The Diagnosis of Renal Cancer using Sugeno Fuzzy Inference System

Nikita, Harsh Sadawarti
School of Engg. & Tech., CT University,
Ludhiana Punjab

***Abstract*:- The renal cancer is a common type of cancer in the old ages and the advancement of renal caner is so rapid that it should be detected at initial stages. In this research work, a multi-layered fuzzy Sugeno model has been developed to diagnose the renal cancer. For the first layer, there are four input variables such as Smoking, Dialysis, Occupational exposure and Genetic or hereditary that detects whether the patient of given data is suffering from renal cancer or not. Hence, the output of first layer is cancer present or no cancer. In the second layer, the seven inputs are taken to decide the stage of renal cancer by the system. These input variables are Haematuria, Red blood cell count, Flank pain, Tumor size, Von Hippel-Lindau gene, High blood pressure and Trichloroethylene exposure. The proposed system helps to classify the different stages of renal cancer in the correct classes. These stages such as stage 1, stage 2, stage 3 and stage 4 of renal cancer are considered as output of the system or the classes in which the given input should be classify. The MATLAB software is used for the development of fuzzy Sugeno model to diagnose the renal cancer. The proposed system has been evaluated on the basis of parameters of performance. The considered performance parameters are classification accuracy, specificity, sensitivity and precision. According to the evaluated result, the developed fuzzy Sugeno model has 96.5% classification accuracy.**

1. INTRODUCTION

The fuzzy set theory has been approved and acknowledge in 1980’s and grab the success in various applications from tiny product to the industrial areas, as from two decades, this theory is an ambiguous and unproven technology [1],[2]. The fuzzy logic works similarly to the way a human thinks and natural language. The traditional classical theory is based on the mathematical models but the quality of fuzzy control is that it works and based on the model of human specialists or experts [3]. As the experts can able to detect the disease without any mathematical computational, the model of fuzzy logic will also control it in the same way [4]. There are two main contexts where the fuzzy models are useful: 1) in the circumstances where the system is too complex and the behaviour of the model is too difficult to understand. 2) where the result is warranted and approximate but it is fast [5]. The fuzzy logic is used many domains such as hand-printed character recognition, medical expert system, washing machines, air conditions, auto-focusing camera, space material, speech recognition [6].

In the passing years, the rate of kidney diseases increasing day by day due to the unhealthy lifestyle of humans and it is also difficult to recover it by an individual [7]. The renal cancer is one of the kidney disease that also increasing rapidly. It begins from the small tubes of kidney, which remove the urine from the body. The cells present in these tubes turn into cancerous cells and it grows with time and age if not controlled [8]. Hence, it is undoubtedly very necessary to detect the renal caner at initial stage. So that it cannot affect the neighbour organs [9]. To detect the renal cancer, it is essential to know about the risk factors and symptoms of this life threatening disease. The main priorities should be discussed such as the biomarker, risk factors, and identification of main causes and many more that associate with the detection of renal cancer [10]. Some symptoms are known as ‘silent killer’ such as hypertension and high blood pressure that cause the kidney failure [11]. The renal tumour is the very crucial symptom that cause the renal cancer [12]. 3 to 5 percent of cases of renal cancer is due to hereditary genes and this percentage is rising with time [13]. The patient of renal cancer has to monitor his/her health regularly because the renal cancer can be re-occur after the few years of diagnose [14]. The researchers to diagnose the renal cancer have used different techniques. The frequently used method for the detection of renal cancer is image-processing technique. In this technique, the computed tomography images or magnetic resonance images of kidney is captured and various methodologies of image processing such as segmentation, fusion, feature extraction etc has been done [15],[16],[17]. The data mining techniques have been applied on the features that are collected from the images [18],[19]. The monitoring of tumor regularly is very important to control the renal cancer. Hence, the growth of tumor tissues has been monitored [20].

The fuzzy expert system is the system made up of a group of membership functions and rules. These rules are generated by gathering information from the experts and used to reason the data given to the system for the diagnosis. The first phase of the fuzzy expert system is Fuzzification, which converts the numeric or crisp data into linguistic terms or fuzzy data. After the Fuzzification phase, the inference engine maps the rules stored in the knowledge base corresponding to the given input to the system and gives an output in the linguistic terms. This outcome in a fuzzy manner is transformed into the numeric data by the defuzzification phase at last. The fuzzy set theory has the ability to deal with ambiguous and inaccurate data or information.

The fuzzy expert system has further two types of models:

The Mamdani-type fuzzy expert system: The Mamdani-type fuzzy expert system is often used because this type of fuzzy expert system stores the knowledge and information more smartly and it is similar to the way human stores the knowledge in the mind. This type of expert system has a computational problem.

The Sugeno-type fuzzy expert system: The Sugeno-type fuzzy expert system does the task in an admirable and preferable way. It uses optimization techniques to reduce the computations and make it simple. It also uses an adaptive technique to fix the membership functions that forge the data more efficiently. These techniques are making the Sugeno model more prominent for dynamic non-linear systems.

Mamdani-type Fuzzy Inference System vs. Sugeno-type Fuzzy Inference System

The prime difference between the Mamdani-type and Sugeno-type fuzzy inference system is the outcome generated by the systems. In the case of Mamdani-types, the centroid method of defuzzification is used and in contrast, the Sugeno-type fuzzy inference system used the weighted average method to convert the fuzzy values into the crisp values. Due to which the processing time is also decreased and this reason overpowers the Mamdani-type fuzzy inference system. The Mamdani-type fuzzy expert system has outcome membership functions while the Sugeno-type fuzzy inference system has not. Mamdani-type fuzzy inference system is not adaptable and responsive, but the Sugeno- type fuzzy inference system is flexible and can be further integrated with the adaptive neuro-fuzzy inference system. These systems cannot replace human experts but can be used as the helping tool for the experts to diagnose renal cancer more efficiently. It also helps to give advice regarding the diet and treatment of the patient. Thus, these systems provide an effective way to decrease the cost of treatment, time of analysis, medical errors and human efforts.

The rest of the paper is systemized as follows: Section 2, presents the work done for the proposed model. Section 3, shows the membership functions of the Sugeno-type fuzzy expert system. Section 4, gives the result analysis of developed model and section 5 deliver the conclusion of work done.

2. PRESENT WORK

Knowledge Acquisition

The prime ambition for knowledge acquisition in this study is to grab all the required information and knowledge regarding renal cancer from doctors or experts. The dataset for this disease has been acquired from the medical experts by considering the parameter or input variables i.e. for first layer, Smoking, Dialysis, Occupational exposure and Genetic or hereditary and for second layer, Haematuria, Red blood cell count, Flank pain, Tumor size, Von Hippel-Lindau gene, High blood pressure and Trichloroethylene exposure. Figure 1 demonstrates the block diagram of the present work.

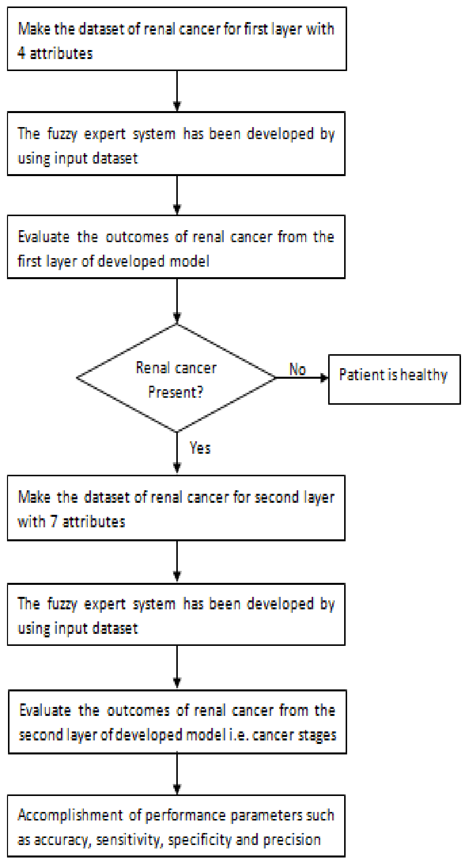

Figure 1: Block diagram of the present work

Implementation of Sugeno-type Fuzzy Expert System

For the diagnosis of renal cancer by utilizing the Sugeno-type fuzzy model, the steps are similar to the Mamdani-type fuzzy model. It takes input variables of renal cancer such as for first layer, Smoking, Dialysis, Occupational exposure and Genetic or hereditary with outcome whether the patient is healthy or has cancer. For second layer, Haematuria, Red blood cell count, Flank pain, Tumor size, Von Hippel-Lindau gene, High blood pressure and Trichloroethylene exposure with the outcome that notify the health of patient such as stage 1 cancer, stage 2 cancer, stage 3 cancer and stage 4 cancer.

The methodology of Sugeno-type Fuzzy Inference System

The different steps for the development of the Sugeno-type fuzzy inference system are given by:

Layer 1:

Step 1: Gather the knowledge from the physician about renal cancer with four attributes and make the data set.

Step 2: Construct the fuzzy expert system by using the functions of the fuzzy inference system.

- **a)** Do
- **b)** Consider the grabbed data set from the medical expert as the input to the medical expert system.
- **c)** Operate the Fuzzification process in which the values of inputs variables will be converted into the linguistic or fuzzy terms from the crisp values of variables.
- **d)** Pick the membership functions of all the input variables according to the requirement.

- **e)** Develop the rules according to the given equation corresponding to the selected membership functions.
  If input1 = x and input2 = y
  Then output = f(input1, input2)
- **f)** By using the given formula, evaluate the firing strength of each generated rule.
  w_i= And (F_1(x),F_2(y))
  where F_1 and F_2 are the membershipfunctions of input1 and input2 respectively.
  The outcome value of the system is computed as:

$$FinalOutcome = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

- **g)** Perform the defuzzification process by converting the final output from the linguistic variables to crisp values.
- **h)** Until all the given inputs are classified into the classes correctly and accurately.

Layer 2:

Step 3: If the outcome of first layer is yes then follow the following steps. Otherwise stop.

Step 4: Gather the knowledge from the physician about renal cancer with seven attributes and make the data set.

Step 5: Construct the fuzzy expert system by using the functions of the fuzzy inference system.

- **a)** Do
- **b)** Consider the grabbed data set from the medical expert as the input to the medical expert system.
- **c)** Operate the Fuzzification process in which the values of inputs variables will be converted into the linguistic or fuzzy terms from the crisp values of variables.
- **d)** Pick the membership functions of all the input variables according to the requirement.
- **e)** Develop the rules according to the given equation corresponding to the selected membership functions.
  If input1 = x and input2 = y
  Then output = f(input1, input2)
- **f)** By using the given formula, evaluate the firing strength of each generated rule.
  w_i= And (F_1(x),F_2(y))
  where F_1 and F_2 are the membershipfunctions of input1 and input2 respectively.
  The outcome value of the system is computed as:

$$FinalOutcome = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

- **g)** Perform the defuzzification process by converting the final output from the linguistic variables to crisp values.
- **h)** Until all the given inputs are classified into the classes correctly and accurately.

Step 6: Measure the different specifications like accuracy, specificity, sensitivity, and precision to evaluate the exact performance of the developed medical expert system for the diagnosis of chronic kidney disease.

There are two types of outputs in the case of the Sugeno-type fuzzy model i.e. linear and constant [21]. Hence, there are four membership functions are selected for the final output of layer 2 of renal cancer, which is constant and shown in table 2. The result of this model will always be in the range of 0 to 1.

Table 2: Output membership functions of layer 2 with constant values.

Sr. No.	Outputs	Constant Values
1.	Stage 1	0
2.	Stage 2	0.33
3.	Stage 3	0.66
4.	Stage 4	1

3. MEMBERSHIP FUNCTION OF SUGENO-TYPE FUZZY EXPERT SYSTEM

Membership function of input variables

As mentioned above, four input variables for first layer and seven input variables for second layer has been considered. The different ranges are considered for all the input variables.

For layer 1

For the smoking, the range is 0 to 10 shown in figure 2. The second input i.e. dialysis has to be considered within the range of 0 to 10 as given in figure 3. Figure 4 depicts the range for the occupational exposure is taken from 0 to 10. Similarly, the input variable genetic or hereditary has to be taken within the ranges of 0 to 10 as demonstrated in figure 5.

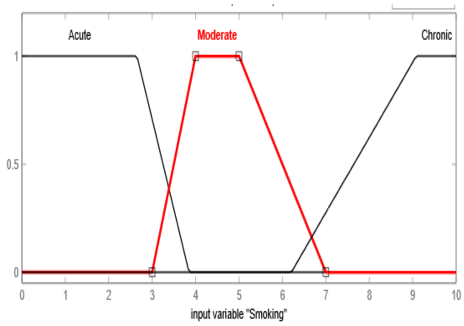

Figure 2: Membership function of Smoking.

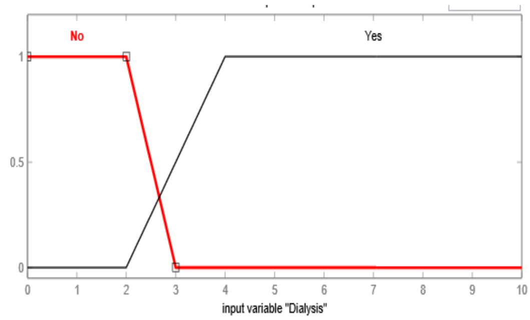

Figure 3: Membership function of Dialysis.

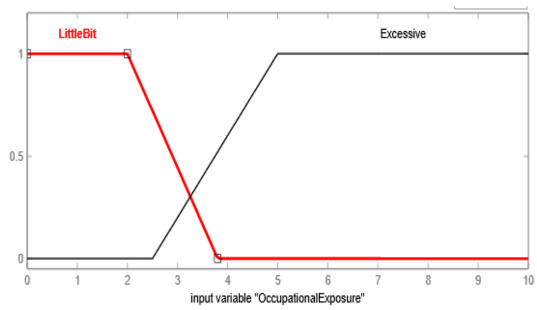

Figure 4: Membership function of Occupational Exposure.

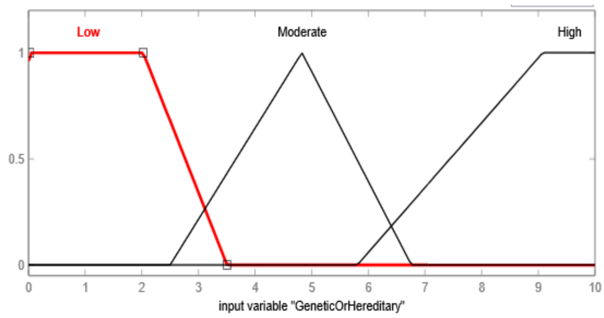

Figure 5: Membership function of Genetic Or Hereditary.

For Layer 2

For the Haematuria, the range is 0 to 250 shown in figure 6. The second input Red blood cell count has to be considered within the range of 0 to 1 as given in figure 7. Figure 8 depicts the range for the Flank pain is taken from 0 to 1. The input variable Tumor size has to be taken within the ranges of 0 to 10 as demonstrated in figure 9. Similarly, figure 10 presents the range taken for Von Hippel-Lindau gene is from 0 to 1. The considered range in figure 11 from 50 to 150 is for Blood pressure. For the last input, Trichloroethylene Exposure, the range is 1 to 10 exhibited in figure 12. The trapezoidal and triangular membership functions are selected for the input variables.

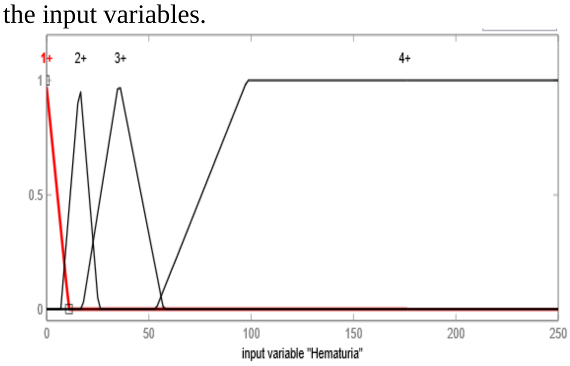

Figure 6: Membership Functions of input variable "Haematuria".

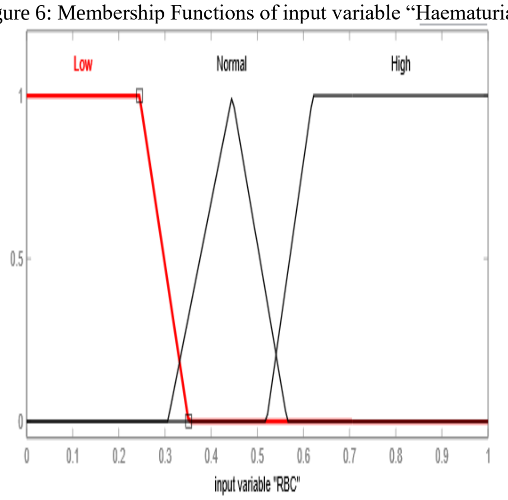

Figure 7: Membership Functions of input variable "RBC".

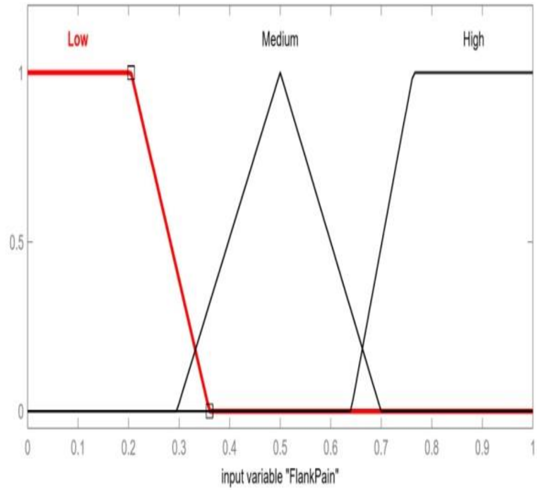

Figure 8: Membership Functions of input variable "Flank Pain".

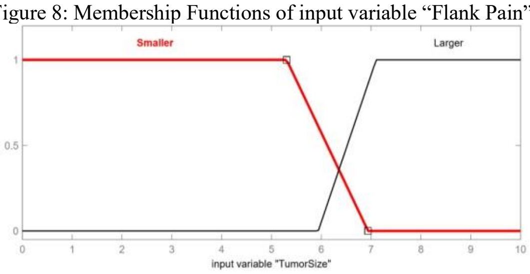

Figure 9: Membership Functions of input variable "Tumor Size".

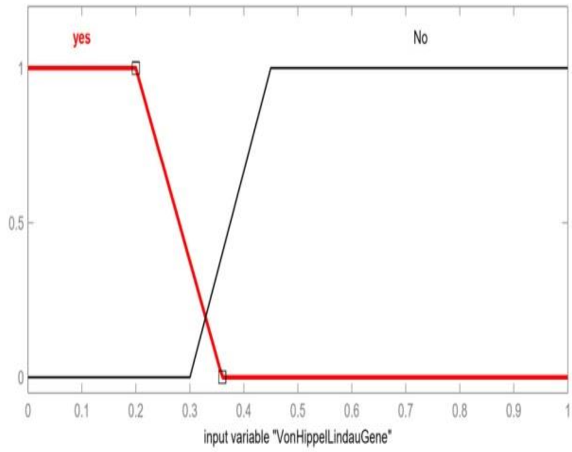

Figure 10: Membership Functions of input variable "Von Hippel-Lindau Gene".

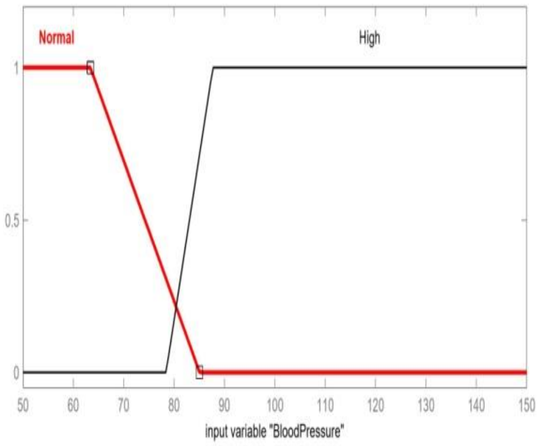

Figure 11: Membership Functions of input variable "Blood Pressure".

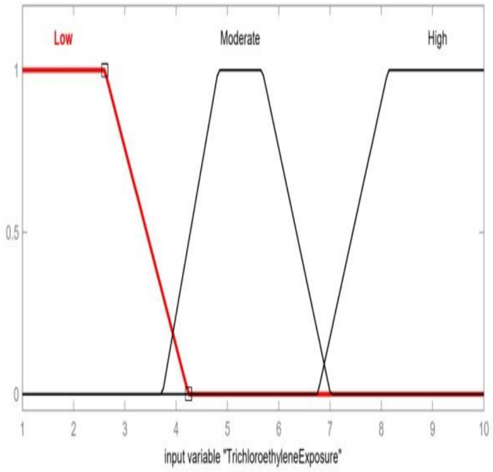

Figure 12: Membership Functions of input variable "Trichloroethylene Exposure".

Membership functions for output variables

The range of output variables for renal cancer for the first layer of developed model is taken from 0 to 1 that depicts whether the patient os suffering from renal cancer or not as shown in figure 13. Similarly, for the second layer, the range for output is from 0 to 1 represents the four stages of renal cancer as shown in figure 14.

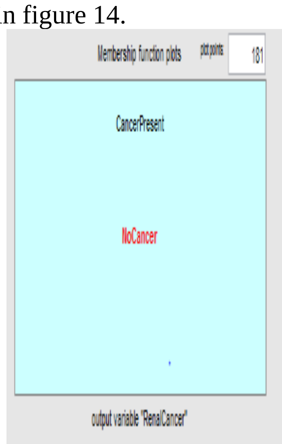

Figure 13: Membership function of output variable "Layer 1".

Figure 14: Membership function of output variable "Layer 2".

4. RESULT ANALYSIS

In this study, the different types of renal cancer stage are classified by using the Sugeno-type fuzzy expert system. This system is tested by the professionals of this domain and categorized the correct and incorrect classification of same patient test cases by comparing the judgement of developed expert system and the judgement of experts. The performance parameters are evaluated according to the test cases. The parameters are classification accuracy, specificity, sensitivity and precision. The formulas for these considered parameters are given by:

$$Sensitivity = \frac{(TP)}{(TP+FN)} = \frac{96}{96+03} = 96.96\%$$

$$Specificity = \frac{(TN)}{(TN+FP)} = \frac{97}{97+04} = 96.03\%$$

$$Precision = \frac{(TP)}{(TP+FP)} = \frac{96}{96+4} = 96\%$$

$$ClassificationAccuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

$$= \frac{96+97}{96+04+97+03} = 96.5\%$$

Where

TP: True positive

FN: False negative

FP: False positive

TN: True negative

The total number of test cases that are considered for result is 200. Out of these 200 test cases, 193 cases are classified correctly by the developed Sugeno-type fuzzy expert system. The rest of 7 cases are classified into false class by the proposed system. Based on the above equations of parameters, the performance of the expert system has been calculated. Figure 15 shows the graphical representation of these evaluated parameters.

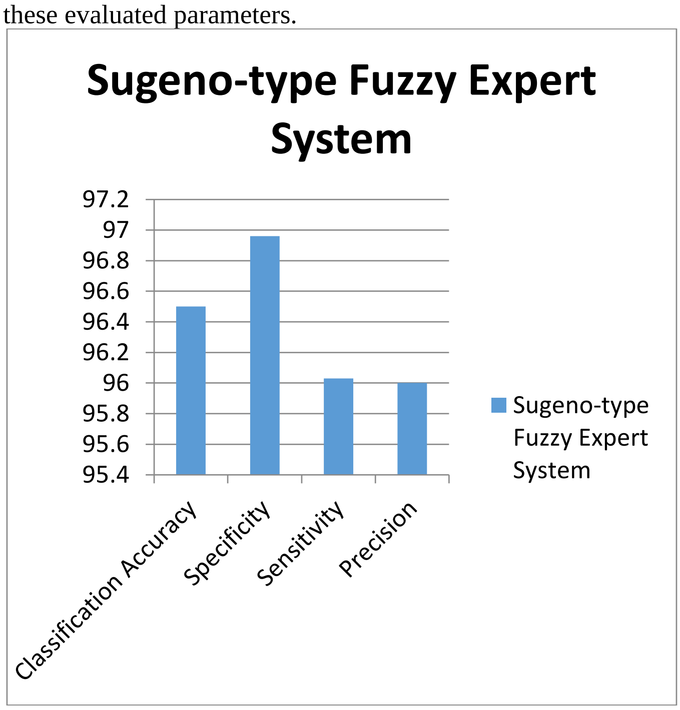

Figure 15: Graphical representation of calculated parameters.

5. CONCLUSION

The main objective of this work is to propose an expert system by using Sugeno-type fuzzy which helps to diagnose the renal cancer by detecting the stage of renal cancer of a particular patient. The developed system fulfils the main objective and also it is very easy to use by the doctors and professionals. An unprofessional can also operate this system for the detection of renal cancer by giving the required inputs to the expert system. Most of the researchers works on this kinds of researches, but not in the particular types. After the implementation of Sugeno-type fuzzy expert system, the results are achieved. From the obtained result, it is observed that the accuracy of Sugeno-fuzzy expert system is 96.5% which is better. Additionally, various parameters are calculated to evaluate the performance such as specificity, sensitivity, precision and classification accuracy.

REFERENCES

[1] H. Ahmadi, M. Gholamzadeh, L. Shahmoradi, M. Nilashi, and P. Rashvand, "Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review," Computer Methods and Programs in Biomedicine, vol. 161, pp. 145–172, 2018.

[2] A. Kaur and A. Kaur, "Comparison of Mamdani-Type and Sugeno-Type Fuzzy Inference Systems for Air Conditioning System," no. 2, pp. 323–325, 2012.

[3] J. H. Holmes, L. Sacchi, R. Bellazzi, and N. Peek, "Artificial Intelligence in Medicine AIME 2015," Artificial Intelligence in Medicine, vol. 81, pp. 1–2, 2017.

[4] V. Novák, "Which logic is the real fuzzy logic ? ◌̈̆," vol. 157, pp. 635–641, 2006.

[5] S. Das and P. K. Ghosh, "Hypertension Diagnosis : A Comparative Study using Fuzzy Expert System and Neuro Fuzzy System," IEEE International Conference on Fuzzy Systems, no. 2005, pp. 1–7, 2013.

[6] I. B. De Medeiros, M. A. Soares Machado, W. J. Damasceno, A. M. Caldeira, R. C. Dos Santos, and J. B. Da Silva Filho, "A Fuzzy Inference System to Support Medical Diagnosis in Real Time," Procedia Computer Science, vol. 122, pp. 167–173, 2017.

[7] S. Varughese, "Chronic Kidney Disease in India A Clarion Call for Change," vol. 13, no. 5, pp. 802–804, 2018.

[8] W. Chow, L. M. Dong, and S. S. Devesa, "Epidemiology and risk factors for kidney cancer," Nature Publishing Group, vol. 7, no. 5, pp. 245–257, 2010.

[9] G. M. Vasilescu et al., "Issues on Early Cancer Detection Using Thermographic Methods," pp. 283–286, 2017.

[10] J. M. Jones et al., "Setting Research Priorities for Kidney Cancer," European Urology, pp. 5–8, 2017.

[11] J. Signorini and P. Greussay, "Silent killing: An object-oriented view of hypertension and kidney failures part I," Proceedings of the 7th IEEE International Conference on Bioinformatics and Bioengineering, BIBE, pp. 635–640, 2007.

[12] A. D. De Leon, P. Kapur, and I. Pedrosa, "Radiomics in Kidney C a n c e r : MR Imaging Radiomics Kidney cancer MR imaging Quantitative imaging," Magnetic Resonance Imaging Clinics of NA, vol. 27, no. 1, pp. 1–13, 2019.

[13] N. B. Haas and K. L. Nathanson, "Hereditary Kidney Cancer Syndromes," Advances in Chronic Kidney Disease, vol. 21, no. 1, pp. 81–90, 2014.

[14] B. Tander, A. Ozmen, and E. Ozden, "Neural network design for the recurrence prediction of post-operative non-metastatic kidney cancer patients," 2015 9th International Conference on Electrical and Electronics Engineering (ELECO), pp. 162–165, 2015.

[15] S. Golodetz, I. Voiculescu, and S. Cameron, "A Proposed Decision-Support System for (Renal) Cancer Imaging," pp. 361–366, 2007.

[16] S. A. Tuncer and A. Alkan, "A decision support system for detection of the renal cell cancer in the kidney," Measurement: Journal of the International Measurement Confederation, vol. 123, no. April, pp. 298–303, 2018.

[17] A. Sridharan, S. Kasoji, E. Chang, and P. A. Dayton, "Contrast-enhanced ultrasound (CEUS) in patients with chronic kidney disease (CKD)," pp. 2–5, 2017.

[18] S. Kothari, J. H. Phan, A. N. Young, and M. D. Wang, "Histological Image Feature Mining Reveals Emergent Diagnostic Properties for Renal Cancer," 2011.

[19] A. Charleonnan, T. Fufaung, T. Niyomwong, W. Chokchueypattanakit, S. Suwannawach, and N. Ninchawee, "Predictive analytics for chronic kidney disease using machine learning techniques," 2016 Management and Innovation Technology International Conference (MITicon), p. MIT-80-MIT-83, 2016.

[20] A. Saribudak, Y. Dong, S. Gundry, J. Hsieh, and M. U. Uyar, "Mathematical models of tumor growth using Voronoi tessellations in pathology slides of kidney cancer," Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, vol. 2015-Novem, pp. 4454–4457, 2015.

[21] V. Bhandari, "Comparative Analysis of Fuzzy Expert Systems for Diabetic Diagnosis," vol. 132, no. 6, pp. 8–14.