Experimenting with neutrosophic ontologies for medical data classification

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***Abstract*— Ontology helps us to think about the real world with its semantic constraints. But there exist different uncertainties and ambiguities that cannot be considered using traditional ontologies. This paper mainly deals with classification using fuzzy ontology and Neutrosophic ontology. Classification based on Neutrosophic ontology employs Neutrosophic logic for its working and is compared with classification based on fuzzy ontology on appendicitis dataset from Knowledge extraction based on evolutionary learning.**

Keywords*— Classification; fuzzy ontology; neutrosophic ontology.

I. Introduction

Classification is defined as a process in which various objects are acknowledged, distinguished and inferenced [1]. There are many techniques which are used for classification of data that give a realistic solution for all feasible inputs [2]. Ontology contains a hierarchical description of classes in a specific domain along with the description of the properties of every concept as shown in Fig. 1. Ontology is a specification of conceptualization[3]. Here, person, state and disease are the various concepts or classes. Priya, Sonam, Tanvi are the individuals or instances of person class. Lives-in and suffers-from represents the relationship of the property.

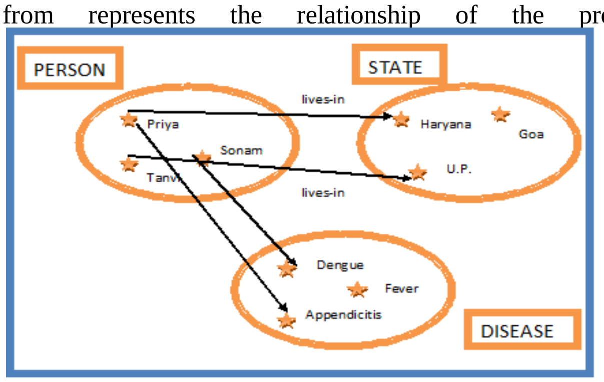

Fig. 1. Basic description of ontology

There are numerous fuzzy approaches which help us to abridge the likelihood of imprecise knowledge demonstration by assigning weights to various links. For example, the patient has appendicitis or not, it is represented using fuzzy ontology. Ontolgy is a better way of representation as it provides the hierarchical description of the membership value belonging to a class. Fuzzy logic is a multi-valued logic in which the truth variable lies in the range of 0-1[4]. Fuzzy ontology is the hierarchical description of every instance with its fuzzy membership value belonging to a class[5] as shown in Fig. 2.

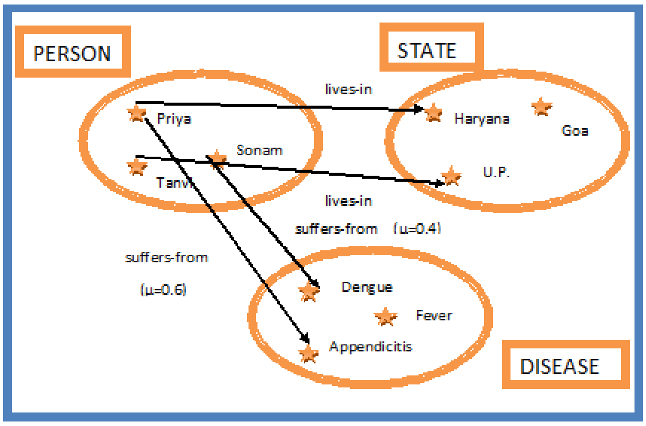

Fig. 2. Basic description of fuzzy ontology

Here, Sonam suffers from dengue with a membership value of 0.6 i.e. Sonam has 60% chances of dengue and 40 % chances of not suffering from dengue. So, fuzzy ontology is the representation of fuzzy membership of an instance belonging to a class. As it is represented in Fig. 1, Sonam suffers from dengue with a membership of 1 i.e. Sonam surely suffers from appendicitis. Classical logic means that the instance surely belong to the class or not but fuzzy logic gives the percentage of membership.

Neutrosophic logic is a logic in which every proposition is estimated to have the degree of truth, indeterminacy and falsity (T,I,F). Fuzzy logic is a subset of Neutrosophic logic as fuzzy logic will provide only fuzzy membership value for any instance. Neutrosophic logic will provide the degree of truth, indeterminacy, falsity for every instance. As it is represented in Fig.2, Sonam suffers from dengue with a membership value of 0.6 i.e. Sonam has 60% chances of dengue and 40 % chances of not suffering from dengue. But in Neutrosophic logic, it is not necessary that there are 40% chances that Sonam does not suffer from dengue. There are some indeterminate factors which are not considered by doctors so, Neutrosophic logic will provide the degree of truth, indeterminacy, falsity that Sonam has in favour of dengue. Authors here propose to experiment with Neutrosophic Logic in building ontological structure, that suitably captures the indeterminacy, which Fuzzy Oontology does not.

Neutrosophic ontology is hierarchical description of instances lying in overlapping sections. Thus, it provides the degree of indeterminacy existing for that instance. In case of appendicitis, if a symptom is not considered by doctors then different doctors will have different views so, indeterminacy exists. Neutrosophic ontology will help us to represent this indeterminacy in a better way. Fuzzy ontology will provide only fuzzy membership value but Neutrosophic ontology will provide degree of truth, indeterminacy, falsity for every instance.

In decision analysis, uncertain information is treated probabilistically in numerical form[6]. Since a lot of uncertainty, indeterminacy and ambiguity exist in medical domain as different doctors disagree on the same diagnosis. So, Neutrosophic logic will consider the indeterminacy existing in medical domain and provide the degree of indeterminacy for every instance.

The remaining of the paper is organized as follows. Section 2 gives the details of dataset used. Section 3 describes the fuzzy ontology for classifying dataset. Section 4 elaborates the Neutrosophic ontology for classifying dataset. Section 5 presents implementation of fuzzy and Neutrosophic ontology on appendicitis dataset. Section 6 presents discussion of results. Section 7 outlines the conclusion and future work.

II. DATASET DETAILS

In this research, appendicitis dataset from knowledge extraction based on evolutionary learning (KEEL)[7] is selected. The appendicitis dataset has different seven attributes of real-value type, two classes and 106 instances. The different seven attributes are multiplied by 100 for simplicity so, all the attributes are in the range of 0-100.

Different attributes to be experimented:-

Attribute 1- WBC1

Attribute 2- MNEP

Attribute 3- MNEA

Attribute 4- MBAP

Attribute 5- MBAA

Attribute 6- HNEP

Attribute 7- HNEA

Classes to be classify:-

0 means the patient is not suffering from appendicitis.

1 means the patient is suffering from appendicitis.

Appendicitis dataset contains 106 instances out of which 96 instances are used for training and 10 instances for testing. 90% of the instances are used for training and 10% of the instances are randomly selected for testing.

III. CLASSIFICATION BASED ON FUZZY ONTOLOGY

Classical ontology languages are not suitable to deal with ambiguity in knowledge [8]. Therefore, Description logic for the ontology can be improved by several approaches to deal with probabilistic or possibilistic uncertainty and vagueness [8]. Fuzzy logic was introduced by L.A.Zadeh in 1965[4], the use of fuzzy logic as the basis for ontology building would be beneficial and solve many problems pertaining to classical ontologies. Fuzzy ontology is different from classical ontology as shown in Table I [9].

TABLE I. DIFFERENCES BETWEEN FUZZY AND CLASSICAL ONTOLOGY

Aspect	Fuzzy ontology	Classical ontology
Multiply-located terms	Does not occur	Issue for disambiguation
Query expansion	Depends on membership value	Depends on location only
Customisation	Simple, based on modification of membership values	Requires new ontology and/or ontology sharing
Intermediate locations for grouping	Unnecessary	Needed for construction-may be useful
Knowledge representation	Related to use	Related to structure
Storage required	Depends on the number of terms in the ontology and membership values of the relations	Depends on the number of terms in the ontology

A fuzzy ontology is a quintuple F=<I,C,T,N,X> [5] where I is the set of instances, C is the set of classes. The set of entities of fuzzy ontology is described by E=C U I. T denotes the taxonomy relations among the set of concepts C. N denotes the set of non-taxonomy fuzzy associative relationships. X is the set of axioms expressed in a proper logical language. Fuzzy ontology representation is shown in Fig 3. Here, I: 106 are the instances of appendicitis, C: appendicitis and non-appendicitis classes.

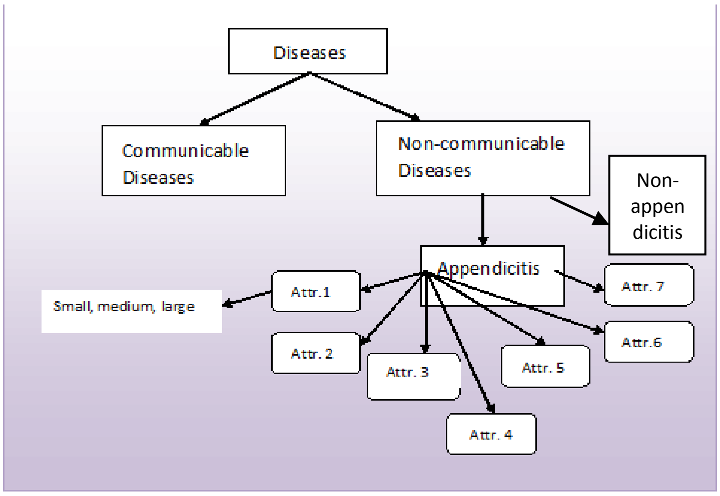

Fig. 3. Fuzzy ontology representation

Considering a taxonomic relation(T):

Appendicitis (instance1, value) = 0.1 i.e. Instance 1 has defuzzified value as 0.1 i.e. instance 1 belongs to appendicitis class. Here, Appendicitis is the name of fuzzy relation, instance 1 is the name of instance and value is the name of property. It is basically a representation of fuzzy membership value of instance 1 belonging to class appendicitis. Defuzzified value is obtained when the fuzzified value taken from the inference module is converted to crisp values using various defuzzification techniques [10]. As it can be seen in Fig. 9, the output membership function of fuzzy component is having a overlapping section of 0.2-0.3. This means that below 0.2, instance belongs to class A, after 0.3 instance belongs to class B, in the range of 0.2-0.3 we are not sure about the belongingness of instance. Fuzzy ontology for appendicitis is shown in Fig. 4.

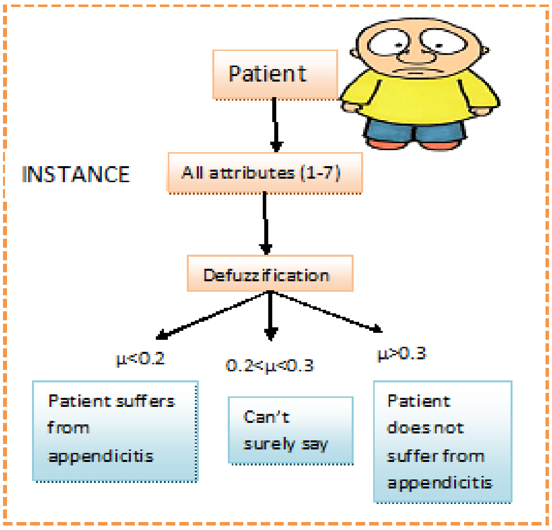

Fig. 4. Fuzzy ontology for appendicitis

A. Basic criteria for determining fuzzy ontology

Classification based on fuzzy ontology is done on the basis of fuzzy logic. The fuzzy membership value of all the attributes will help us to determine whether the patient is suffering from appendicitis or not. As overlapping is expected in fuzzy logic so suitable rules are designed for all the appendicitis dataset attributes and output classes. It can be observed that the outputs produced after defuzzification in inference system can be of three types as shown in Fig. 5.

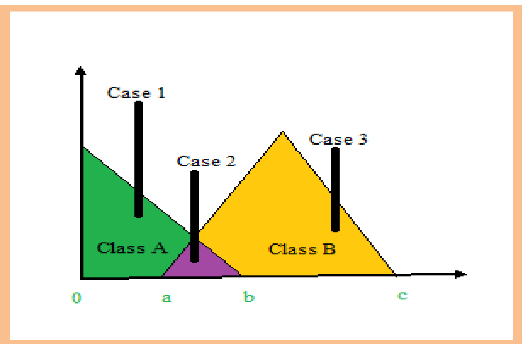

Fig. 5. Criteria for assigning fuzzy values

Case 1. If the output lies in the range of 0-a then it supports higher membership value for class A and lower membership value for class B.

Case 2. If the output value lies in the overlapping range of a-b, then there is some degree of indeterminacy. For range a-a+b/2, it shows higher belongingness to class A, for range a+b/2-b, it shows higher membership to class B. At point a+b/2, it shows equal membership to both classes that we cannot classify it in any class. In this overlapping region, we cannot surely say that the instance belongs to class A or class B so, Neutrosophic logic is applied in this region. Neutrosophic logic was introduced by Florentine Smarandache to represent mathematical model of uncertainty and ambiguity. It is a logic in which every proposition is estimated to have the degree of truth, indeterminacy and falsity (T,I,F)[11,12]. Thus, Neutrosophic logic helps us to deal with the results of overlapping region.

Case 3. If the output lies in the range of b-c, then it supports higher membership value for class B and lower membership value for class A.

IV. Classification Based On Neutrosophic Ontology

In real life, indeterminacy can be seen everywhere. If weather reports say that the probability of rain tomorrow is 70% then it does not mean that the probability of not raining is 30% because there are some hidden weather factors like jet stream, weather fronts etc that the reporters are not aware of. So, there is some ambiguity that leads to indeterminacy. Different doctors have different views on the same diagnosis of patient's disease so, indeterminacy exists there.

Neutrosophic logic is a logic in which every proposal is approximated to have the percentage of truth, indeterminacy and falsity in a subset T, I and F where T, I, F are real subsets of $]^{-}0,1^{+}[$[11,12]

The three sets T, I and F are not intervals, it can be real subsets: distinct or constant; union or joint of various subsets; single-element, finite, or infinite; etc.

Neutrosophic ontology is simplification of the traditional and imprecise ontologies. Neutrosophic ontology is a hierarchical description of every instance belonging to the overlapping region. Every instance will provide the degree of truth, indeterminacy, falsity in that range which will help us to determine the possibility of belongingness to a class. Thus, Neutrosophic ontology will provide better results for classifying the data into appendicitis class, non-appendicitis class and indeterminate class.

Definition 1: Neutrosophic Ontology: A neutrosophic ontology is a sextuple NO = <I,C,T,N,X,indeterminacy> where I is the set of instances, C is the set of classes. T denotes the taxonomy relations among the set of concepts C. N denotes the set of non-taxonomy neutrosophic associative relationships. X is the set of axioms expressed in a proper logical language. Indeterminacy is the degree of indeterminacy existing in the overlapping region.

If the defuzzified value lies in the range of 0.2-0.3 as shown in Fig. 9, so neutrosophic logic will be applied to determine the degree of truth, indeterminacy, falsity for that instance. Neutrosophic ontology for appendicitis is shown in Fig 6.

Considering a taxonomic relation:

Appendicitis (instance1, value) = 0.29 i.e. Instance 1 has defuzzified value as 0.29 i.e. instance 1 value lies in the overlapping region so, Neutrosophic logic will be applied on that instance and hence, the degree of truth, indeterminacy and falsity is (0.29,0.25,0.25). Neutrosophic result is (t, i, f) = (<0.5, 1,0.5); indicating that truth values recorded are smaller than 0.5 , with indeterminacy recorded is as high as 1 and falsity 0.5 .

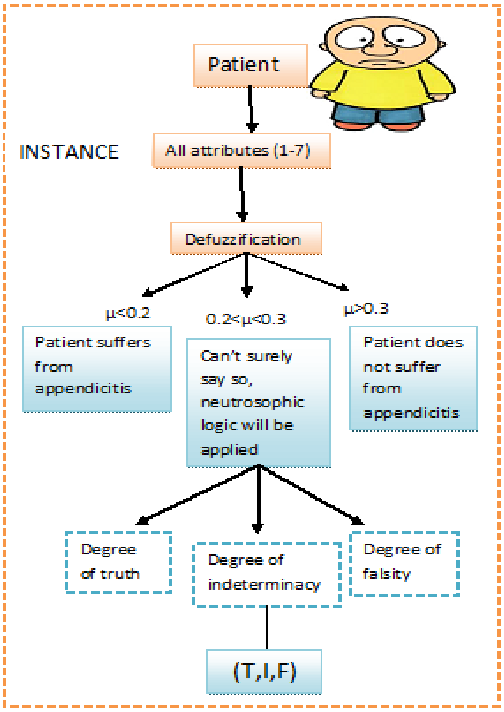

Fig. 6. Neutrosophic ontology for appendicitis

A. *Basic criteria for determining neutrosophic ontology*

Neutrosophic ontology works on the same concept like fuzzy ontology but after defuzzification, output value is represented in the triplet format i.e. truthness, indeterminacy, falsity[10,11]. Neutrosophic logic will be applied for the overlapping regions where we are not sure about the instance belonging to class appendicitis or not. Designing of Neutrosophic components is shown in Fig. 7.

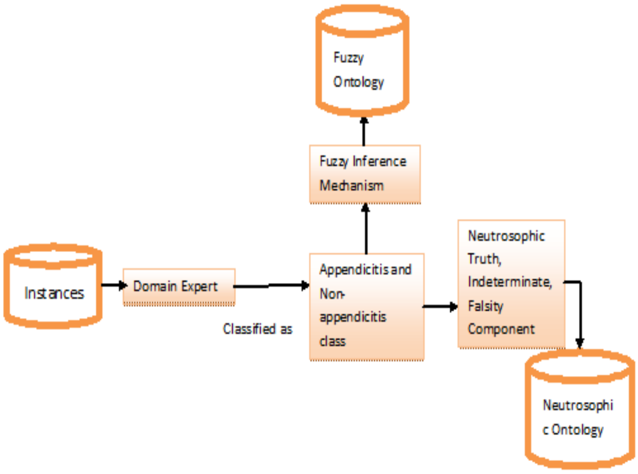

Fig. 7. Block diagram of neutrosophic ontology

The following steps are followed for classifying data using Neutrosophic ontology:

1) First of all, create the training and testing sets for every class. Here, 96 instances are used for training and 10 instances are used for testing.

2) Neutrosophic logic is expressed in terms of three components: Neutrosophic truth, indeterminacy and falsity component [13].

3) Neutrosophic truth component is designed as follows:

a) Memberships functions are designed for all the variables i.e. input and output variables such that no overlapping exists between the two membership functions.

b) Suitable rules are created using rule editor.

4) Neutrosophic indeterminacy component is designed as follows:

a) Memberships functions are designed for all the variables i.e. input and output variables such that no overlapping exists between the two membership functions Indeterminacy and falsity components are designed only for overlapping regions of two membership functions

b) Suitable rules are created using rule editor.

5) Neutrosophic falsity component using training set is designed in the same way as it is done for indeterminacy component but height of every membership function is 0.5.

6) After training is done, all the components are tested independently using the testing data.

V. Implementation of Fuzzy Ontology and Neutrosophic Ontology on Appendicitis Dataset

The designing of Fuzzy and Neutrosophic component for appendicitis dataset is described as:

1) The input variable 1 range from 0 to 100 is composed of trapezoidal membership functions as shown in Fig. 8.

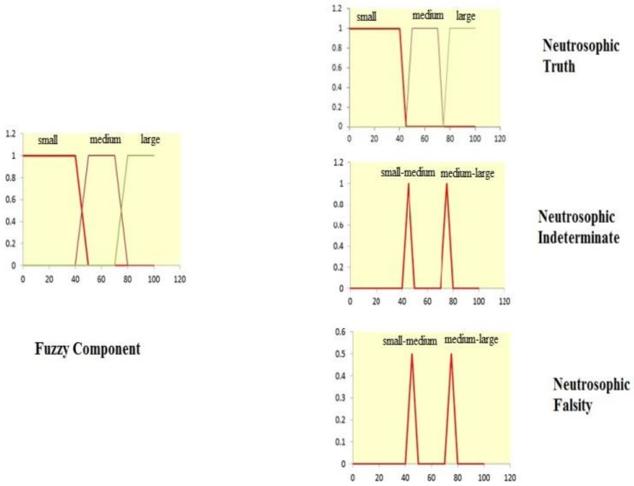

Fig. 8. Membership function for input 1

2) Similarly for all other attributes, input membership is defined.

3) Design output membership for two classes i.e. 1 and 0 represented by A and B as shown in Fig. 9.

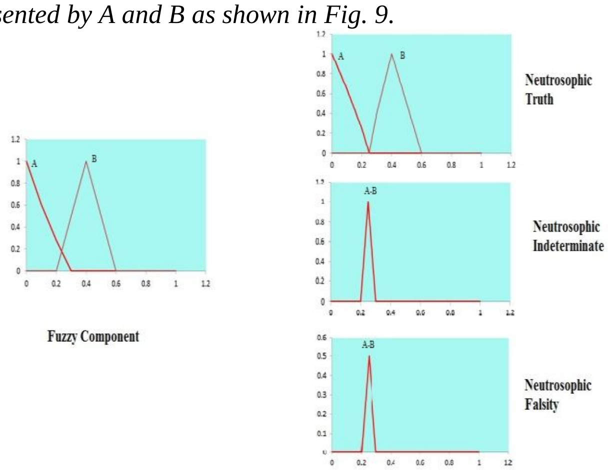

Fig. 9. Membership function for output class.

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

VI. Experiments And Results

The Table II shows the rules formed, training and testing samples for fuzzy and Neutrosophic component.

TABLE II. Details of training and testing data

Component	Training samples used	Testing samples used	Number of rules
Fuzzy	96	10	35
Neutrosophic Truth	96	10	40
Neutrosophic Indeterminate	96	10	11
Neutrosophic falsity	96	10	11

Summary of fuzzy output of all instances is shown in Fig. 10. As it is a fuzzy ontology representation, it will provide fuzzy membership value for every instance. As it can be seen that if μ<0.2 i.e. Both cases indicate clear belongingness to class A. If μ> 0.3 i.e. 6 cases indicate clear belongingness to class B. If 0.2<μ<0.3 i.e. 2 cases generated results lying in overlapping zone of class A and class B. so, neutrosophic ontology will be applied in those 2 cases.

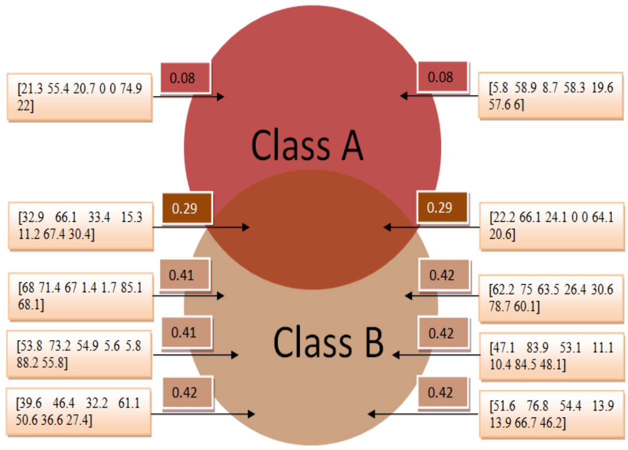

Fig. 10. Summary of results of fuzzy ontology

Summary of Neutrosophic output of all instances is shown in Fig. 11. Both cases of class A indicate that the degree of truth is higher than degree of indeterminacy and falsity. Neutrosophic result is (t, i, f) = (>0, 0,0); indicating that truth values recorded are higher than 0 with indeterminacy and falsity recorded as 0 so, these two instances are correctly classified in class A. Here, 6 cases of class B indicate that degree of truth is higher than degree of indeterminacy and falsity because the neutrosophic result is (t,i,f)=(>0,0,0). 2 instances indicate that the degree of indeterminacy is higher than degree of truth and falsity because the neutrosophic result is (t,i,f)= (<0.5,1,0.5).

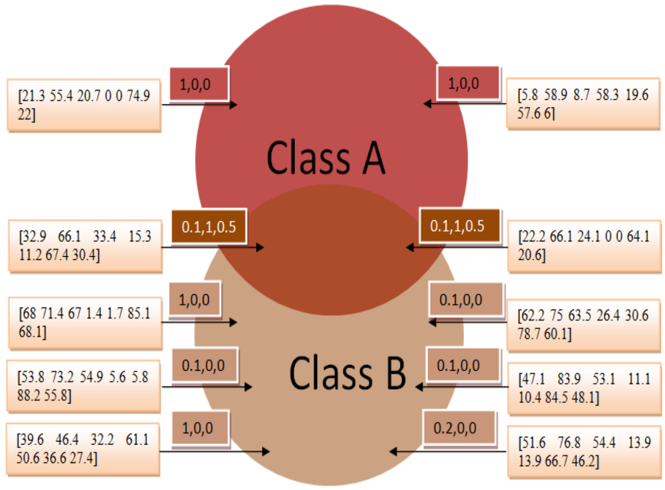

Fig. 11. Summary of results of neutrosphic ontology

If the defuzzified value lies in the overlapping region i.e. 0.2-0.3 then it will give ambiguous results because we are not certain to which class the instance belongs to. Fig. 12 shows the details of ambiguous results found using fuzzy and Neutrosophic ontology. Here, green line shows the degree of truth, dotted red line shows the degree of indeterminacy and blue line shows the degree of falsity. It can be seen that the value of (t,i,f) is (0.1,1,0.5) which indicates that the membership of indeterminacy is highest in those instances. So, we cannot surely say to which class these instances belong to. Thus, instances belonging to overlapping region has highest degree of indeterminacy which can be represented using Neutrosophic ontology.

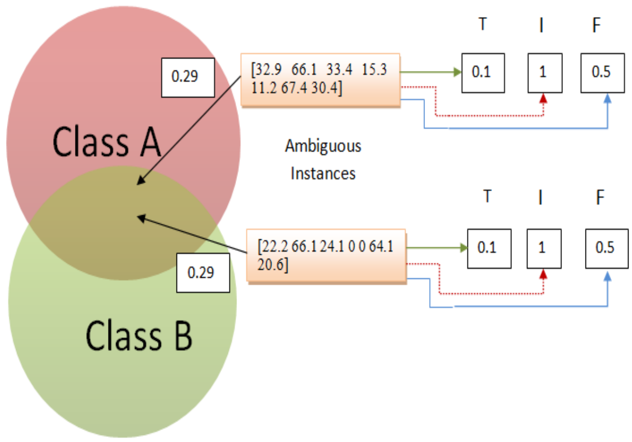

Fig. 12. Ambiguous results

VII. Conclusion And Future Scope

Classification using neutrosophic ontology provides more practical results as compared to fuzzy ontology as it classifies the data into appendicitis, non-appendicitis and uncertainty class. If the membership value lies in the overlapping region then it cannot be classified into appendicitis or non-appendicitis class. As Neutrosophic ontology involves indeterminate sample space that exists in the real world. It provides results in the triplet form i.e. truth, indeterminate and falsity. It provides the degree of truth, indeterminacy, falsity for every instance present in the class. It also provides the relation existing between the classes. It can be seen in section VI that some instances are showing results in overlapping section i.e. indeterminacy which can be handled with Neutrosophic logic. Neutrosophic ontology has several advantages over fuzzy ontology which are described as:

1) Neutrosophic ontology considers the indeterminacy existing in the real world.

2) Neutrosophic ontology considers neutrosophic logic.

3) Neutrosophic ontology provides the degree of truth, indeterminacy, falsity for every instance lying in the overlapping region. Fuzzy ontology only provides the fuzzy membership value for that instance.

4) Neutrosophic ontology also provides a different class of indeterminacy i.e. the instance may or may not belong to appendicitis. Hence, it provides better results than fuzzy ontology.

It is a sample study as it is implemented on 106 instances. In future it can be extended on complex datasets or those datasets which contains more overlapping regions which can be deal with Neutrosophic logic. A real time application can be created using Neutrosophic logic and Neutrosophic ontology that could replace the existing fuzzy based applications. Also there is a need of more experiments in medical domain that justifies that Neutrosophic ontology is a better model than fuzzy ontology in medical domain.

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