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Research Article

Development of a Multilayer Fuzzy Expert System for the Diagnosis of Chronic Kidney Disease

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ABSTRACT

In the initial stages of chronic kidney disease, it has some hidden characteristics that lead to a delay in its detection and diagnosis. The growth of kidney impairment or damage can be stopped or slowed down by making an early diagnosis. Hence, in this paper, to overcome this issue, a multilayer fuzzy expert system has been developed by using fuzzy logic, which assists in the diagnosis of chronic kidney disease at its early stages. The developed system has two layers in which the first layer is used to detect if a patient has clinical symptoms of having CKD. Similarly, the second layer of the system is used to evaluate the current stage of chronic kidney disease from which an individual is suffering. The input variables for layer 1 are age, diabetic Mellitus, smoking, hypertension and family history. Moreover, the laboratory tests are considered as the input variables for later 2 to confirm the stage of the disease. Hence, glomerular filtration rate, serum creatinine, albumin, blood urea nitrogen and pus cell in urine are the input variables for layer 2. This research work also evaluated the performance of the developed system on the basis of classification accuracy. As a result, this system provided 99.33% classification accuracy for the diagnosis of chronic kidney disease.

Keywords: Multilayer fuzzy expert system, medical diagnostic systems, chronic kidney disease, machine learning, healthcare, artificial intelligence.

INTRODUCTION

A condition or disease which compromises the functioning capability of the kidney and causes damage to the kidney to worsen with the passage of time is known as chronic kidney disease [1]. Chronic kidney diseases got ample attention because of its increased death rate, and WHO stated that this illness has arisen as a threat to developing countries, with CKD ranking among the top 20 most lethal diseases worldwide [2]. This disorder is differentiated by a slowly decrease in functionality of the kidney, which tends to result in total kidney function loss [3]. In the initial stages, the clinical signs of disease are not visible. As a result, the detection of CKD is challenging until the kidney has lost around twenty-five percent of its functionality [4]. Moreover, this disease has the potential to cause cardiovascular diseases in the human body. It is a pathologic syndrome that develops and is irreversible. Therefore, diagnosis and detection of CKD in its initial phase is crucial, as it may allow patients to obtain appropriate treatment to slow the disease's growth. In addition, it also provides ample time for doctors to choose a wise and adequate treatment plan for CKD patients [5].

Machine learning, or ML, is a computer programme that evaluates as well as determines information related to the task and accesses the features of the relevant pattern [6]. As this methodology can provide precise and profitable as well as cheap illness diagnostics, it could be a potential method to diagnose CKD. Nowadays, due to the rapid advancement in information technology, machine learning evolved into a brand-new type of medical tool [7]. This approach has already been utilized in the medical domain to predict the state of a human body [8], assess disease related parameters [9] as well as diagnose a number of illnesses [10]. For example, various medical diagnostic tools based on machine learning technologies can diagnose CKD in its early stages [11]. A medical diagnostic system is a mechanism or procedure utilized by experts and doctors in order to diagnose any illness for which it has been educated. By utilising information and expertise, these systems aid in the classification of disorders matching specific symptoms [12]. In making an accurate clinical decision, these systems assist specialists. As a result of developing technology, a variety of ways are available by which the testing and treatment of CKD can be accomplished [13]. But, these models might endanger a patient's life if it contains errors such as improper knowledge, wrong observations, incorrect interpretations, judgment errors and others [14]. However, these faults must be reduced by thorough testing and training to ensure that the system can assist doctors in the identification of CKD.

The quality of diagnosis and treatment of CKD is enhanced by using various approaches of machine learning such as deep learning [15], [16], gradient boosting tree [17], [18], Random forest [19],[20], Convolutional Neural Network [21], [22], Decision tree [23], [24], K- nearest neighbor [25] and other hybrid systems [26]. However, these models have limitations and can not process the data if the input is in the form of fuzzy values. Hence, in this conducted work, fuzzy logic is utilized to develop a multilayer expert system to diagnose CKD. Fuzzy logic is a multivalued logic that addresses the vagueness phenomena and models the development tool using truth values gathered from an ordered scale [27]. Expert knowledge will be transferred from an expert to an expert system. Following that, this information will be applied to solve the specific situation. At the moment, expert systems are used to solve 70% of medical problems [28].

METHODOLOGY

The method utilized in the development of this proposed model is fuzzy logic. The flowchart of the procedure followed during the development process can be seen in figure 1. The algorithm of the developed medical expert system is shown in Table 1

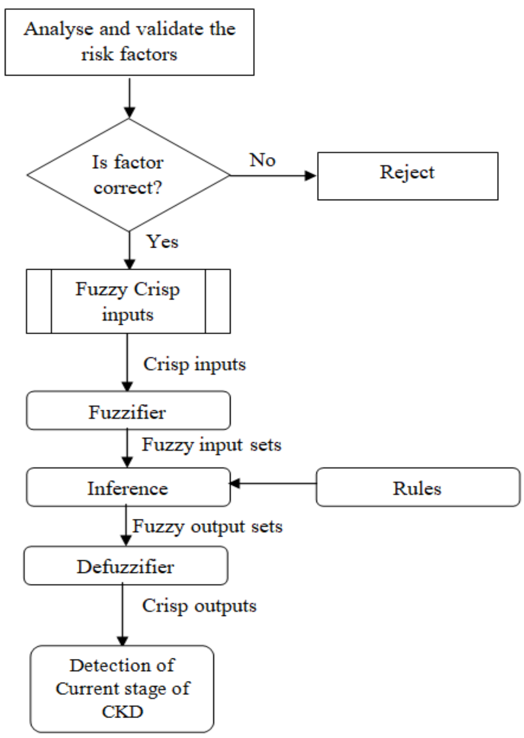

Figure 1: Flow chart of the developed model

Table 1: Proposed algorithm

Layer 1:
1. Acquire the information and knowledge from experts related to chronic kidney disease risk factors and their impact on the output of the disease for layer 1 to make an appropriate dataset. 2. Develop the medical inference system by using beneficial attributes of fuzzy logic. i. Do ii. The data gathered from the professional or doctor is the input data for the developed diagnostic model. iii. The conversion of crisp input to fuzzy values is done by using the fuzzification process of the medical inference system. iv. The suitable and relative membership functions are selected for each and every considered input in such as way that it takes less computational time. v. The IF-THEN rules are developed by using the knowledge gathered from a specialist, and the equation of these rules should look like this: IF (Input 1 = a) and/or (Input 2 = b), THEN output vi. The inference engine of the system will map the accurate rule to the given input and then fire it to obtain the correct output. vii. The conversion of fuzzy output generated in the previous step is converted into crisp values by using the defuzzification method. viii. Defuzzifier is responsible for obtaining the final outcome of layer 1 ix. Exit
Layer 2:
3. The process of layer 2 only starts if the output generated by layer 1 is "Yes". 4. Acquire the information and knowledge from experts related to chronic kidney disease risk factors and their impact on the output of the disease for layer 2 to make an appropriate dataset. 5. Follow step 2 again, and the final output for this layer will be the current stage from which a patient is suffering from five different stages of CKD

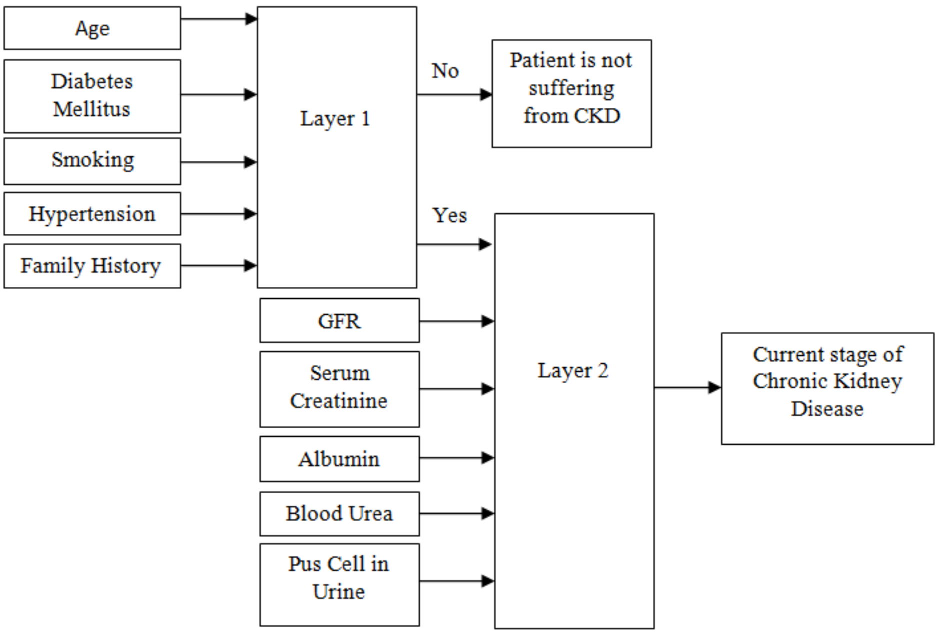

Figure 2: Development of multilayer fuzzy expert system

1.1. Input variables

The input variables are selected by thoroughly reviewing the clinical signs and laboratory tests which can aid in the identification of CKD. Table 2 and Table 3 display the input variables considered in the development of the multilayer fuzzy expert system with their type of membership function and ranges.

Table 2: Input variables of layer 1

Sr. no.	Input variable	Ranges	Sign
1.	Age	<36	Young
		33-66	Middle
		>66	Old
2.	Diabetes Mellitus	<0.6	No
		>0.4	Yes
3.	Smoking	<2.64	Low
		1.8-9.5	Medium
		>8.5	High
4.	Hypertension	<0.6	No
		>0.4	Yes
5.	Family History	<0.6	No
		>0.4	Yes

Table 3: Input variables of layer 2

Sr. no.	Input variable	Ranges	Sign
1.	GFR	<15	G5
		13-29	G4
		28-44	G3b
		42-59	G3a
		57-89	G2
		>88	G1
2.	Serum Creatinine	<1.4	Mild
		1.2-2.4	Moderate
		>2.2	Severe
3.	Albumin	<30	A1
		25-300	A2
		>290	A3
4.	Blood Urea Nitrogen	<8	Low
		4-24	Normal
		>22	High
5.	Pus Cell in Urine	<5	Normal
		>4	Abnormal

1.2. Membership Functions

The membership functions explain fuzziness which means that it assists in evaluating the nature of the elements given in the fuzzy set, whether they are continuous or discrete. It is a way of solving practical problems based on experience instead of knowledge. Moreover, graphical forms are used to express membership functions. The MF used for the input and output variables of layer 1 and layer 2 are demonstrated in Figures 3 to 14.

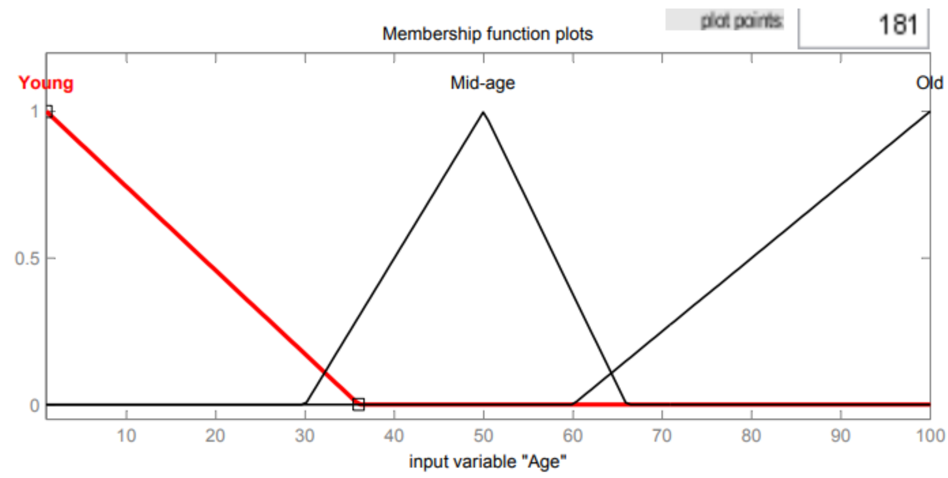

Figure 3: Layer 1- Input “Age” Membership Function

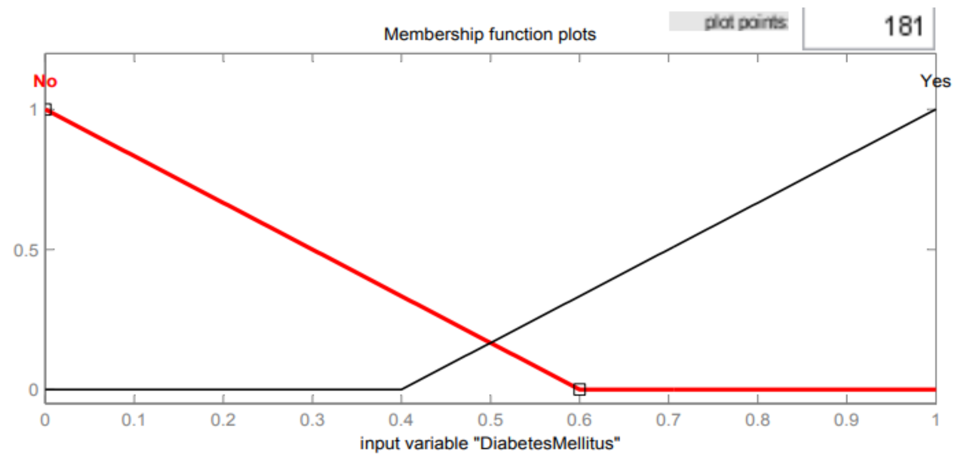

Figure 4: Layer 1 - Input “Diabetes Mellitus” Membership Function

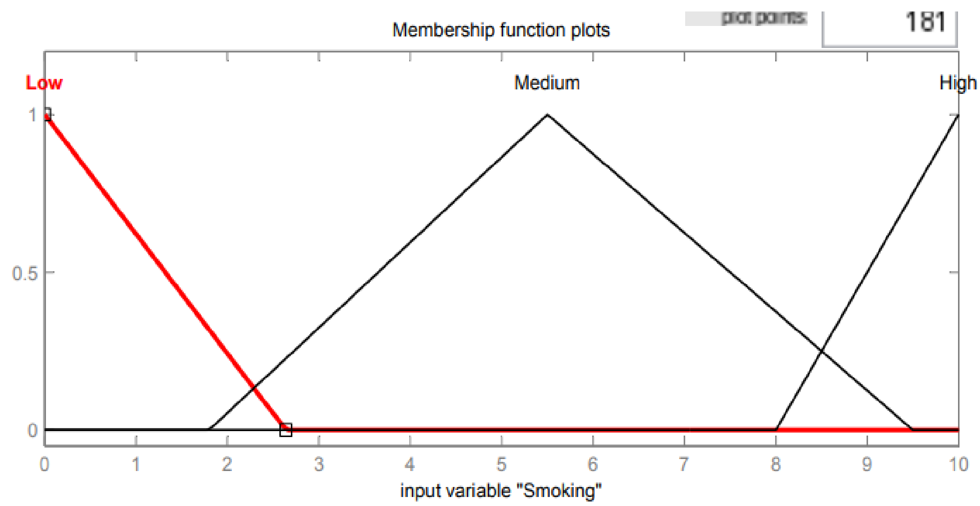

Figure 5: Layer 1- Input “Smoking” Membership Function

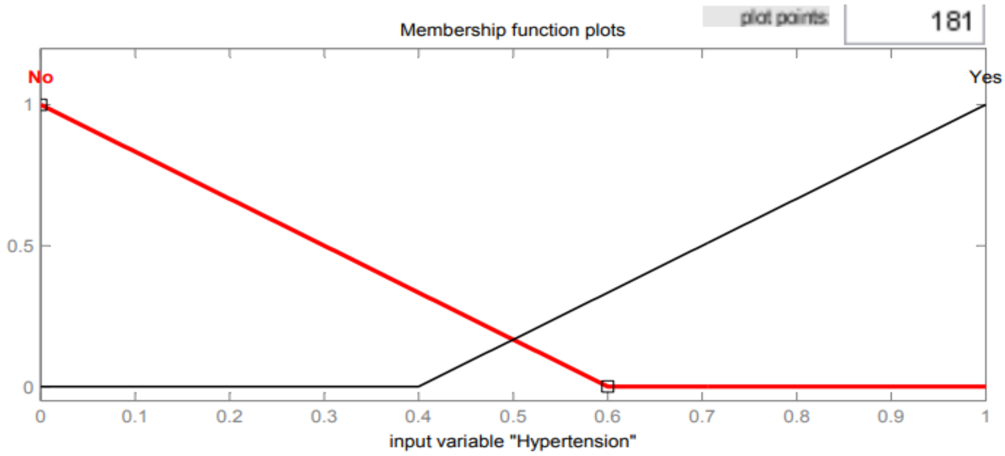

Figure 6: Layer 1- Input “Hypertension” Membership Function

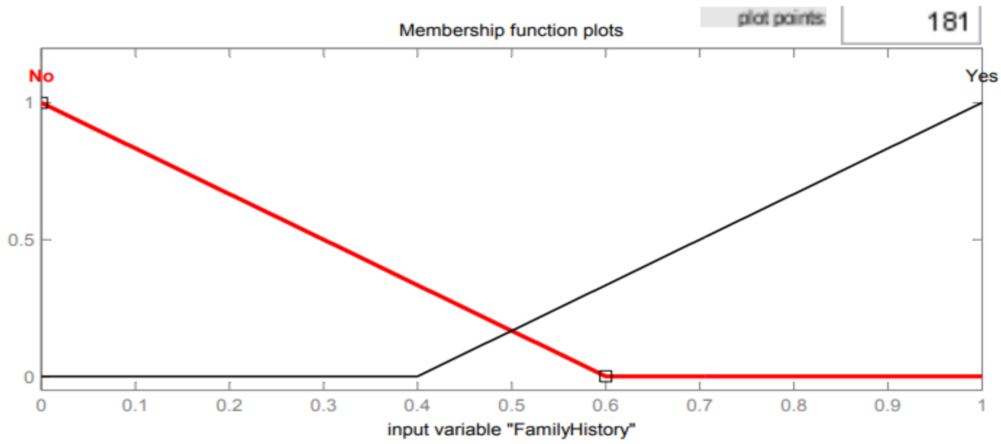

Figure 7: Layer 1- Input “Family History” Membership Function

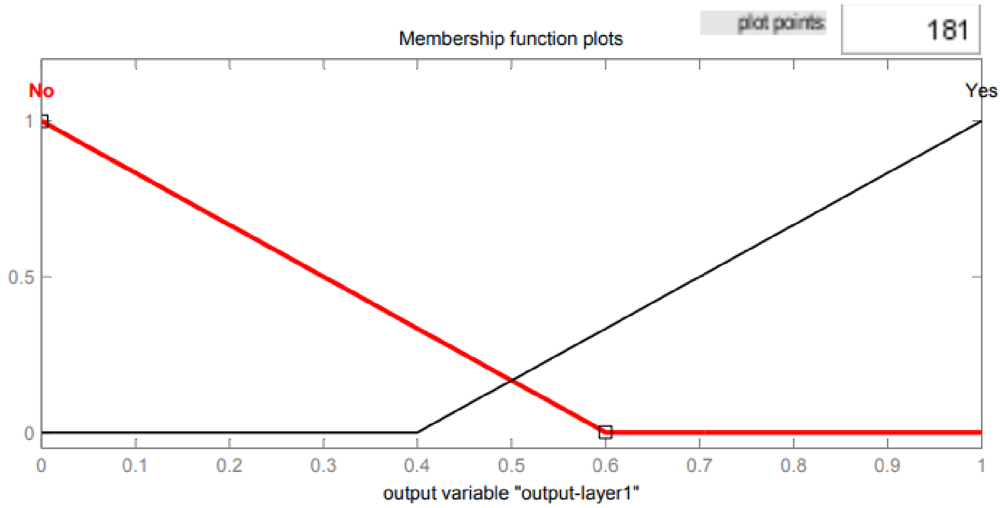

Figure 8: Layer 1- Output Membership Function

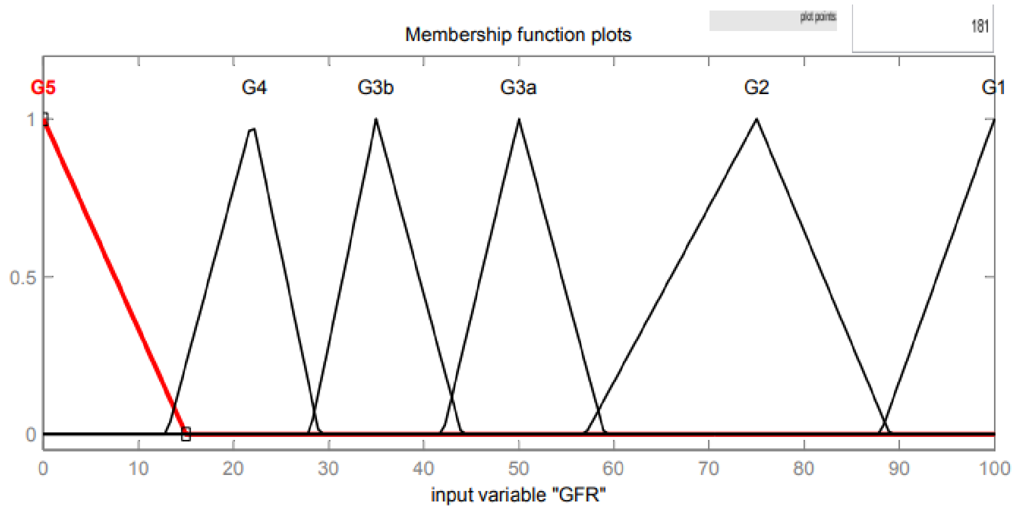

Figure 9: Layer 2- Input “GFR” Membership Function

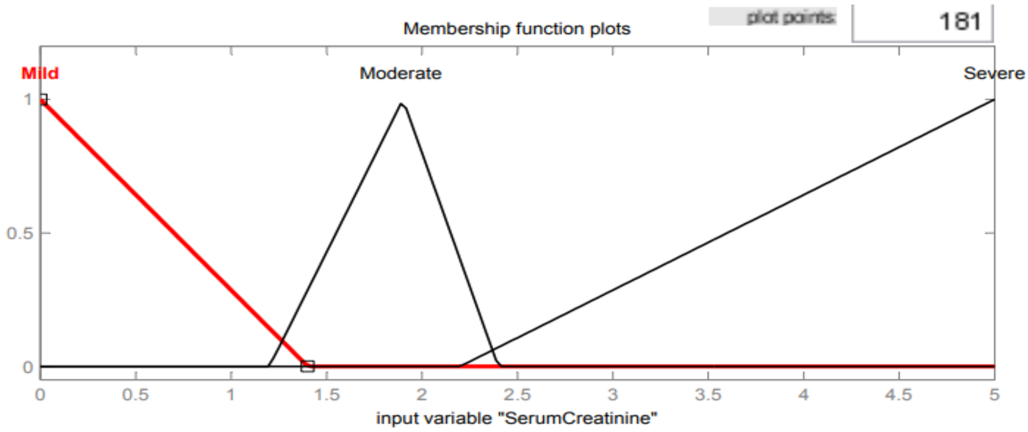

Figure 10: Layer 2- Input “Serum Creatinine” Membership Function

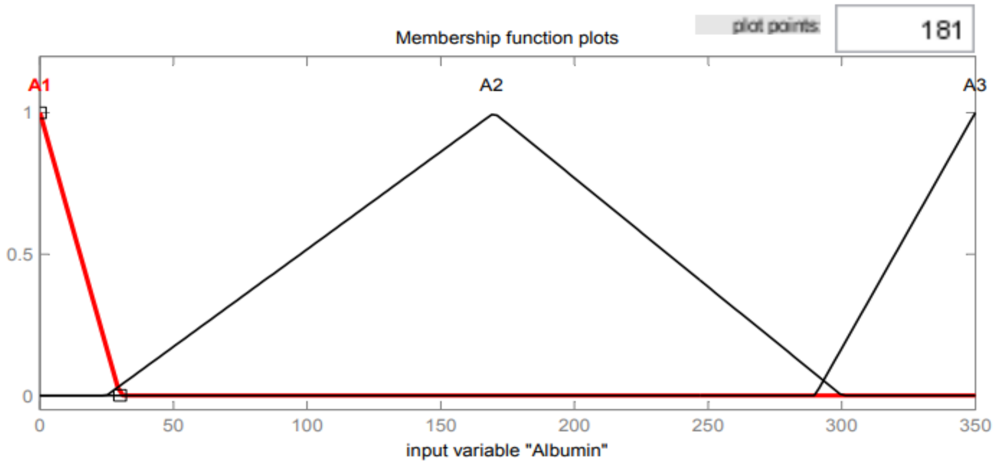

Figure 11: Layer 2- Input “Albumin” Membership Function

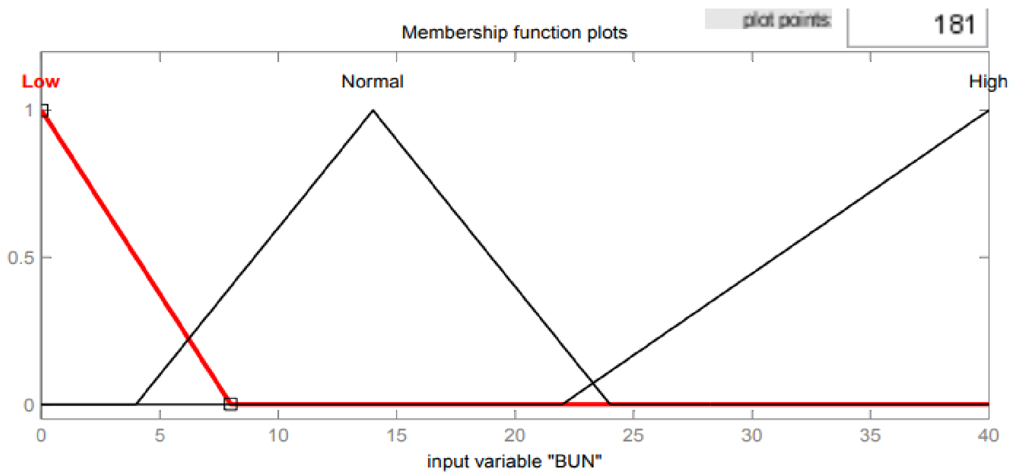

Figure 12: Layer 2- Input “Blood Urea Nitrogen” Membership Function

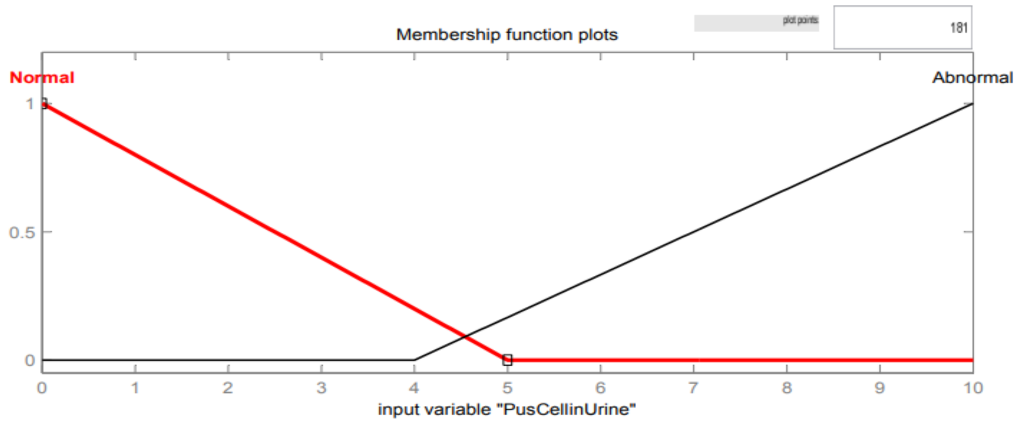

Figure 13: Layer 2- Input “Pus Cell in Urine” Membership Function

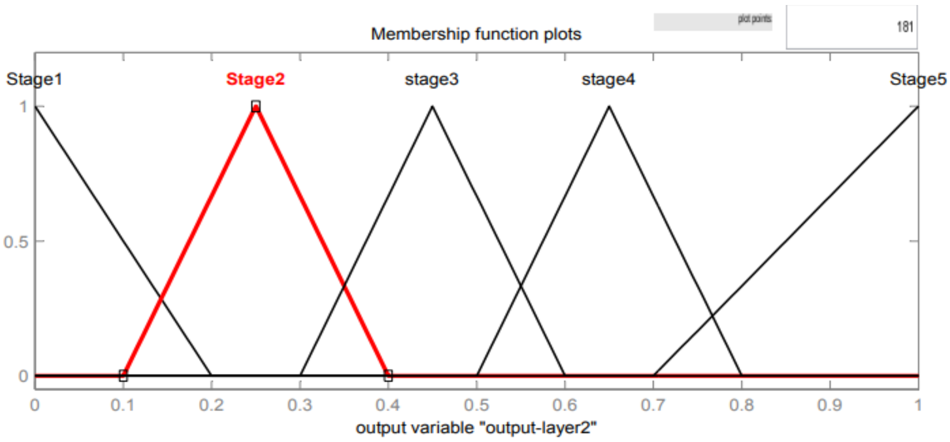

Figure 14: Layer 2- Output Membership Function

1.3. Rules

In any expert system, the rules have an essential role to play. The generated rules are only responsible for the performance of the developed diagnostic system. Hence, it is very necessary to make the rules accurate and correct. These rules are formulated in an IF-THEN manner. The total number of rules of a system is measured by multiplying the number of membership functions of each input variable. In this research work, the number of rules for layer 1 and layer 2 is 72 and 324, respectively. The frameworks of rules for both layers are displayed in Figures 15 and 16.

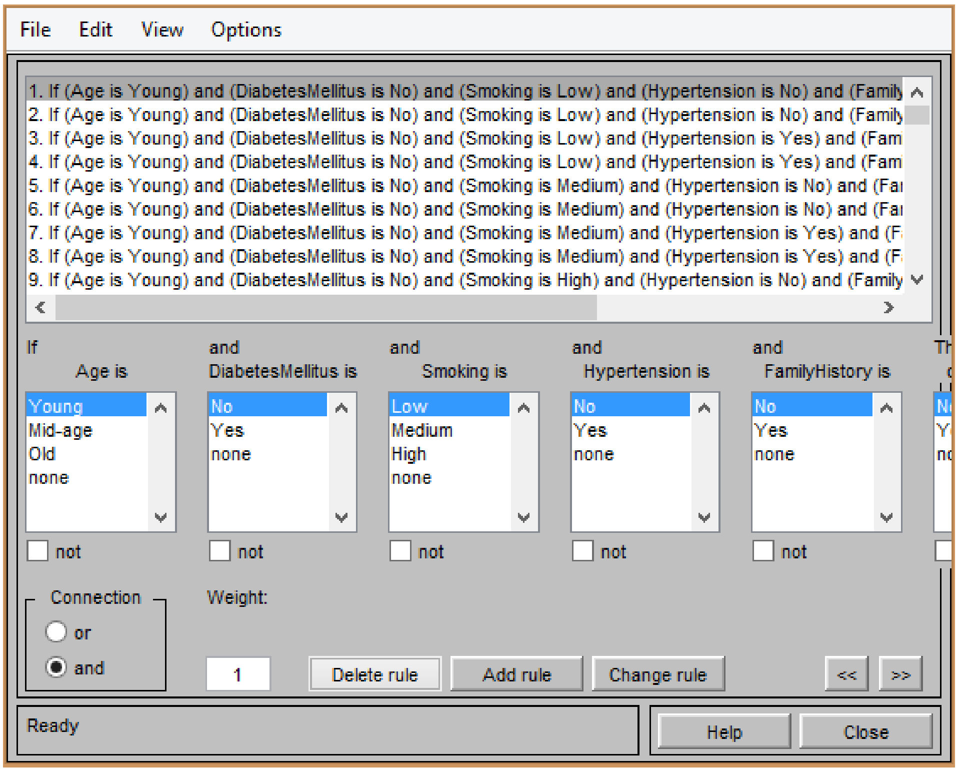

Figure 15: Framework of rules for layer 1

1.4. Inference Engine

To deliver an output, an inference engine assesses and interprets the information stored in the knowledge base. It allows the developed models to derive conclusions by using correct rules. Basically, the expert system's brain is its inference engine as it chooses rules and facts and executes them to offer an accurate output to the user. In this research work, the Mamdani inference engine is being used in the development of a multilayer fuzzy expert system for the diagnosis of CKD.

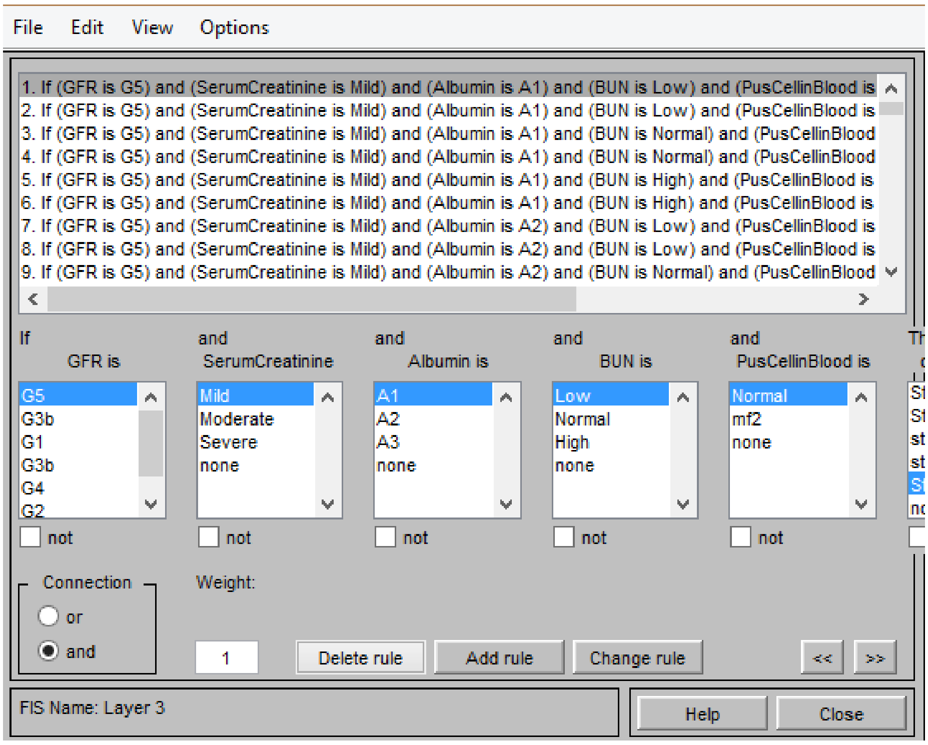

Figure 16: Framework of rules for layer 2

1.5. *Output Variables*

As the built model have 2 layers, so there are two outputs of the system. The first layer obtains the outcome to check if the patient is suffering from CKD and gives an output of either yes or no. Similarly, layer 2 is responsible for evaluating the current stage of chronic kidney disease from which a patient is suffering. Hence, layer 2 has 5 output variables which are 5 stages of CKD. Table 4 illustrates the output variables of both layers, along with their linguistic variables.

Table 4: Output variable of both layers

Sr. no.	Layer	Output variables	Linguistic variables
1.	Layer 1	Output layer 1	No Yes
2.	Layer 2	Output layer 2	Stage 1 Stage 2 Stage 3 Stage 4 Stage 5

RESULT

The entire simulation of the system is done by using MATLAB software. After the development process, the testing of the system was conducted in order to measure the performance. The easy and effective method of evaluating the accuracy of the system is by comparing the actual outcome with the obtained outcome. As a result, if the values of both outcomes are the same, then the system is perfect and accurately classifies the given inputs. In contrast, if the obtained outcome is not identical to the expected outcome, that means the system is classifying the provided inputs in incorrect classes. Hence, the classification accuracy of the system can be examined by dividing the number of correct classified tests and a total number of test cases and then multiplying by 100.

Mathematically,

$$\text{Classification Accuracy} = \left(\frac{Number\ of\ test\ cases\ classified\ correctly}{Total\ number\ of\ tests\ cases} * 100\right)$$

For the testing process, the dataset having 150 test cases was considered, and these test cases are unseen to the system. Out of them, only one test case was incorrectly classified by the developed multilayer fuzzy expert system. Therefore,

Total number of tests cases = 150

The number of improperly classified test samples = 1

Hence, the number of properly classified test samples = 150 – 1 = 149

$$\text{Thus, Classification Accuracy} = \left(\frac{149}{150} * 100\right) = 99.33\%$$

The measured accuracy for classifying the given input is 99.33% which implies that the developed multilayer expert system for the diagnosis of chronic kidney disease provides exact and accurate outcomes.

CONCLUSION

The development of a multilayer expert system which can able to diagnose chronic kidney disease is the primary intent of this research work. The developed system has the tendency to do so, which fulfils the main aim. This system is user-friendly and effortless to use for all users, whether a user has a background in the medical domain or not. It can be used as a supportive and professional tool to detect if the patient is suffering from CKD and then if the patient has CKD, layer 2 assist in recognition of the current stage in which the patient is suffering. The performance of the developed multilayer expert system has been evaluated on the basis of classification accuracy. As a result, it is observed that the system has 99.33% accuracy in classifying the provided unseen input into the correct class.

For future work, the other machine learning approaches can be implemented by taking similar inputs, which can help in improving the productivity and performance of the system. Moreover, this research work can also be continued by examining more accurate inputs which can able to recognize the disease in its introductory phase.

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