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Neutrosophic Rough Soft Set – A Decision Making Approach to Appendicitis Problem

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***Abstract*—Classification based on fuzzy logic techniques can handle uncertainty to a certain extent as it provides only the fuzzy membership of an element in a set. This paper implements the extension of fuzzy logic: Neutrosophic logic to handle indeterminacy, uncertainty effectively. Classification is done on various techniques based on Neutrosophic logic i.e. Neutrosophic soft set, rough Neutrosophic set, Neutrosophic ontology to provide better results in comparison to fuzzy logic based techniques. It is proved that rough neutrosophic soft set will handle indeterminacy effectively that exists in the medical domain as it provides the minimum and maximum degree of truth, indeterminacy, falsity for every element.**

Keywords—Fuzzy set; Neutrosophic soft set; Rough Neutrosophic set, Rough Neutrosophic soft set.

I. Introduction

Classification can be described as a procedure in which different items are identified, differentiated and inferenced [1]. Classification is followed by collecting the instances of appendicitis disease of different patients so that we would be able to do a comparative study on the various symptoms of the disease. There exist many techniques which are used for classification and give a practical answer to feasible inputs [2]. Fuzzy logic is of great interest because of its ability to deal with non-statistical ambiguity. In decision making, ambiguous data is treated probabilistically in numerical format. Indeterminacy is present everywhere in real life. If a die is tossed on a irregular surface then there is no clear face to see. Indeterminacy occurs due to defects in creation of physical space or defective making of physical items involved in the events. Indeterminacy occurs when we are not sure of any event. Neutrosophic logic will help us to consider this indeterminacy.

This paper is written to concentrate on the classification of ambiguous, uncertain and incomplete data. Authors here propose a new technique of classification based on Neutrosophic rough soft set to handle indeterminacy. Neutrosophic rough soft set helps us to calculate the lower and upper approximation for every class.

II. Preliminaries & Basic definitions

This section provides the definition of various techniques based on fuzzy logic and Neutrosophic logic. In further sections, these techniques are used for classification of data. Fuzzy logic was described by L.A.Zadeh in 1965[3].Fuzzy logic is a multivalued logic in which the membership of truth lies in 0-1[3].

Definition 1. Fuzzy set

A fuzzy set *X* over *U*which is considered as Universe is a function defined as[4]:

$$X = \{\mu_x(u)/u : u \in U\} \quad (1)$$

where $\mu_x : U \to [0,1]$ μ_x is known as the membership function of *X*, the value $\mu_x(u)$ is known as the degree of membership of $u \in U$ .Membership value can lie between *0* and *1*.

Definition 2. Neutrosophic set[5]

A Neutrosophic set *A* in *U*which is considered as a space of items, is described by a truth-membership function T_A, a indeterminacy-membership function I_A and a falsity-membership function F_A[5].An element belonging to *U*is represented by*u*.

$$A=\{<x,(T_A(x),I_A(x),F_A(x))>: x\in U, T_A(u), I_A(u), F_A(u)\subseteq[0,1]\} \quad (2)$$

There is no restriction on the sum of $T_A(u)$, $I_A(u)$ and $F_A(u)$, so $^{-}0 \le \sup T_A(u)+\sup I_A(u)+\sup F_A(u) \le 3$. The sum of the three degrees has no restriction as it can lie from 0-3.

Definition 3. Soft set[6]

A soft set F_A over *U*which is considered as Universe, is a set defined by a set valued function f_A representing a mapping

$$f_A : E \to P(U) \text{ such that } f_A(x)=\varnothing \text{ if } x\in E-A \quad (3)$$

where f_A is called approximate function of soft set F_A.

$$F_A=\{(x, f_A(x)) : x\in E, f_A(x)=\varnothing \text{ if } x\in E-A \quad (4)$$

*E*is the set of parameters that describe the elements of *U* and $A\in E$. The subscript *A* in f_A indicates that f_A is approximate function of F_A and is called as called *x-element* of soft set for every $x\in E$.

Definition 4. Neutrosophic soft set (NSS)[7]

Let U be a universe, $N(U)$ is the set of all neutrosophic sets on U, E is the set of parameters that describe the elements of U and . A Neutrosophic soft set N over U is a set described by a set valued function f_N representing mapping

$f_N : A \to N(U)$ such that $f_N(x) = \emptyset$ if $x \in E - A$ (5)

where f_N is called approximate function of Neutrosophic soft set N.

$$N = \{(x, f_N(x)) : x \in E, f \ (x) = \emptyset \text{ if } x \in E - A\} \quad (6)$$

Definition 5. Rough Neutrosophic set (RNS)[8]

Let U be a Universe of non-null values and R is any equivalence relation on U. Consider F is any Neutrosophic set in U with its belonginess, ambiguity and non-belonginess function. The lower and higher approximations of F in the approximation(U,R) which is represented by $\underline{N}(F)$ and $\overline{N}(F)$ are defined as

$$\underline{N}(F) = \{< x, \mu_{\underline{N}(F)}(x), v_{\underline{N}(F)}(x), \omega_{\underline{N}(F)}(x) > \mid y \in [x]_R, x \in U\} \quad (7)$$

$$\overline{N}(F) = \{< x, \mu_{\overline{N}(F)}(x), v_{\overline{N}(F)}(x), \omega_{\overline{N}(F)}(x) > \mid y \in [x]_R, x \in U\} \quad (8)$$

where

$$\mu_{\underline{N}(F)}(x) = \wedge_{y \in [x]_R} \mu_F(y), v_{\underline{N}(F)}(x) = \vee_{y \in [x]_R} v_F(y), \omega_{\underline{N}(F)}(x) = \vee_{y \in [x]_R} \omega_F(y) \quad (9)$$

$$\mu_{\overline{N}(F)}(x) = \vee_{y \in [x]_R} \mu_F(y), v_{\overline{N}(F)}(x) = \wedge_{y \in [x]_R} v_F(y), \omega_{\overline{N}(F)}(x) = \wedge_{y \in [x]_R} \omega_F(y) \quad (10)$$

where $\wedge$ and $\vee$ mean min and max operators. The pair $(\underline{N}(F), \overline{N}(F))$ is called rough Neutrosophic set in (U,R). R is an equivalence relation over U.

Definition 6. Rough Neutrosophic soft set (RNSS)

Authors here propose a new technique of Neutrosophic rough soft set by combining the concept of Neutrosophic soft set and rough Neutrosophic set. RNSS will provide the lower and upper approximations for every class available.

Let U be a Universe of non-null values and R is any equivalence relation on U. Consider F is a set of every neutrosophic set in U with its belonginess, ambiguity and non-belonginess function. Thelower and upper approximations of all the Neutrosophic sets can be calculated with min and max operator using eq. 9,10.

Indeterminacy is present everywhere in real life. If weather experts will say that there is a chance of rain tomorrow is 60% then it does not specify that the chance of not raining is 40% as there are many factors like weather fronts etc which are not considered in weather reports. Various doctors may have different opinions on the same disease diagnosis so, indeterminacy can be seen in real life.

Neutrosophic logic was proposed by Florentine Smarandache to present mathematical model of uncertainty and indeterminacy.In Neutrosophic logic, each idea is estimated to have the percentage of truth, indeterminacy and falsity. [5]

Consider U be any set of buildings and E is the set of parameters. Every parameter is a Neutrosophic word. Consider E= {wooden, expensive, beautiful, cheap}. To define a Neutrosophic soft set, there is a need to point out wooden buildings, expensive buildings and so on. Let us assume that there are three buildings in the universe U given by U={b1,b2,b3} and set of parameters A={e1,e2,e3,e4} where e1 represents wooden, e2 represents expensive and so on.

F(wooden)={<b1,0.6,0.3,0.4>,<b2,0.4,0.6,0.6>,<b3,0.6,0.4,0.2>},

F(expensive)={<b1,0.7,0.4,0.5>,<b2,0.6,0.2,0.4>,<b3,0.7,0.4,0.3>},

F(beautiful)={<b1,0.8,0.2,0.1>,<b2,0.6,0.7,0.6>,<b3,0.8,0.4,0.3>},

F(cheap)={<b1,0.8,0.2,0.7>,<b2,0.4,0.6,0.4>,<b3,0.7,0.3,0.2>}.

F(e1) means buildings(wooden) whose value of function is the Neutrosophic set {<b1,0.6,0.3,0.4>, <b2,0.4,0.5,0.6>,<b3,0.6,0.4,0.2>}.

Each approximation has two parts: predicate p and an approximate value-set v. For the approximation 'wooden buildings={<b1,0.6,0.3,0.4>,<b2,0.4,0.6,0.6>,<b3,0.6,0.4,0.2>}, predicate is wooden buildings and approximate value set is {<b1,0.6,0.3,0.4>, <b2,0.4,0.6,0.6>,<b3,0.6,0.4,0.2>}.

The concept rough neutrosophic concept is introduced by combining both rough set and Neutrosophic set. These are the generalizations of rough fuzzy sets and rough intuitionistic fuzzy sets[8].

Let U={p1,p2,p3,p4} be a universe and R be an equivalence relation its partition of U is given as

U/R = {{p1,p2},p4}

Let N(F)={(p1.(0.3,0.2,0.5)),(p2,(0.3,0.2,0.5)),(p3,(0.4,0.5,0.2))}.

$\underline{N}(F)$ ={(p1,(0.3,0.2,0.5)),(p2,(0.3,0.2,0.5)),(p3,(0.4,0.5,0.2))}

$\overline{N}(F)$ ={(p1,(0.3,0.2,0.5)),(p2,(0.3,0.2,0.5)),(p3,(0.4,0.5,0.2))}

RNSS will calculate the lower and upper approximations for all the elements of universe U. All elements must exist in one of those partition elements.

III. How Rough Neutrosophic Rough Set is Better Than Fuzzy Set

Rough Neutrosophic soft set is combination of Neutrosophic soft set and rough Neutrosophic set. RNSS is based on Neutrosophic logic and fuzzy set is based on fuzzy logic instituted by L.A. Zadeh. In this logic, every proposition is estimated to have the degree of truth, indeterminacy and falsity (T,I,F). Neutrosophic soft set will provide predicate and approximate value set for every instance of classification data. Fuzzy set is a subset of Neutrosophic set and it provides the degree of membership and non-membership of any instance.

Rough Neutrosophic soft set provides the lower and upper approximations i.e. minimum and maximum degree of truth, indeterminacy and falsity.

For example, In case of fuzzy logic if a person is suffering from dengue havingdegree of membership as 0.6 i.e. Person is said to be having 60% chance of dengue and 40 % chance of not suffering from dengue. So, fuzzydegree of membership to a class is represented by fuzzy set.

In case of Neutrosophic logic if a person is suffering from dengue havinga membership value of 0.6 i.e. Person is said to be having 60% chances of dengue but not necessarily having 40% chances of not suffering from dengue, no inference can be made about the 40%. In reality Neutrosophic logic is effective in providing the degree of truth, indeterminacy, falsity that a person has in favour of dengue as there are many indeterminate factors which are not considered by doctors. Authors here propose torepresent Neutrosophic logic by experimenting with Rough Neutrosophic soft set, that suitably captures the indeterminacy, which is not captured by fuzzy set.

IV. Details of Appendicitis Dataset

Appendicitis dataset is chosen here for research from knowledge extraction based on evolutionary learning (KEEL)[9]. This dataset has 7 attributes which are defined in 2 classes and are of real- value type. It has 106 instances as shown in Fig. 1. The seven different attributes are standardised in the range of 0-100 by multiplying each attribute by 100.

The various attributes to be tested are WBC1, MNEP, MNEA, MBAP, MBAA, HNEP, HNEA.

Classes to be classify:-

0 means the patient suffers from appendicitis.

1 means the patient does not sufferfrom appendicitis.

In this research, we have collected the appendicitis dataset samples from knowledge extraction based on evolutionary learning. Using some training we have designed a fuzzy inference system that is able to classify an unknown appendicitis sample and on the behalf of the learning tuples it is able to predict the class to which that particular unknown sample belongs to whether the patient has appendicitis or not. Pursuing this research further will contribute us in designing a Neutrosophic inference system or Neutrosophic classifier. It has been suggested on the lines of fuzzy logic but instead of giving one defuzzified value, output value in neutrosophic classifier takes the neutrosophic format of the type: output (truthness, indeterminacy, falsity) . Then we will be able to predict more accurately in the overlapping sections of the attributes. Here, 96 instances are used for training and 10 instances which are randomly selected are used for testing i.e. 9:1.

V. Fuzzy set Based Classification

Fuzzy set is a component of standard information theory. It shows vague probabilities with ties to concepts of random sets. It shares the frequent attribute of all uncertain probability models, the indeterminacy of an object is described in terms of probability or with bounds on probability. Fuzzy logic is a many-valued logic that deals with reasoning which is approximate not exact. Comparing with traditional binary sets, fuzzy logic variables may have a truth value that ranges between 0 and 1. Fuzzy classification is the process of collecting elements into a fuzzy set whose membership function is described by the truth value of a fuzzy propositional function. In fuzzy classification, a sample can have membership in various classes to varying degrees.Typically, the membership values are restricted so that all of the membership values for a specific sample sum to Linguistic rules related to the control system composing two parts; an antecedent part (between the IF and THEN) and a consequent part (after THEN). A variable is fuzzy if its ambiguity arises as a consequence of imprecision and vagueness and is describes by a membership function. There can be unlimited number of membership functions that can be used to represent a fuzzy set. For fuzzy sets, membership function increases the flexibility by sacrificing distinctiveness as we can regulate a membershipfunction so as to expand the service for a specific purpose. We use membership function as a curve or shape to describethe degree of membership each point in the input zone or universe of discourse. The mandatory condition for a membership function to satisfy is that it must be in the range of [0,1]. The membership functions constitute of different types of mathematical expressions and geometric shapes like triangular, trapezoidal, bell etc. We can choose a membership function from a wide selection range provided by MATLAB Fuzzy Logic ToolBox. There are 11 in-built membership functions included in Fuzzy Logic ToolBox, Triangular and Trapezoidal membership functions

A. Determination of fuzzy membership and non-membership values

Fuzzy logic determines the basis of classification for fuzzy set. For all the attributes and output classes of appendicitis dataset, suitable rules are designed to account for the overlapping expected in fuzzy logic. As per observation, in the inference system, three types of outputs are produced after defuzzification as shown by Fig. 1. Defuzzified value or crisp value is obtained by applying various defuzzification techniques [10] to fuzzified value given by the inference module.

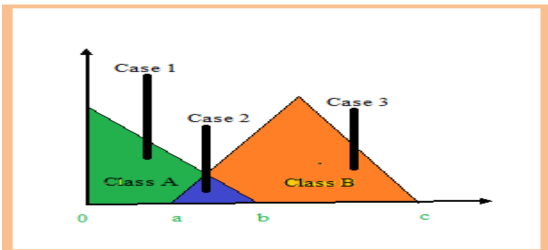

Fig.1. Criteria for assigning fuzzy values

Case 1. It provides the grade of membership and non-membership to class A. So, an output which belongs in the range of 0-a will support greater membership value for class A and smaller membership value for class B.

Case 2. There is some degree of indeterminacy for the output value lying in the overlapping range of a-b. Higher membership to class A is shown by range a-a+b/2, greaterdegree of belongingness to class B is shown by range a+b/2-b. Equal degree of membership to both classes is shown at point a+b/2, that cannot be classifiedinto any class. Neutrosophic logic is applied in the overlapping region where we are not sure about the existence of instance to class A or class B. In neutrosophic logic, every proposition is estimated to have some grade of truth, indeterminacy and falsity (T,I,F)[5]. Thus, to find the solution in overlapping areas, Neutrosophic logic comes to the rescue.

Case 3. It provides the grade of membership and non-membership to class B.So, an output lying in the range of b-c, will support greaterdegree of membership for class B and smaller degree of membership for class A.

VI. Rough Neutrosophic Soft Setbased Classification

Rough Neutrosophic soft set is a description of each instance that belongs to the overlapping area. Each instance of rough Neutrosophic soft sethelps us to examine the probability of existence to a class with grade of truth, indeterminacy, falsity in that range.In the medical domain, there is a lot of ambiguity, indeterminacy and uncertainty as different doctors have different opinions on the same diagnosis. So, Neutrosophic logic would prove effective by considering the existing indeterminacy in medical domain and by providing the grade of indeterminacy for each instance. Hence by classifying the appendicitis data into three classes, the Neutrosophic logic will provide better results.

A. *Determination of Neutrosophic membership values*

Rough Neutrosophic soft set works on the same dimension like fuzzy set, however it differs in the representation of output value. Output value after defuzzification, is described in the triplet format i.e. truthness, indeterminacy, falsity [5]. After obtaining the value in triplet form, it calculates the lower and upper approximations for every class existing in the universe. Neutrosophic logic will be applied in the overlapping regions to check whether the instance exists in class appendicitis or not. The design of Neutrosophic components is described in Fig. 2.

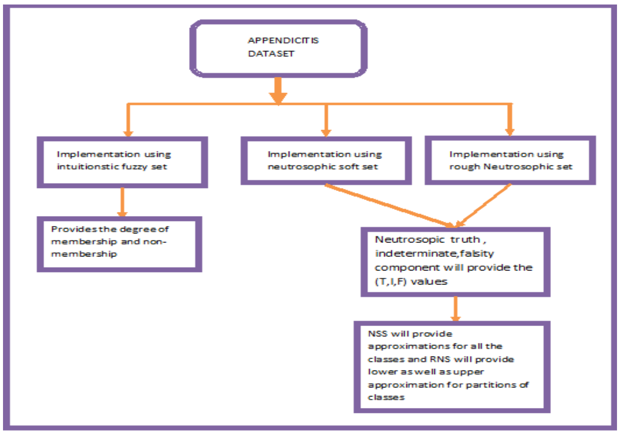

Fig. 2.Block diagram of neutrosophic components

Data using Rough Neutrosophic soft set is classified using the following steps:

1. The training sets and the testing sets are createdfor each class. Out of the 106 instances, 96 instances i.e. 90% of the total are used for training and 10 instances i.e. 10% of the total are used for testing.

2. Three components are used to express Neutrosophic logic: Neutrosphic truth, neutrosophic indeterminacy and neutrosophic falsity component[11]

3. Truth component of Neutrosophic logic is descibed as follows:

a) For all the variables (input and output), membership functions are designedso that there is no overlap between the two defined membership functions.

b) Using rule editor, appropriate rules are produced.

4. Indeterminacy component of Neutrosophic logic is designed as follows:

a) For all the variables (input and output), membership functions are designed in such a way as to overcome the overlapping regions. The other two components i.e. indeterminacy component and falsity components are designed for overlapping regions

b) Using rule editor, appropriate rules are produced.

5. Falsity component of Neutrosophic logic using training set is designed similarto indeterminacy component. In falsity component, the maximum value of every membership function i.e. height is considered as 0.5.

6. After training is done, all the three components i.e. truth, indeterminate and falsity are verified using the 10 testing instances.

7. All these values will help us to determine the NSS i.e. predicate and approximate value-set for all testing instances.

8. After creation of approximation value set, lower and upper approximations are calculated for RNSS.

VII. MATLAB Implementation of Fuzzy and Rough Neutrosophic Soft Set On Datase

There are various techniques available for classification of data[12]. Here, fuzzy and Neutrosophic logic are used for the classification of data. Fuzzy and neutrosophic components are designed for appendicitis dataset as described below:

1) Trapezoidal membership functions are designed for input variable 1 which is ranging between 0 to 100 as shown below in Fig. 3.

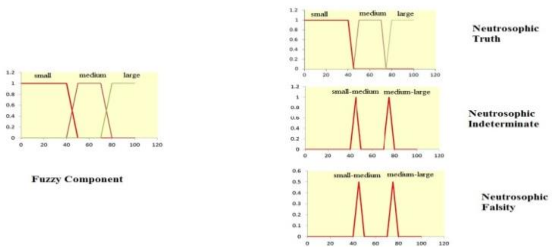

Fig. 3. Trapezoidal Membership function for input 1

2) Input membership function is defined for all other attributes.

3) Output membership function is designed for two classes i.e. 1 and 0 represented by A and B as shown below in Fig. 4.

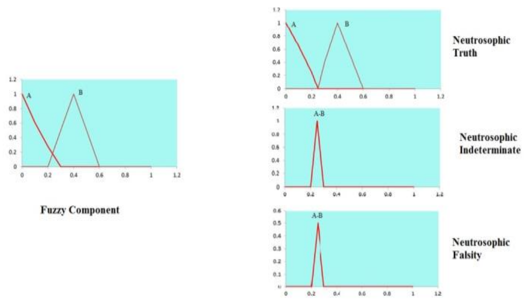

Fig. 4. Triangular Membership function for output class.

4) The fuzzy component contains 35 If-Then Rules. The rule base of neutrosophic truth, neutrosophic indeterminate and neutrosophic falsity component contain 40, 11 and 11 rules.

5) Fuzzy component will provide the degree of membership of belonginess. Its non-membership can be calculated as Non-membership= 1 – membership.

6) Neutrosophic components will provide the (T,I,F) values. Then the Neutrosophic result is calculated for all classes.

7) Lower and upper approximations are calculated with the approximations available.

VIII. EXPERIMENTS AND RESULTS

The Table I shows the details of the testing instances for fuzzy component on appendicitis dataset.

TABLE I. DETAILS OF TESTING INSTANCES USING FUZZY SET

S.no.	Instance/class	Degree of membership	Degree of non-membership	Analysis
1.	[21.3 55.4 20.7 0 0 74.9 22]/A	0.08	0.92	Here, all instances lies in their classes correctly except two instances. Instance 5 and 6 lies in overlapping range. In the overlapping region we cannot surely say about the belongingness of an instance so, fuzzy logic cannot handle indeterminate data.
2.	[5.8 58.9 8.7 58.3 19.6 57.6 6]/A	0.08	0.92	
3.	[14.2 58.9 15.7 70.8 32.5 93.8 18.6]/B	0.41	0.59	
4.	[53.8 73.2 54.9 5.6 5.8 88.2 55.8]/B	0.41	0.59	
5.	[32.9 66.1 33.4 15.3 11.2 67.4 30.4]/B	0.29	0.71	
6.	[75.1 82.1 79.7 29.2 39.2 74.7 70]/B	0.29	0.71	
7.	[57.3 75 59 36.1 39.2 95.6 61.9]/B	0.41	0.59	
8.	[51.6 76.8 54.4 13.9 13.9 66.7 46.2]/B	0.42	0.58	
9.	[47.1 83.9 53.1 11.1 10.4 84.5 48.1]/B	0.42	0.58	
10.	[62.2 75 63.5 26.4 30.6 78.7 60.1]/B	0.42	0.58	

The Table II shows the details of testing instances using Neutrosophic soft set. As we can see here that all instances exist in their classes accurately but 2 instances are having their membership values in overlapping areas. So, neutrosophic logic will be applied on those instances to get better results.

TABLE II. DETAILS OF TESTING INSTANCES USING NEUTROSOPHIC SOFT SET

Instance	(T,I,F) values generated after defuzzification	Neutrosophic result of appendicitis class (class A)	Neutrosophic result of non-appendicitis class (class B)
[21.3 55.4 20.7 0 0 74.9 22]	(0.08,0.5,0.5)	(1,0,0)	(0,1,1)
[5.8 58.9 8.7 58.3 19.6 57.6 6]	(0.08,0.5,0.5)	(1,0,0)	(0,1,1)
[14.2 58.9 15.7 70.8 32.5 93.8 18.6]	(0.41,0.5,0.5)	(0,1,1)	(1,0,0)
[53.8 73.2 54.9 5.6 5.8 88.2 55.8]	(0.20,0.4,0.4)	(0,1,0.1)	(0.1,0,0)
[32.9 66.1 33.4 15.3 11.2 67.4 30.4]	(0.2901,0.25,0.25)	(0.5,0,0.1)	(0.1,1,0.5)
[75.1 82.1 79.7 29.2 39.2 74.7 70]	(0.29,0.25,0.25)	(0.5,0,0.1)	(0.1,1,0.5)
[57.3 75 59 36.1 39.2 95.6 61.9]	(0.4204,0.5,0.5)	(0,1,1)	(1,0,0)
[51.6 76.8 54.4 13.9 13.9 66.7 46.2]	(0.2865,0.5,0.5)	(0,1,0.2)	(0.2,0,0)
[47.1 83.9 53.1 11.1 10.4 84.5 48.1]	(0.2841,0.5,0.5)	(0,1,0.1)	(0.1,0,0)
[62.2 75 63.5 26.4 30.6 78.7 60.1]	(0.2877,0.5,0.5)	(0,1,0.1)	(0.1,0,0)

As it can be seen in Table II, NSS will provide the predicate and approximate value-set for every instance of every parameter. Predicate is class A instances and approximation value-set is <1,0,0>, <1,0,0>. Predicate is class B instances and approximation value-set for third instance is <0,1,1> and so on. Instance 5 and 6 lies in the overlapping region, Neutrosophic result is (0.1,1,0.5). So, it provides maximum value of indeterminacy in class B.

The neutrosophic components will provide the Neutrosophic results for instances of class A and B. The Neutrosophic result of instances of class A can be calculated for class B using the complement. The complement can be calculated as:

$$T\ (x) = F_B(x)$$
$$I\ (x) = 1 \quad I_B(x)$$
$$F_A(x) = T\ (x)$$

The Table III shows the details of testing instances using Rough Neutrosophic soft set. Here, U be a universe of 10 instances and R be an equivalence relation its partition of U is given as

U/R = {{p1,p2}}, p1 and p2 are the classes A and B.

TABLE III. DETAILS OF TESTING INSTANCES USING ROUGH NEUTROSOPHIC SOFT SET

Instance	Neutrosophic result of appendicitis class(p1)	Neutrosophic result of non-appendicitis class(p2)	Lower approximation	Higher approximation
[21.3 55.4 20.7 0 0 74.9 22]	(1,0,0)	(0,1,1)	(0,1,1)	(1,0,0)
[5.8 58.9 8.7 58.3 19.6 57.6 6]	(1,0,0)	(0,1,1)	(0,1,1)	(1,0,0)
[14.2 58.9 15.7 70.8 32.5 93.8 18.6]	(0,1,1)	(1,0,0)	(0,1,1)	(1,0,0)
[53.8 73.2 54.9 5.6 5.8 88.2 55.8]	(0,1,0.1)	(0.1,0,0)	(0,1,0.1)	(0.1,0,0)
[32.9 66.1 33.4 15.3 11.2 67.4 30.4]	(0.5,0,0.1)	(0.1,1,0.5)	(0.1,1,0.5)	(0.5,0,0.1)
[75.1 82.1 79.7 29.2 39.2 74.7 70]	(0.5,0,0.1)	(0.1,1,0.5)	(0.1,1,0.5)	(0.5,0,0.1)
[57.3 75 59 36.1 39.2 95.6 61.9]	(0,1,1)	(1,0,0)	(0,1,1)	(1,0,0)
[51.6 76.8 54.4 13.9 13.9 66.7 46.2]	(0,1,0.2)	(0.2,0,0)	(0,1,0.2)	(0.2,0,0)
[47.1 83.9 53.1 11.1 10.4 84.5 48.1]	(0,1,0.1)	(0.1,0,0)	(0,1,0.1)	(0.1,0,0)
[62.2 75 63.5 26.4 30.6 78.7 60.1]	(0.1,0,0)	(0,1,0.1)	(0,1,0.1)	(0.1,0,0)

Lower and higher approximation provide the minimum and maximum value of truth, indeterminacy and falsity component for every instance. Lower and higher approximations can be calculated using eq. 9,10.

IX. Discussion of results

Classification using RNS i.e. rough neutrosophic sets presents more realistic results as it classifies the dataset into three classes. If it belongs to overlapping regions, we cannot be sure about its existence in either class. It is discussed in section 8 that various instances are having results in overlapping areas which can be handled with neutrosophic logic easily. Rough neutrosophic soft set has prons over fuzzy set which are discussed as:

1. Neutrosophic logic can handle indeterminacy of overlapping areas which is used byRough Neutrosophic soft set.

2. Membership value and non-membership value for every instance is considered by fuzzy logic whereasRough Neutrosophic soft set considers the membership value in truth class, indeterminate class and falsity class.

3. Lower as well as upper approximations are provided by Rough Neutrosophic soft set.

X. Conclusion

The proposed rough Neutrosophic soft set divides the classification domain into overlapping and non-overlapping sections. RNSS will provide better results as it allows us to consider the indeterminacy present in the medical domain. There are many cases in which the doctors may vary in their decisions and cannot surely say whether the person suffers from that disease or not, so indeterminacy exists in medical field. Neutrosophic logic based techniques provide the grade of truth, indeterminacy, falsity for every instance but fuzzy logic based techniques provides the degree of membership and non-membership. Also, the results generated by RNSS provide the minimum and maximum degree of truth, indeterminacy and falsity. Here, authors have confined the application of RNSS to a small dataset.

As the results are encouraging, it can be applied on other complex datasets or which are having more ambiguous results which can be provided solution with Neutrosophic logic. Hybridization of other soft computing techniques with techniques based on neutrosophic logic can be done to analyze the indeterminacy present in the data.

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