choosing the lowest number in the variable as the lower bound while the highest number in the variable as the upper bound in the interval. For $v' = \frac{v - \min_A}{\max_A - \min_A}$, v is the original value of the attribute, v' is the value after normalization process, $\min_A$ is the minimum value of the attribute and $\max_A$ is the maximum value of the attribute.

2.3 Construction of the inference engine

The membership function for the system was used to map the input and output variables into a [0,1] interval with the use of mainly trapezoidal membership functions based on the pattern range distribution. Table 1 shows a comprehensive explanation of the values of the labels to be used for each variable alongside with their respective membership functions. Then, the fuzzy inference engine that contains 18 (3 variables × 3 variables × 2 outputs) IF-THEN rules was created (as shown in Table 2).

Table 1: Description of the Labels for Each Variable

No.	**Variable**	**Membership function mapping (label=value)**			**Membership function**
1.	Blood Urea Nitrogen Test	$t_1 < 0.1017$	$0.1017 \leq t_1 \leq 0.322$	$t_1 > 0.322$	trapmf
2.	Serum Creatinine Test	$t_2 < 0$	$0 \leq t_2 \leq 0.0363$	$t_2 > 0.0363$	trapmf
3	eGFR	$t_3 < 0.5321$	$0.5321 \leq t_3 \leq 0.8073$	$t_3 > 0.8073$	trapmf
4.	Likelihood of CKD	No x		Yes x = 1	

		= 0		

Table 2: Fuzzy Rules for the Inference System

No.	IF-Then Rules
1	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $0.5321 \le t3 \le 0.8073$) then (output is No)
2	If (BloodUreaNitrogen is $t1 < 0.1017$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $0.5321 \le t3 \le 0.8073$) then (output is No)
3	If (BloodUreaNitrogen is $t1 > 0.1017$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $t3 \ge 0.8073$) then (output is No)
4	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $t3 > 0.8073$) then (output is No)
5	If (BloodUreaNitrogen is $t1 < 0.1017$) or (SerumCreatinine is $0 \le t2 \le 0.0363$) or (eGFR is $0.5321 \le t3 \le 0.8073$) then (output is No)
6	If (BloodUreaNitrogen is $t1 < 0.1017$) or (SerumCreatinine is $0 \le t2 \le 0.0363$) or (eGFR is $t3 > 0.8073$) then (output is No)
7	If (BloodUreaNitrogen is $t1 > 0.3220$) and (SerumCreatinine is $t2 > 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
8	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) and (SerumCreatinine is $t2 > 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
9	If (BloodUreaNitrogen is $t1 < 0.1017$) and (SerumCreatinine is $t2 > 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
10	If (BloodUreaNitrogen is $t1 > 0.3220$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
11	If (BloodUreaNitrogen is $t1 < 0.1017$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
12	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) and (SerumCreatinine is $0 \le t2 \le 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)
13	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) or (SerumCreatinine is $0 \le t2 \le 0.0363$) or (eGFR is $t3 < 0.5321$) then (output is Yes)
14	If (BloodUreaNitrogen is $t1 > 0.3220$) and (SerumCreatinine is $t2 > 0.0363$) and (eGFR is $t3 < 0.5321$) then (output is Yes)

15	If (BloodUreaNitrogen is $0.1017 \le t1 \le 0.3220$) or (SerumCreatinine is $t2 > 0.0363$) or (eGFR is $t3 < 0.5321$) then (output is Yes)
16	If (BloodUreaNitrogen is $t1 > 0.3220$) or (SerumCreatinine is $0 \le t2 \le 0.0363$) or (eGFR is $t3 < 0.5321$) then (output is Yes)
17	If (BloodUreaNitrogen is $t1 < 0.1017$) or (SerumCreatinine is $0 \le t2 \le 0.0363$) or (eGFR is $t3 < 0.5321$) then (output is Yes)
18	If (BloodUreaNitrogen is $t1 < 0.1017$) or (SerumCreatinine is $t2 > 0.0363$) or (eGFR is $t3 < 0.5321$) then (output is Yes)

2.4 Rule Aggregation

Rule aggregation is needed to produce a single output. In this study, the “And” and “Or” operators were applied to determine the output for each rule. Aggregation just happens once for each output variable, which is before the last defuzzification step.

2.5 Defuzzification of output

Here the output of predictive model was analyzed to determine the status of CKD. The defuzzification of the output membership function following the growth of fuzzy rules shows that the likelihood of CKD is “No” if the probability value is from 0 to 0.49. Meanwhile, it is a “Yes” of CKD if the value is from 0.5 to 1.0.

3. Results and Discussions

From the output of the predictive model, the status of CKD for every patient was determined. The findings of this study shows that the reading of variables used (blood urea nitrogen test, eGFR and serum creatinine test) influenced the prediction of CKD. In addition, the prevalent factors that influenced the presence of CKD were diabetes, high blood pressure, heart disease, age, ethnicity and family history.

Figure 1: Sample Result of CKD for a patient

The input was taken from the normalized data. For the patient above, the input data is $[0.542, 0.610, 0.0459]$ which represents the column for blood urea nitrogen test, serum creatinine test and eGFR. Since the output is 0.829 then the patient is a CKD patient.

The classification of CKD patients can be divided into 5 stages according to the value of eGFR (Nelson, Mackinnon, Traynor, & Geddes, 2006). The observation shows that many of the complications of CKD can be prevented through early detection. The treatment prompted the Kidney Disease Outcome Quality Initiative (K/DOQI) guidelines for dialysis patients to develop a formal staging system for stratification of CKD.

Table 3: Patients stage classification base on GFR

Stage	Glomerular filtration rate (GFR) value
1	Greater and equal to 90 $ml/\min/1.73m^2$
2	Between 60 to 89 $ml/\min/1.73m^2$
3	Between 30 to 59 $ml/\min/1.73m^2$
4	Between 15 to 29 $ml/\min/1.73m^2$
5	Less than 15 $ml/\min/1.73m^2$

Based on the information in Table 3, 70 patients were classified into the 5 stages based on the reading of eGFR. Table 4 shows the classification of the data into the stages. It is found that, among 70 patients of CKD, 20 patients are in stage 5 which is end stage of CKD. Patients in stage 5 indicates end-stage renal disease (ESRD) which means the kidney have lost the ability to do their job effectively or commonly known as kidney failure. The patients need to consult with nephrologist whether to do the dialysis or a kidney transplant in order to survive.

Table 4: The classification of patient for every stage

Stage	Number of Patients
1	10
2	13
3	18
4	9
5	20

4. Conclusion

There are many approaches that have been explored to predict chronic kidney failure and disease using different indicators and methods. This study applied the prediction model in detecting chronic kidney failure and disease using fuzzy logic. The proposed model for the prediction of CKD was presented using 3 input variables namely: blood urea nitrogen test, serum creatinine test and estimated glomerular filtration rate (eGFR). Five step-wise procedures were successfully implemented, thus provide the status of CKD for every patient. The value of variables was used in developing the inference system of the fuzzy inference engine. The min-max normalization was employed to convert the crisp value into fuzzy value in ranges between 0 to 1. Next, the values of variables were all fuzzified and the fuzzified input variables were fed to the inference engine. The 18 rules that were developed after the inference engine were aggregated to a single output. It was defuzzified to get the output and the probability was applied to get the result whether it is a “Yes” or “No”. The result of the predictive model showed the status of CKD for every patient. Thus, there were 47 out of 70 were detected as CKD patients while others showed the absence of CKD.

In conclusion, it is believed that this model will help nephrologists to detect the chronic kidney failure and disease that has a record containing the three variables. Besides, this model helps to reduce haemodialysis treatment costs and also helps to reduce the number of untimely deaths which occur as a result of the late detection. Future research might consider a bigger number of patients to get a more generalized assessment analysis. In addition, the number of indicators used may be increased, depending on the objectives and limitations of the study. Apart from fuzzy logic, other methods such as Neuro-Fuzzy and Hierarchical Clustering Algorithm can be applied to analyse the data.

5. References

[1] Zadeh, L. A. (1988). *Fuzzy Logic.* Berkeley: IEEE.

[2] *National Kidney Foundation*. (2018). Retrieved from About Chronic Kidney Disease: National Kidney Faundation. (2018). Rethttps://www.kidney.org/atoz/content/about-chronic-kidney-disease

[3] Michael, A., & Olayinka, A. (2018). Predictive model for likelihood of detecting chronic kidney failure and disease using fuzzy logic. *The International Journal of Computational Science, Information Technology and Control Engineering (IJCSITCE).*

[4] Balanică, V., Dumitrache, I., Caramihai, M., Rae, W., & Herbst, C. (2011). Evaluation of breast cancer risk by using fuzzy logic. *University Politehnica of Bucharest Scientific Bulletin, Series C, 73(1),*, 53-64.

[5] Gharibdousti, M. S., Azimi, K., Hathikal, S., & Won, D. H. (2017). Prediction of chronic kidney disease using data mining technique. *Proceedings of the 2017 industrial and systems engineering conference,* 2135-2140.

[6] Kowsigan.M, Saravanan, S., Jebamalar, A. C., & Roshini, R. (2017). Heart disease prediction by analysing various parameters using fuzzy logic. *Pakistan Journal of Biotechnology*, 157-161.

[7] Chimwayi, K. B., Haris, N., Caytiles, R. D., & Iyenger, N. S. (2017). Risk level prediction of chronic kidney disease using neuro-fuzzy and hierarchical clustering algorithm(s). *International Journal of multimedia and ubiquitous engineering*, 23-26.

[8] Locatelli, F., Vecchio, L. D., & Pozzoni, P. (2002). The importance of early detection of chronic kidney disease. *Nephrology Dialysis Transplantation*, 2-7.

[9] Hooi, L. S., Ong, L. M., Ahmad, G., Bavanandan, S., Ahmad, N. A., Naidu, B. M., et al. (2013). A population-based study measuring the prevalence of chronic kidney disease among adults in West Malaysia. *International Society of Nephrology*, 1034-1040.