



PROGNOSIS OF KIDNEY INFECTION USING SOFT-COMPUTING TECHNOLOGY

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Abstract— *The kidneys, organs with several functions, serve essential regulatory roles and are therefore very vital organs in the human body. Any defect to the kidneys might affect the heart, the pancreas, the pelvis, lead to blood poisoning and eventual kidney failure. Therefore the need for early diagnosis of any kidney infections is very essential to get rid of the infections. A shocking analysis evaluates the supply of medical professionals to be on the low side, compared to the myriads of patients needing medical attention. This therefore calls for a holistic step in resolving this challenge. This paper presents an attempt in the application of soft computing techniques comprised of fuzzy logic, genetic algorithm and neural network in the prognosis of kidney infections. The real procedure of medical diagnosis was analyzed and converted to machine implementable format. Seven major symptoms of kidney infection were applied in the diagnosis process. Outcomes suggests the effectiveness of genetic algorithm in the optimization of symptom to get the fitness function, the self-learning and adaptive nature of neural networks in determining the inference rules and the approximation power of fuzzy logic in handling the uncertainties often associated with the diagnosis of kidney infection.*

Keywords: *Kidney Infection, Genetic Algorithm, Fuzzy Logic, Neural Network*

I. INTRODUCTION

The kidney is a very delicate organ which serves several purposes and is usually affected by several infections. An individual maturing cycle can slowly influence the capacity and by and large activity of the kidney. The greater part of the anatomic and physiologic cycles of the kidney follow a slow decay with maturing and abuse of certain unfamiliar consumable things, for example, liquor. Indications of the kidney disease extend from blood in the pee; to aggravation of the kidney, increment in weight e.tc. Kidney contamination, if not analyzed early go far in hampering the capacity of others organs, for example, the eyes. Ordinary methodologies for the finding of kidney disease depend on abstract experts/genuine belief or experience.

Prognosis in medicine implies anticipating the course of an infection or disease. This must be done after an analysis is made of a specific condition. Visualization assumes a significant part in quiet administration assignments like conclusion and treatment plan. Moreover, prognostic models establish instruments to assess the nature of medical services and the outcomes of medical care strategies by contrasting expectations agreeing with care standards with genuine outcomes. The word etiology is the investigation of causation. Etiology is basically

utilized in Medicine, where the science manages the investigation of causes or starting point of illness, the components which create or incline toward a specific disease or infection.

The procedures of artificial intelligence found in soft computing are oftentimes applied together. The motivations to consolidate these three ideal models emerge from the challenges and inalienable constraints of each secluded worldview. Conventionally, when they are utilized together, they are called soft-computing systems. This term, notwithstanding, is frequently used to allot a particular sort of system that incorporates a few procedures. This sort of system is portrayed by a fuzzy system where fuzzy sets and fuzzy rules are balanced utilizing input-yield designs. There are a few distinct usages of delicate processing systems, where each creator characterized his own model.

A neural network gains without any preparation by changing the interconnections between layers. Fuzzy derivation system is a famous registering system dependent on the idea of fuzzy set theory, fuzzy in the event that rules, and fuzzy thinking, while hereditary algorithm actualizes search and improvement approach in normally a huge example space. The advantages of a combination of neural networks, fuzzy logic and genetic algorithm are self-evident.

An investigation uncovers that the disadvantages relating to these approaches appear to be reciprocal and subsequently it is normal to consider building an incorporated system consolidating the ideas [20]. While the learning ability and improvement is a preferred position from the perspective of neural organization and hereditary calculation individually, the programmed development of semantic guideline base will be advantage from the perspective of fuzzy induction system.

Kidney diseases present incredible dangers and wellbeing threats to its victims. A few methods have been concocted in the past to analyze and treat these diseases, with vulnerabilities and close to misses being their result. It is likewise pitiful to take note of the fact that the quantity of doctors per individual per family in Nigeria is very poor [21]; the worth which was assessed at 28 doctors for each 100,000 individuals, as against that of nations like the United States (230 doctors for every 100,000 individuals) or even South Africa (77 doctors for each 100,000 individuals). With this issue of lack of specialists, there is the requirement for a comprehensive way to deal with and fix the issue.

This study presents a hybrid soft-computing based system which comprises of neural networks, fuzzy logic and genetic algorithm for conducting kidney infection diagnosis and prognosis. This method when employed could assist doctors to battle the scourge of kidney infections.

II. LITERATURE REVIEW

Overview of Fuzzy Systems

Fuzzy components appropriate for jobs that involve ability to reason have been proposed as an augmentation to traditional conventional rationale. They were first presented in set theory. The idea of a "fuzzy set" has been utilized to expand old style sets, which are portrayed by fresh limits. This expansion allows a level of adaptability for each item having a place with a specific set. This quality is acknowledged by the meaning of enrollment works that give fuzzy sets the limit of displaying etymological, dubious articulation [33]). Fuzzy logic systems usually contain master IF-THEN standards and can be described as far as their major constituents: fuzzification, rule base, derivation, and defuzzification. Figure 1 is a schematic portrayal of such a fuzzy system.

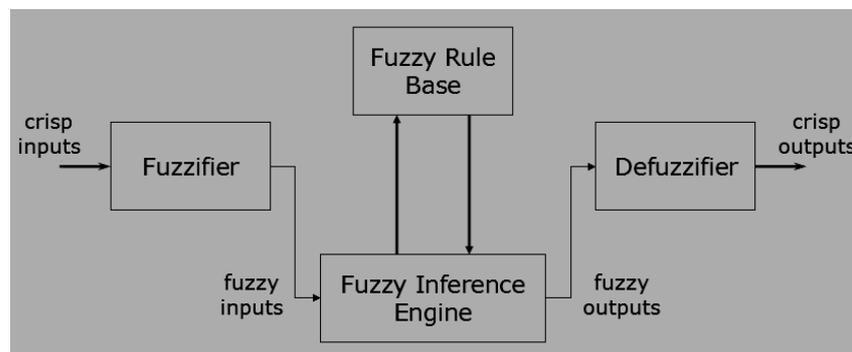


Fig.1: The basic components of a fuzzy system

Fuzzification is a mapping from a crisp input space to fuzzy sets in a defined universe:

$$U : x_i \in R \rightarrow X \in U \subset R^q. \quad (1)$$

Here x_i represents a crisp value and q is the number of fuzzy classes. The fuzzy sets are characterized by membership functions which portray the degree of belonging of x_i to the values in U , $\mu_F(x_i) : U \rightarrow [0, 1]$. The rule base is constituted by an ensemble of fuzzy rules and the knowledge is expressed in the following form:

$$\text{IF } x_1 \text{ is } A_1^k \text{ AND } \dots \text{ AND } x_n \text{ is } A_n^k \\ \text{THEN } y_1 \text{ is } b_1^k \text{ AND } \dots \text{ AND } y_m \text{ is } b_m^k, \quad (2)$$

where the index $k = 1, \dots, K$ indicates the k -th rule among the K rules in the rule base; A_i^k and b_j^k are fuzzy sets. These are defined over the input components $x_i, i = 1, \dots, n$, and the output components $y_j, j = 1, \dots, m$, respectively. The rule is a fuzzy implication that is usually represented by a Cartesian product of the membership functions of antecedents and consequents.

The fuzzy inference process can be depicted by beginning with the meaning of the participation capacities $\mu_{ik}(\cdot)$ identified with the k th fuzzy principle and assessed for each information segment of an example vector $x = (x_1, \dots, x_n)$. The most usually utilized enrollment capacities are the three-sided and the Gaussian capacities. Finally, the defuzzification process is utilized to reconvert the fuzzy yield esteems, getting from the induction system, into fresh qualities. These would then be able to be inevitably utilized in various settings. The most well-known approach for defuzzification is to utilize the focal point of territory technique which gives the focal point of gravity of the yield participation work.

2.2 Overview of Neural Networks

Neural networks are versatile factual models dependent on a similarity with the structure of the cerebrum. They are versatile in light of the fact that they can figure out how to assess the boundaries of some populace utilizing few models (one or a couple) at once.

The goal of the network is to learn or to find some relationship among info and yield designs, or to break down, or to discover the structure of the information designs. The learning cycle indicates the "calculation" used to assess the boundaries.

Neural networks are made of essential units (see Figure 2) arranged in layers. A unit gathers information gave by different units (or by the outside world) to which it is associated with weighted associations called neurotransmitters. These loads, called synaptic loads increase (i.e., enhance or lessen) the information data: A positive weight is viewed as excitatory, a negative weight inhibitory.

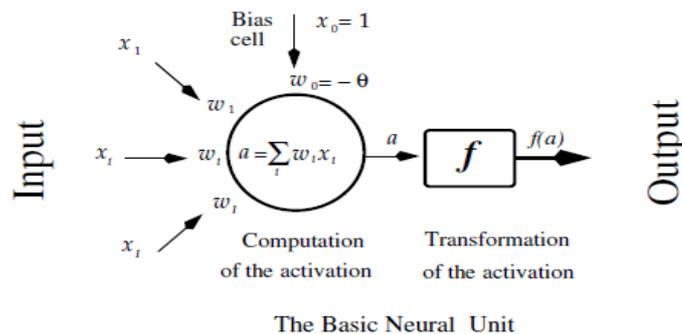


Figure. 2: The basic neural unit processes the input information into the output information.

Every one of these units is an improved model of a neuron and changes its info data into a yield reaction. This change includes two stages: First, the actuation of the neuron is registered as its weighted whole sources of info, and second this initiation is changed into a reaction by utilizing an exchange work. Officially, on the off chance that each information is meant x_i , and each weight w_i , at that point the initiation is equivalent to $a = \sum x_i w_i$, and the yield signified o is gotten as $o = f(a)$. Any capacity whose area is the genuine numbers can be utilized as an exchange work. The most mainstream ones are the direct capacity ($o \propto a$), the progression work (initiation esteems not exactly a given edge are set to 0 or to -1 and different qualities are set

to +1), the logistic function $f(x) = \frac{1}{1 + \exp\{-x\}}$ which maps the real numbers into the interval $[-1 + 1]$ and whose derivative, needed for learning, is easily computed $\{f'(x) = f(x) [1 - f(x)]\}$, and the normal or Gaussian function $[o = (\sigma\sqrt{2\pi})^{-1} \times \exp\{-\frac{1}{2}(a/\sigma)^2\}]$. Some of these functions can include probabilistic variations; for example, a neuron can transform its activation into the response +1 with a probability of 1/2 when the activation is larger than a given threshold.

Overview of Genetic Algorithm

One of the authors of evolutionary computation, John Holland, in the mid-1970s, presented the idea of hereditary calculations [27]. Genetic algorithms, as a class of stochastic search calculations depend on natural development. They are versatile calculations for finding the worldwide ideal answer for an improvement issue [3]. Genetic algorithms are probabilistic pursuit and streamlining techniques dependent on regular hereditary qualities,

working with limited series of pieces that speak to the arrangement of boundaries of the issue, and with a wellness work for assessing every last one of these strings.

Genetic Algorithms (GA) are relevant to numerous improvement issues [27]. Improvement is basically the way toward finding a superior answer for an issue. This infers that the issue has more than one arrangement and the arrangements are not of equivalent quality. A genetic algorithm produces a populace of contending competitor arrangements and afterward makes them develop through the cycle of characteristic choice – helpless arrangements will in general cease to exist, while better arrangements endure and imitate. By rehashing this cycle again and again, the genetic algorithm breeds an ideal arrangement [22].

Chromosomes speak to arrangements inside the genetic algorithm. Two essential segment of chromosome are coded arrangement and its wellness esteem.

Chromosomes are assembled into populace (set of arrangements) on which the hereditary calculation works. In each progression (age) genetic algorithm chooses chromosomes from populace (determination is generally founded on wellness estimation of chromosome) and joins them to create new chromosomes (posterity). These posterity chromosomes structure new populace (or supplant a portion of the chromosomes in the current populace) with the expectation that new populace will be superior to past. Populaces monitor the most noticeably terrible and the best chromosomes and stores extra factual data which can be utilized by gen.

Chromosome in some way stores solution which it represents. This is called representation (encoding) of the solution. A GA operates through a simple cycle of stages [34]

- a. Creation of a “population” of strings,
- b. Evaluation of each string,
- c. Selection of best strings and
- d. Genetic manipulation to create new population of strings

Kidney Infections

Kidney infection might be analyzed by a doctor by playing out a total physical assessment and taking a point by point clinical history. The assessment incorporates checking the fundamental signs (pulse, circulatory strain, temperature, and respiratory rate), evaluating for indications of drying out, and checking for delicacy on the mid and lower back. In youthful, female patients a pelvic assessment may likewise be important to assess for pelvic contamination (pelvic fiery ailment or PID).

The sign/symptoms of kidney infection include:

- a. Fever,
- b. Nausea,
- c. Vomiting,
- d. Abdominal pain,
- e. Painful urination (dysuria),
- f. Frequent urination (urinary frequency),
- g. Swollen body parts and

When a kidney becomes infected, the condition is medically referred to as pyelonephritis.

III. METHODOLOGY

To design the soft-computing system for diagnosis and prognosis of kidney infection, we designed a system which consists of a set of parameters needed for diagnosis (here, we are using 7 basic and major symptoms of kidney infections) :

1. Fever,
2. Nausea,
3. Vomiting,
4. Abdominal pain,
5. Painful urination (dysuria),
6. Frequent urination (urinary frequency),
7. Swollen body parts

Figure 3 presents the model of delicate registering system for the conclusion of kidney disease. The information base comprises of the information base, which comprise of seven essential parameters referenced before. The estimations of the parameters are ambiguous and loose consequently the selection of fuzzy rationale as methods for dissecting these data. Those parameters accordingly comprise the fuzzy parameter of the information base. The fuzzy arrangement of parameters is spoken to by 'P' which is characterized as

$$P = \{P_1, P_2, \dots, P_n\}$$

Where P_i represents the j^{th} parameter and n is the total number of parameter (in this case $n=7$). The set of linguistic values which is modeled as a linker scale denoted by 'L' is given as

$$L = \{Low, Average, High\}$$

Neural networks give the structure to the parameters which fills in as a stage for the induction motor. The derivation motor comprises of thinking algorithms driven by creation rules. These creation rules are assessed by utilizing the forward tying approach of thinking. The induction component is fuzzy logic driven. The intellectual channel of the choice help motor takes as info the yield report of the surmising motor and applies the target rules to rank the person on the presence or nonattendance of kidney disease. The enthusiastic channel takes as info the yield report of the psychological channel and applies the emotional standards in the area of kidney disease concentrates so as to rank people on the degree of the kidney contamination.

Genetic Algorithm was used to advance the fuzzy set (side effects) in other to show up at the best arrangement of choices for displaying our system. A normal informational collection that contains the seven parameters is introduced in Table 4. This shows the level of power (enrollment) of Kidney disease. The more the worth tends towards 1.0, the more the odds that it is kidney contaminated. The core of item situated critical thinking is the development of a model. The model modified works the basic subtleties of the fundamental issue from its confounded genuine world.

The expert system is created in a situation described by Microsoft Windows Operating System (Vista form), My Structural Query Language (MySQL), and Hypertext Preprocessor (PHP) programming language. Neural arrangements and precious stone report were utilized for Neural Networks investigation and graphical portrayal separately.

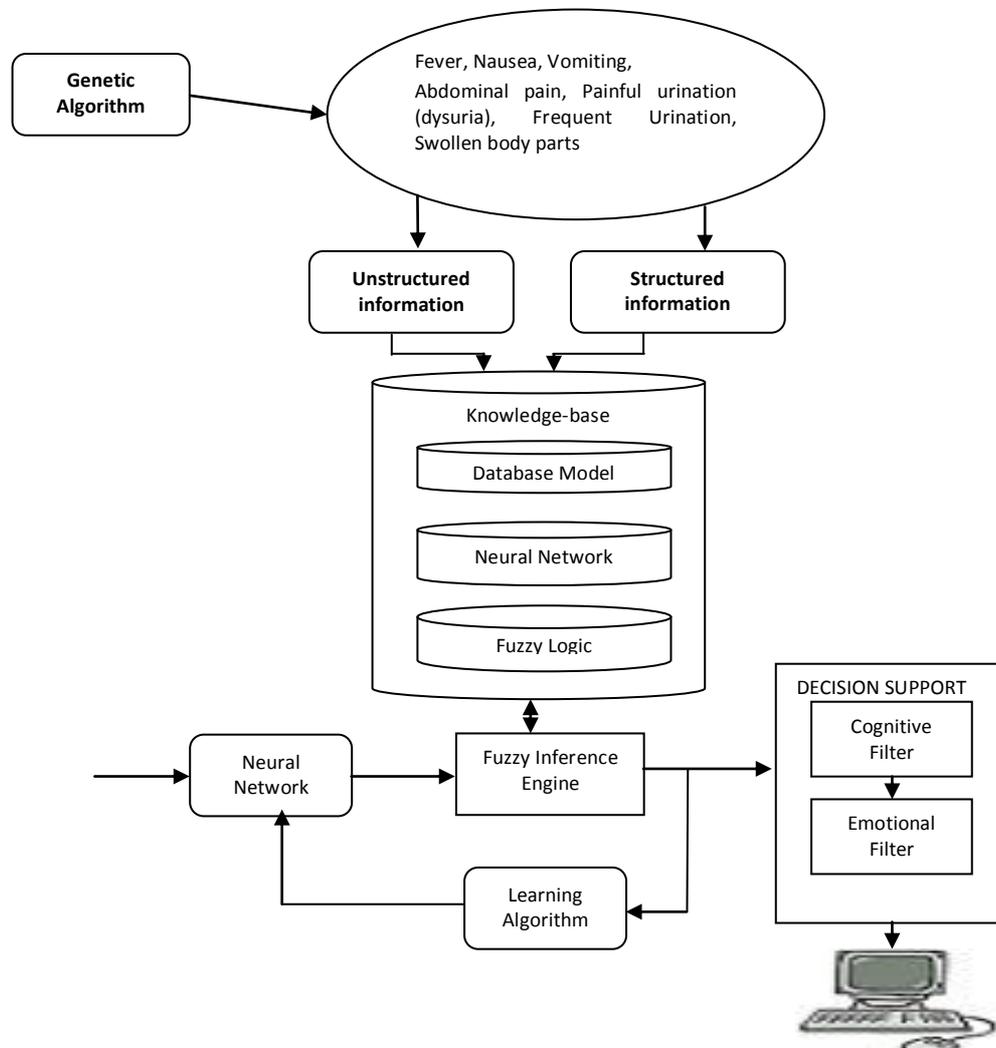


Figure 3: Model of the soft-computing system for kidney infection

The operational procedure of the model in Figure 3 is spoken to in Figure 4. The widespread arrangement of parameters is set up for analysis where the clinical/research center chaperon is required to choose from the arrangement of parameters took care of into the system. We utilized a basic double encoding plan wherein the presence of a boundary is spoken to by 1 in the info vector and 0 else (we call this the parameter vector). The arrangement of parameters is taken care of into the organization. The clinical/research facility orderly is required to look over the rundown of parameters; the one relating to what in particular is available or apparent.

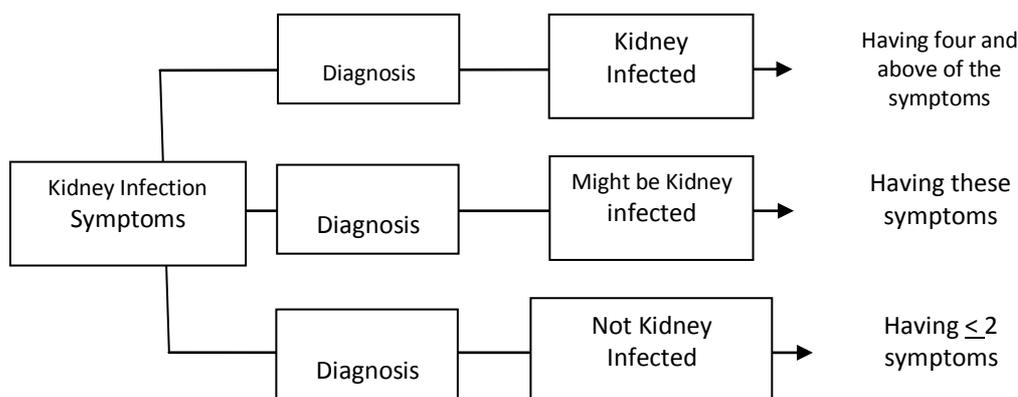


Figure 4: Operational procedure of the soft-computing system for the diagnosis of Kidney infection

Fuzzy classifier is applied to the finding of kidney contamination utilizing the model endorsed in Figure 3. The Fuzzy Classifier Rule Based Expert Model (Figure 5) induces end dependent on fuzzy set and fuzzy standards. The expert system is created in a domain described by Microsoft Windows Operating System (Vista form), My Structural Query Language (MySQL), and Hypertext Preprocessor (PHP) programming language. Neural arrangements and precious stone report were utilized for Neural Networks investigation and graphical portrayal separately.

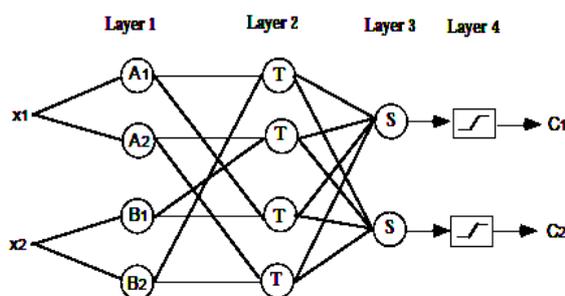


Figure 5: Fuzzy Classifier System for the Diagnosis of kidney infection

The system parades two input variables X_1 and X_2 which are symptoms of kidney infection. The training data are categorized by two classes C_1 and C_2 . Each input is represented by the two linguistic terms, thus we have four rules.

Layer 1: The output of the node is the degree to which the given input satisfies the linguistic label associated to this node. This is governed by the bell-shaped membership functions

$$A_i(u) = \exp[-1/2 (u-a_{i1})/b_{i1}^2],$$

$$B_i(v) = \exp[-1/2 (v-a_{i2})/b_{i2}^2],$$

Which represent the linguistic terms, where $\{a_{i1}, a_{i2}, b_{i1}, b_{i2}\}$ is the parameter set. As the estimations of these parameters change, the ringer molded capacities fluctuate in like manner, subsequently displaying different types of enrollment capacities on semantic marks A_i and B_i . Truth be told, any continuum, for example, trapezoidal and three-sided molded participation capacities are additionally evaluated contender for hub works in this layer. The underlying estimations of the parameters are set so that the enrollment capacities along every hub fulfill; culmination, ordinariness and convexity. The boundaries are then tuned with a plummet type technique.

Layer 2: Each node generates the signal corresponding to the conjunctive combination of individual degrees of match of kidney infection symptoms. The output signal is the firing strength of the fuzzy rule with respect to kidney infection.

We take the linear combination of the firing strengths of the rules at Layer 3 and apply sigmoidal function at Layer 4 to calculate the degree of belonging to a certain class. Given training set $\{(x^k, y^k), k = 1 \dots K\}$ where x^k refers to the k^{th} input pattern then

$$Y^K = \begin{cases} (1, 0)^T & \text{If } X^K \text{ belongs to Class 1} \\ (0, 1)^T & \text{If } X^K \text{ belongs to Class 2} \end{cases}$$

The error function for pattern k can be defined by

$$E_K = 1/2 [(O_1^K - Y_1^K)^2 + (O_2^K - Y_2^K)^2]$$

Where y^k is the desired output and o^k is the computed output.

Using fuzzy IF-THEN rules to describe a classifier, assume that K patterns $x_p = (x_{p1}, x_{pn})$, $p = 1, \dots, K$ are given from two classes, where x_p is an n -dimensional crisp vector. Typical fuzzy classification rules for $n = 2$ are like
 IF x_{p1} is small and x_{p2} is very large THEN $x_p = (x_{p1}, x_{p2})$ belongs to Class C_1
 IF x_{p1} is large and x_{p2} is very small THEN $x_p = (x_{p1}, x_{p2})$ belongs to Class C_2
 where x_{p1} and x_{p2} are the features of pattern (or object) p , small and very large are linguistic terms characterized by appropriate membership functions.

The undertaking of fuzzy order of kidney contamination is to produce a proper fuzzy segment of the component space. In this setting the word suitable implies that the quantity of misclassified designs is little or zero. At that point the standard base ought to be advanced by erasing rules which are not utilized. The plan is extensible to quite a few information and classes.

IV. DISCUSSION AND RESULT

The fuzzy partition for each input include comprises of the parameters of kidney disease. In any case, it can happen that if the fuzzy partition of spam mail is not set up accurately, or if the quantity of phonetic terms for the information highlights isn't sufficiently enormous, at that point a few examples will be misclassified. The principles that can be created from the underlying fuzzy segments of the order of kidney contamination are subsequently:

- a. Not Kidney infected (Class: C_1)
- b. Might be kidney infected (Class: C_2)
- c. Kidney infected (Class: C_3)

If the user is experiencing less than or equal to two (2) of the parameters of kidney infection THEN (C_1), if the user is experiencing three (3) of the parameters of kidney infection THEN (C_2) and if the user is experiencing four (4) or more parameters of kidney infection THEN (C_3)

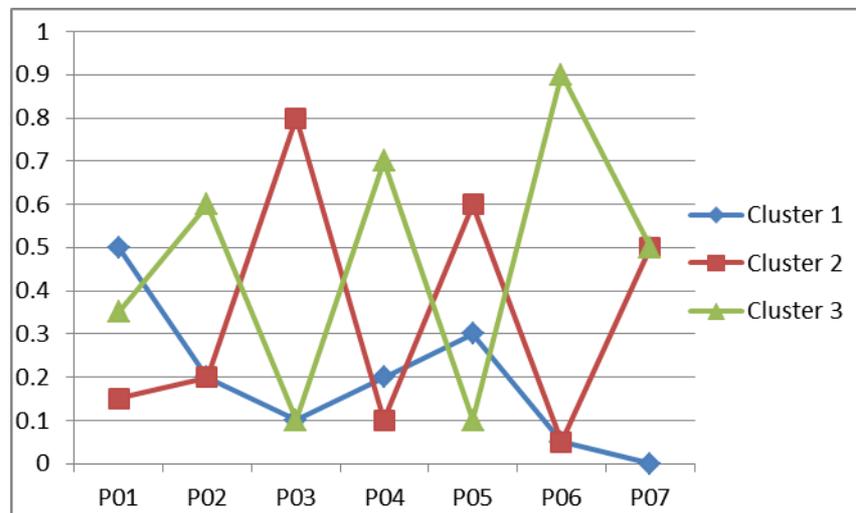
The Fuzzy IF-THEN Rules (R_i) for kidney infection is thus:

- R1:** IF the user is experiencing **fever** THEN it is in class C_1 .
R2: IF the user is experiencing **fever** and **nausea** THEN it is in class C_1 .
R3: IF the user is experiencing **fever**, **nausea** and **vomiting** THEN it is in class C_2 .
R4: IF the user is experiencing **fever**, **nausea**, **vomiting** and **abdominal pain** THEN it is in class C_3 .
R5: IF the user is experiencing **fever**, **nausea**, **vomiting**, **abdominal pain** and **painful urination** THEN it is in class C_3 .
R6: IF the user is experiencing **fever**, **nausea**, **vomiting**, **abdominal pain**, **painful urination** and **frequent urination** THEN it is in class C_3 .
R7: IF the user is experiencing **fever**, **nausea**, **vomiting**, **abdominal pain**, **painful urination**, **frequent urination** and **swollen body parts** THEN it is in class C_3 .

Table 1: Data Set showing the Degree of membership of kidney infection

| PARAMETERS OR FUZZY SETS OF KIDNEY INFECTION | CODES | DEGREE OF MEMBERSHIP OF KIDNEY INFECTION | | |
|--|-------|--|----------------------------------|-------------------------|
| | | Cluster 1 (C_1) | Cluster 2 (C_2) | Cluster 3 (C_3) |
| Fever | R01 | 0.50 | 0.15 | 0.35 |
| Nausea | R02 | 0.20 | 0.20 | 0.60 |
| Vomiting | R03 | 0.10 | 0.80 | 0.10 |
| Abdominal pain | R04 | 0.20 | 0.10 | 0.70 |
| Painful urination (dysuria) | R05 | 0.30 | 0.60 | 0.10 |
| Frequent urination | R06 | 0.05 | 0.05 | 0.90 |
| Swollen body parts | R07 | 0.00 | 0.50 | 0.50 |
| RESULTS | | NOT KIDNEY INFECTION | MIGHT BE KIDNEY INFECTION | KIDNEY INFECTION |

Kidney Infection Prognosis is very severe, if a patient is diagnosed with Cluster 3, (table 1,) then the patient should consult a physician immediately to avoid untimely death. While moderate when diagnosed with Cluster 2, the patient should also consult a physician to avoid total deterioration to Cluster 3.



Graph 1: A Graphical Representation of table 1

Genetic Algorithm Inference:

The algorithm terminates when the stop criterion is met. The Genetic algorithm utilizes the following conditions to determine when to stop: Generations or Fitness limit. In this case, we used the number of generation (4th generation) to determine the stopping criterion.

R1: IF R01 THEN C1 = 0.50

R2: IF R01 AND R02 THEN C2 = 0.18

R3: IF R01, R02 AND R03 THEN C2 = 0.38

R4: IF R01, R02, R03 AND R04 THEN C3 = 0.44

R5: IF R01, R02, R03, R04 AND R05 THEN C3 = 0.37

R6: IF R01, R02, R03, R04, R05 AND R06 THEN C3 = 0.46

R7: IF R01, R02, R03, R04, R05, R06 AND RO7 THEN C3 = 0.46

We then convert these resolved values into whole numbers and imply them to be the fitness function (f) of the initial generation (Parents)

R1: 50, **R2:** 18, **R3:** 38 **R4:** 44 **R5:** 37 **R6:** 46 **R7:** 46

Table 2: 1st and 2nd Generation Table

| S/N | Selection | Chromosomes (Binary; 0 or 1) | | | Fitness function |
|-----|-----------|------------------------------|-----------|------------------------------|------------------|
| | | Parent (1 st Gen) | Crossover | Parent (2 nd Gen) | |
| 1 | 50 | 110010 | 1 & 6 | 110101 | 53 |
| 2 | 46 | 101110 | 2 & 4 | 101100 | 44 |
| 3 | 46 | 101110 | Mutation | 101100 | 44 |
| 4 | 44 | 101100 | 2 & 4 | 101110 | 46 |
| 5 | 38 | 100110 | 5 & 7 | 100010 | 34 |
| 6 | 37 | 100101 | 1 & 6 | 100010 | 34 |
| 7 | 18 | 010010 | 5 & 7 | 010110 | 22 |

Table 3: 2nd and 3rd Generation Table

| S/N | Selection | Chromosomes (Binary; 0 or 1) | | | Fitness function |
|-----|-----------|------------------------------|-----------|------------------------------|------------------|
| | | Parent (2 nd Gen) | Crossover | Parent (3 rd Gen) | |
| 1 | 53 | 110101 | 1 & 3 | 110100 | 52 |
| 2 | 46 | 101110 | 2 & 6 | 101010 | 42 |
| 3 | 44 | 101100 | 1 & 3 | 101101 | 45 |
| 4 | 44 | 101100 | 4 & 5 | 101010 | 42 |
| 5 | 34 | 100010 | 4 & 5 | 100100 | 36 |

| | | | | | |
|---|----|---------------|----------|---------------|-----------|
| 6 | 34 | 100010 | 2 & 6 | 100110 | 38 |
| 7 | 22 | 010110 | Mutation | 010100 | 20 |

Table 4: 3rd and 4th Generation Table

| S/N | Selection | Chromosomes (Binary; 0 or 1) | | | Fitness function |
|-----|-----------|------------------------------|-----------|------------------------------|------------------|
| | | Parent (3 rd Gen) | Crossover | Parent (4 th Gen) | |
| 1 | 52 | 110100 | Mutation | 110110 | 54 |
| 2 | 45 | 101101 | 2 & 3 | 1011 10 | 46 |
| 3 | 42 | 101010 | 2 & 3 | 1010 01 | 41 |
| 4 | 42 | 101010 | 6 & 4 | 1010 00 | 40 |
| 5 | 38 | 100110 | 5 & 7 | 1001 00 | 40 |
| 6 | 36 | 100100 | 6 & 4 | 1001 10 | 38 |
| 7 | 20 | 010100 | 5 & 7 | 0101 10 | 22 |

To create our 2nd and 3rd generation from the parents (1st generation) we chose the third bit from the left to be our crossover point. In the 4th generation each bold bit signifies the cross-over bits, a single bold bit signifies mutation of that bit and an italicized chromosomes signifies elitism. The best fourth generation (stopping criterion) is that with the best fitness function, 54. This implies that the clusters of the various parameters has been searched and optimized to 0.54. Therefore combination of parameters which produce a membership function $< 0.54 = C1$, $0.54 = C2$ and $\geq 0.54 = C3$ as presented in Figure 6

Membership Function

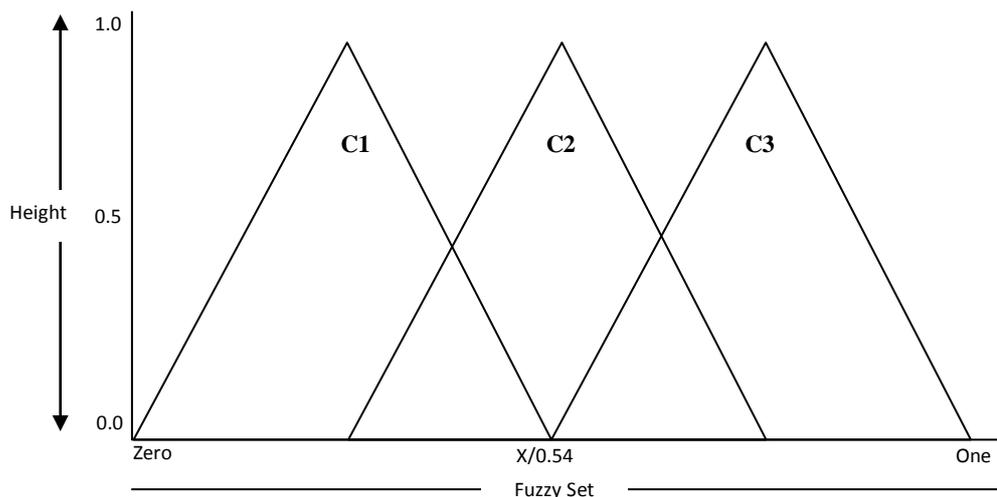


Figure 6: Degree of membership function

V. CONCLUSION

Kidney infections pose great threats and health dangers to its sufferers. Several means have been devised in the past to diagnose and treat these infections, with uncertainties and near misses being their outcome. This study offered a hybrid computerized telemedical system to assist professionals in kidney infection diagnosis and prognosis. Due to the large number of kidney infections, disorders and diseases, this study was limited to kidney infection. This advanced system which uses a set of fuzzified data set is more precise than the traditional system.

REFERENCES

- [1] Adil, B. Alex, R., John, Y., (2001). A global optimization approach to classification in medical diagnosis and prognosis, Proc. Of the 34th IEEE Hawaii International Conference on Systems Sciences, p. 3.
- [2] Amit K. (1999). Artificial intelligence and Soft Computing: Behavioral and Cognitive Modeling of the Human Brain, Department of Electronics and Tele-communication Engineering, Jadavpur University, Crc press Calcutta, India.
- [3] Cao Y. J. and Wu Q. H. (1999). Teaching Genetic Algorithm Using Matlab, Int. J. Elect.Enging. Educ., Vol. 36, pp. 139–153. Manchester U.P. Printed in Great Britain.
- [4] Chin-Ming Hong (2006). A Novel and Efficient Neuro-Fuzzy Classifier for medical diagnosis? IEEE international Joint Conference on Neural Networks.

- [5] Cordon O., Alcalá R., J. Alcalá-Fernández, and Rojas I. (2007). Genetic fuzzy systems: What's next? An introduction to the special section, *IEEE Trans. Fuzzy Systems*, 15(4):533{535}.
- [6] Cox E. (1999), "The Fuzzy Systems Handbook: A practitioner's Guide to building, using and maintaining fuzzy systems, 2nd edn. Academic press, san Diego, California, U.S.A.
- [7] Dorigo M. and Gambardella L. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation*, 1(1):53{66}.
- [8] Ekong, V.E., Onibere E.A., Imianvan A.A. (2011). Fuzzy Cluster Means System for the Diagnosis of Liver Diseases:, *International Journal of Computer Science and Telecommunication IJCST Vol 2, Issue 3*.
- [9] Fernandez A., Del Jesus M. J., and Herrera F. (2009). Improving The Performance Of Fuzzy Rule Based Classification Systems For Highly Imbalanced Data-Sets Using An Evolutionary Adaptive Inference System", In *Proc of IWANN'09*.
- [10] Galushkin I. (2007),. *Neural Networks Theory*, Springer books.
- [11] Haykin S. (1999). *Neural Networks: A comprehensive Foundation*, 2nd, Prentice Hall, England wood cliffs, NJ, U.S.A.
- [12] Imianvan A.A., Anosike U.F., Obi J.C. (2011). An Expert System for the Intelligent Diagnosis of HIV Using Fuzzy Cluster Means Algorithm, *Global Journal of Computer Science and technology*, Vol 11, Issue 12.
- [13] Imianvan, A. A, Obi, J. C, (2011). Fuzzy Cluster Means expert System for the Diagnosis of Tuberculosis, *Global Journal of Computer Science and Tech.*, Vol. 11, No. 6, , p 41-48.
- [14] Inyang, U.G, Akinyokun, O. C (2006, "Fuzzy cluster means system for matching human behavior patterns to ethnic groups", *Proceedings of the International Conference on New Trends in Mathematics and Computer Science (NTMCS2006)*, Covenant University, Ota, Nigeria, , pp. 429-434.
- [15] Jang J.S.R and Sun C.T. (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to learning and machine Intelligence*, Prentice Hall.
- [16] Julian P., Moreno G., and Penabad J. (2009). On the declarative semantics of multi-adjoint logic programs, In *Proc of IWANN'09 (this issue)*.
- [17] Kennedy J and Eberhart R.C (1992) Particle swarm optimization. In *IEEE International Conference on Neural Networks*.
- [18] Mamdani H. and Assilian S. (1975), "An experiment in linguistic synthesis with a fuzzy logic controller", *Int. J. Man-Machine Studies*, 7:1{13}.
- [19] Margartide S. (2002), "Introduction to Neural Networks in healthcare".
- [20] Mitra S. & Hayashi Y. (2000), "Neuro-fuzzy rule generation: survey in soft computing framework", *IEEE Trans. Neural Networks*, Vol. 11, No. 3, pp. 748-768.
- [21] NationMasters.com (2011), "Health Statistics > Physicians > per 1,000 people (most recent) by country" Pulled from the World Development Indicators Database (<http://devdata.worldbank.org/query/default.htm>), retrieved online at http://www.nationmaster.com/graph/hea_phy_per_1000_peo-physicians-per-1-000-people.
- [22] Negnevitsky M. (2005). *Artificial intelligence: A Guide to Intelligent Systems*, Second Edition. ISBN 0-321-20466-2.
- [23] Obi J.C.and Imianvan A.A. (2011). Breast Cancer Recognition using Fuzzy Classifier, *International Journal of Academic Research*, Vol 3, No 3
- [24] Pearl J. (1988). *Probabilistic Reasoning in Intelligent Systems*, Morgan Kaufmann.
- [25] Pearlmutter A. (1990). *Dynamic Recurrent Neural Networks*, Technical Report CMU-CS- 90-190.
- [26] Poli R., Kennedy J., and Blackwell T. (2007). Particle swarm optimization, *Swarm Intelligence*, 1(1):33{57}.
- [27] Randy L. H. and Sue E. H.A. (2004). *Practical Genetic Algorithm*. Published by John Wiley & Sons, Inc., Hoboken, New Jersey.
- [28] Robert F. (2000). *Introduction to Neuro-Fuzzy Systems*, *Advances in Soft Computing Series*, Springer-Verlag, Berlin/Heidelberg, 289 page (ISBN3-7908-1256-0) and (MR1760972).
- [29] Roger J.S. (1993). ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans. Syst., Man, and Cybernetics*, 23. Pp. 665-685.
- [30] Rudolf K. (2008). Neuro-fuzzy systems, retrieved from ww.surrey.ac.uk/computing/people/yaochu_jin/.
- [31] Sanchez, Shibata T., and Zadeh L.A (1997). *.Genetic Algorithms and Fuzzy Logic Systems: Soft Computing Perspectives*, World Scientific.
- [32] Statsoft Incorporated (2008). *Neural Networks*, retrieved from Zadeh L.A (1965) Fuzzy sets. *Information Control*, 8:338{353}.
- [33] Zadeh L.A. (1965). Fuzzy set and systems In: Fox J, editor, *System Theory*: Polytechnic Press, Brooklyn, NY.
- [34] Zhang, D. and Nguyen, D. (1993). A tool for knowledge base verification, In *Knowledge Engineering Shells: Systems and Techniques*, Bourbakis, G. N., Ed., World Scientific, Singapore.