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RESEARCH ARTICLE

Neutrosophic Logic - A Better Approach to Execute Imprecise Queries Through the Neutrosophic Database Model

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Abstract

Objectives: The neutrosophic set has a more powerful ability to process imprecise information compared to the vague set. The objective of the authors is to process the uncertain query using vague as well as neutrosophic logic and compare the result. **Methods:** Authors have designed a new architecture to process uncertain queries using vague as well as neutrosophic sets. In the architecture at first, the imprecise query has been taken as input. From the inputted imprecise query uncertain data and fuzzy attributes are identified. Next, using the truth membership algorithm the truth membership value between uncertain data and the fuzzy attribute value for each tuple is calculated. This truth membership value is used to obtain the false and indeterminacy membership value to represent the domain of fuzzy attribute in vague or neutrosophic form. Then, the tolerance membership value of each tuple corresponding to the imprecise query is determined by using the similarity measures formula for vague as well as neutrosophic set. **Findings:** Using the truth membership algorithm and similarity measures formula, the tolerance membership value for each tuple of the relation corresponding to an imprecise query is obtained. If an imprecise query consists of more than one fuzzy attribute then the fuzzy intersection is used to obtain the membership value of the tuple. After obtaining the tolerance membership value of each tuples, the decision maker will provide a threshold (α-cut) value based on which an SQL is generated which fetched a set of tuples whose membership value meets the threshold (α-cut) value for vague as well as neutrosophic set. Authors have considered a patient database to process uncertain queries using a neutrosophic set and claimed neutrosophic set gives better results compared to vague. Novelty: The novelty of this work is to train the computer using a soft set to obtain desired outcomes while processing imprecise query in the database.

Keywords: Fuzzy data; Vague set; Neutrosophic Set; Similarity Measures; α -Equal neutrosophic data

1 Introduction

Nowadays, people use fuzzy data for their day-to-day activities. Suppose a person wants to know the current salary of his friend. Generally the reply comes from his friend, "around Rs. 50000" or "more or less Rs. 50000". Here the terms "**around**" and "**more or less**" are fuzzy data. Similarly, if the selector wants to select the batsman with an excellent batting average, then the term "excellent" is fuzzy data. Human beings from their intelligence can easily identify the output range of such fuzzy data, but the traditional relational data model cannot process any query containing such fuzzy data. The aim of present research work is to make the computer system intelligent using neutrosophic set theory in order to process such fuzzy data to obtain accurate output from the database.

Initially, **fuzzy set theory** introduced by Zadeh [1] in 1965 has been used to process queries containing fuzzy data in different literature. The idea of fuzzy set theory is to assign a single truth membership value i.e., the grade of membership in the sub interval [0,1] to any element of the set.

Next, the Vague set theory introduced by Gau and Buehrer [2] in 1993, a powerful tool compare to fuzzy set theory has been used by several authors to process queries containing such ambiguous data. A vague set is characterized by two membership functions such as a truth-membership function and a false-membership function to provide membership value in the subinterval [0,1] for "evidence for" and "evidence against" of an element in the set respectively. In vague set certain portion remain undetermined.

In 2001, Smarandache [3] introduced one of the most efficient concepts of neutrosophic set theory to process uncertain information in a database. This new concept of neutrosophic set is characterized by a truth-membership value, a false-membership value and also provides a grade of membership about the undetermined portion of the vague set in the sub interval [0,1].

Efficiency of vague sets over fuzzy while processing uncertain information from the database is reported in the literature [4]. In the present work, authors have claimed while processing uncertain queries using neutrosophic set theory provide more accurate result compare to vague set theory. The efficiency of neutrosophic set over vague set as well as fuzzy set in processing uncertain data can also be cleared by the example as stated below.

In the cancer diagnosis process of a medical system, the medical experts represent the report about the cancer germ of a patient in fuzzy form as having cancer germ of the patient is **0.05** as in a **fuzzy set** only truth membership i.e., "evidence for" is represented. From this representation of a fuzzy set, the patient party can retrieve single valued information i.e., "the chances of having cancer germ of the patient" is very less i.e., **0.05**. This also be concluded by the patient party that "not having cancer germ of the patient" is high i.e., (1-0.05) = **0.95**. So, the patient party may get relaxed about the patient and not go for further treatment. Whereas in **a vague set** both the evidence for and evidence against an event are represented. So, in the same diagnosis process, the medical experts need to represent the report about the cancer germ of the patient in vague form as evidence for having cancer germ is **0.05** and evidence against having cancer germ is **0.4**. From this representation, it is clear to the patient party that "the chance of having cancer germ to the patient" is **0.05** and "not having cancer germ to the patient" is **0.4**. But still there is some portion which is undetermined. Here the undetermined portion is 1- (0.05+0.4) = **0.55** which may occur on either side of evidence for or evidence against. In this situation, patient party may be serious about the patient though the report shows "not having caner germ" is more than "having cancer germ".

Along with a truth membership and false membership, the neutrosophic set is used to define a value in the interval [0,1] of the undetermined portion of vague set for every element. In such situation medical expert team represent the report about the cancer germ of the patient in neutrosophic form as evidence for having cancer germ is **0.05**, evidence against having cancer germ is **0.4** and the deterministic value for cancer of undetermined portion is **0.5**. From this report it has been concluded that "chances of having cancer" is **0.55** (=0.05+0.5) which is high. Therefore, the patient party certainly takes care of the patient.

A very few research works in designing relational data model using neutrosophic set is reported in the literature [5–8].

This study is motivated by the desire to investigate and highlight the possible benefits of using Neutrosophic Logic as a more efficient method compared to vague, to handle imprecise queries within the framework of a Neutrosophic Relational Database Model. Inaccurate findings and incomplete information retrieval originate from traditional database systems' inability to handle uncertainty and ambiguity in real-world data. In order to overcome these drawbacks and offer a strong framework that can handle erroneous data, ambiguous information, and conflicting qualities, Neutrosophic Logic is integrated into the relational database architecture. This study aims to develop database technology by improving query processing effectiveness and enabling applications in a variety of fields, including decision support systems, medical diagnostics, and natural language processing, where uncertainty is a common occurrence. This work ultimately intends to open the way for more precise, dependable, and flexible information retrieval systems in complex and unpredictable contexts by illuminating the advantages of Neutrosophic Logic in a database context. The database model's use of neutrosophic logic shows promise in tackling the problems brought on by ambiguous and uncertain information. Neutrosophic Logic is the α -cut similarity measure approach [9,10] where the closeness of two attributes or tuples of a neutrosophic relational instance is measured by a similarity measure function. Next, compared the closeness of tuples of a neutrosophic relation instance with the α -cut tolerance limit given by a decision maker where the tolerance limit $\alpha \in [0,1]$.

Currently, the use of a neutrosophic environment is still new and not fully explored. Until now little importance has been placed on the development of a neutrosophic database. It is important to develop a new mechanism to process uncertain query using neutrosophic set. Therefore, to fill this gap, the concept of the vague set has been extended to the neutrosophic set where along with truth and false membership value, the membership value of the undetermined portion of the vague set is also considered. The neutrosophic set is a useful tool to deal with uncertainty and incomplete information. This study proposes a new framework for the neutrosophic database. In addition, a PATIENT relation has been considered to demonstrate the proposed approach. Finally, a comparative analysis to check the accuracy of the proposed method with the existing method is presented. It demonstrates that the neutrosophic approach produces better results than other existing approaches.

2 Preliminaries

Here, we have discussed preliminary concepts of fuzzy, vague, and neutrosophic sets along with similarity measures of the corresponding imprecise data sets.

2.1. Fuzzy Set

Fuzzy set theory, introduced by Zadeh [2] in 1965, has been widely used in different application areas where we have to deal with imprecise or ambiguous data. A fuzzy set is defined as a generalization of a crisp set. In this section, we will explain some basic definitions of fuzzy set theory. Let U be a classical set of elements, called the universe of discourse and an element of $U$is denoted by$u$.

Definition 1 *Fuzzy Set*

A **fuzzy set** F In a universe of discourse U is characterized by a membership function $\mu_F : U \to [0,1]$ and is defined as a set of ordered pair $F = ((u, \mu_F(u)) : u \in U\}$, where $\mu_F(u)$ for each $u \in U$ denotes the grade of membership of u in the fuzzy set F.

2.2. Vague Set

In fuzzy set theory, each element is associated with a point-value selected from the unit interval [0,1], which is termed as the grade of membership in the set. A vague set, introduced by Gau and Buehrer [3] in 1993 is a further generalization of a fuzzy set. Instead of using point-based membership values as in fuzzy sets, an interval-based membership value is used in a vague set. The interval-based membership value used in vague sets is more expressive in capturing the vagueness of data. In this section, we review some basic definitions on the theory of vague sets. Let U be the universe of discourse where an element of U is denoted by u.

Definition 2 *Vague Set*

A **vague set**V in the universe of discourse U is characterized by two membership functions given by:

(i) a truth membership function $t_V : U \to [0,1]$ and

(ii) a false membership function $f_V : U \to [0,1]$,

where $t_V(u)$ is a lower bound of the grade of membership of u derived from the ‘evidence for u’, and $f_V(u)$ is a lower bound on the negation of u derived from the ‘evidence against u’, and $t_V(u) + f_V(u) \leq 1$.

The grade of membership $\mu_V(u)$ of u in the vague set V is bounded by a subinterval $[t_V(u), 1 - f_V(u)]$ of [0,1] i.e., $t_V(u) \leq \mu_V(u) \leq 1 - f_V(u)$. Then, the **vague set** V is written as $V = \{\langle u, [t\_V\ (u), 1 - f\_V\ (u)]\rangle : u \in U\}$.

Definition 3 *Similarity Measure between two vague values.*

Let and be any two vague values such that $x = [t_x, 1 - f_x]$ and $y = [t_y, 1 - f_y]$, where $0 \leq t_x \leq 1 - f_x \leq 1$and $0 \leq t_y \leq 1 - f_y \leq 1$. Let $SM(x,y)$ denote the similarity measure between x and y Then,

$$SM(x,y) = \sqrt{\left(1 - \frac{((t_x - t_y) - (f_x - f_y)|}{2}\right)\left(1 - ((t_x - t_y) + (f_x - f_y)|\right)}$$

2.3. Neutrosophic Set

Neutrosophic set as introduced by Smarandache, is a mechanism which gives conclusion about undetermined portion of vague set and obviously provides better outcome compare to vague set. In this work, authors used neutrosophic set for processing uncertain query in relational database and compare the results with vague set through a real-life example.

Definition 4 *Neutrosophic Set*

Let U_1 be the universe. A neutrosophic set Z in U_1 is characterized by a truth membership function t_z, an indeterminacy membership function $i_z$and a false membership function f_z where t_z, i_z and f_z are real standard elements of [0,1]. Neutrosophic set Z can be written as $Z = \{\langle m, [t\_z\ (m), i\_z\ (m), f\_z\ (m)] \rangle, m \in U\_1\ \}$ satisfying conditions $t_z(m) + f_z(m) \leq 1$and $t_z(m) + f_z(m) + i_z(m) \leq 2$. Let two neutrosophic values of p and q represented as $p = [t_p, i_p, f_p]$ and $q = [t_q, i_q, f_q]$ where $0 \leq t_p \leq 1, 0 \leq i_p \leq 1, 0 \leq f_p \leq 1$ and $0 \leq t_q \leq 1, 0 \leq i_q \leq 1, 0 \leq f_q \leq 1$ with $0 \leq t_p + f_p \leq 1$, $0 \leq t_q + f_q \leq 1, 0 \leq t_p + i_p + f_p \leq 2, 0 \leq t_q + i_q + f_q \leq 2$.

Definition 5 *Similarity Measure of two neutrosophic data*

Let, x and y are the two neutrosophic data represented as $x = [t_x, i_x, f_x]$ and $y = [t_y, i_y, f_y]$ then the similarity measures of these two neutrosophic data is defined as

$$SM(x, y) = \sqrt{\left(1 - \frac{|(t_x - t_y) - (i_x - i_y) - (f_x - f_y)|}{3}\right)\left(1 - |(t_x - t_y) + (i_x - i_y) + (f_x - f_y)|\right)}$$

2.4 α -equal of two neutrosophic data

Let, x and y are the two neutrosophic data represented as $x = [t_x, i_x, f_x]$ and $y = [t_y, i_y, f_y]$ then these two neutrosophic data are said to be α -equal if $SM(x, y) \geq \alpha$.

3 Methodology

Objective of this section is to explain the concept of neutrosophic database model and also the process of executing uncertain queries based on neutrosophic data.

3.1. Uncertain Query Processing using Vague as well as Neutrosophic set

Uncertain query means the query based on imprecise data. Such queries may be processed using fuzzy, vague or neutrosophic logic. To process uncertain query in vague as well as neutrosophic set, the authors have considered the following PATIENT relation given in Table 1.

Table 1. PATIENT Relation

PName (PK)	PWeight (kg)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)
Sania	28	100	80	85
Bell	51	99	98	83
Jackson	37	98	112	90
Bishop	41	101.5	100	95
Ritesh	38	99.5	102	98
Frank	40	101	99	80
Virat	44	102	97	88
Rose	39	98.4	90	92
David	47	99.7	103	87
Smriti	53	98.5	101	86

Motive of the authors is to process any uncertain query using vague as well as neutrosophic set and established that the output obtained through neutrosophic set is more accurate compare to vague. In Figure 1, authors have depicted architectural mechanism to process uncertain query in neutrosophic data model using neutrosophic and vague set.

Input: PATIENT relation, imprecise query, α-tolerance value given decision maker.

Neutrosophic Interface: It consists of two components SM_Interpreter and neutrosophic SQL. The component SM_Interpreter is used for calculating similarity measure between two imprecise data either using vague set or neutrosophic set and the component neutrosophic SQL is used to generate an SQL statement corresponding to imprecise query. This SQL in the data to retrieve resultant tuples.

SM_Interpreter: In this phase, the tolerance value of each tuple of the relation with respect to uncertain query is determined. At first, vague attribute for vague set and neutrosophic attributes for neutrosophic set are identified based on imprecise data given in the uncertain query. Next, the algorithm presented below in section 3.2 is used to determine the truth membership value

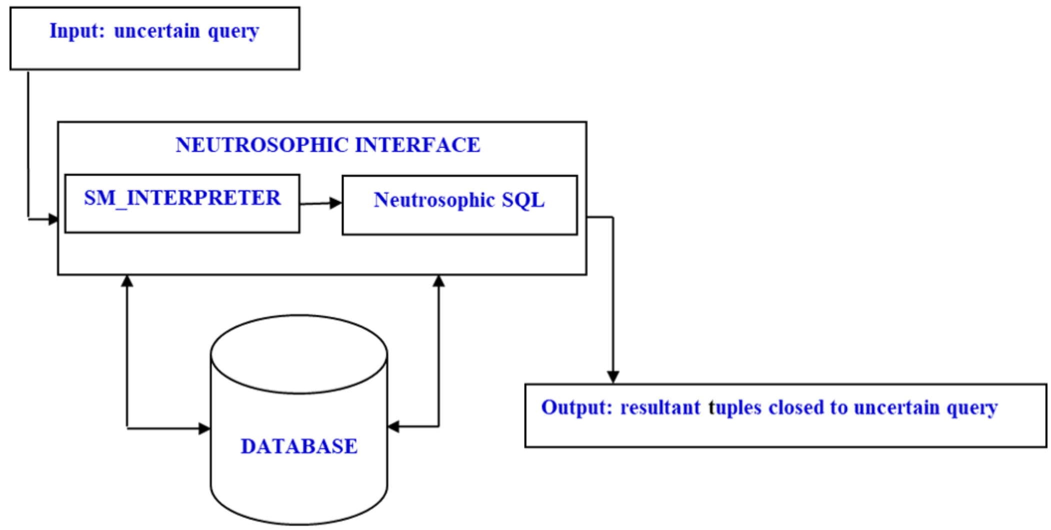

Fig 1. Architecture of Imprecise Query Processing

for each domain value of the vague or neutrosophic attribute with respect to imprecise data present in the uncertain query. Then the false membership value for the vague as well as neutrosophic set is provided by the decision maker satisfying the condition (truth membership + false membership) $\leq$ 1. And the indeterminacy membership for the neutrosophic set is determined satisfying the condition (truth membership + indeterminacy + false membership) $\leq$ 2. Truth and false membership values are used for vague representation. Truth, indeterminacy and false membership values are used for neutrosophic representation. Finally, similarity measure formula for vague as well as neutrosophic set as defined in the Definition 3 and Definition 5 in section **2** are used respectively to obtain the similarity measure of the corresponding domain value with respect to imprecise data given in the query for vague as well as neutrosophic set. The similarity measure such obtained provides the tolerance value of the corresponding tuple the relation. If the uncertain query consists of more than one vague or neutrosophic attribute than the intersection of all the similarity measures obtained for different vague or neutrosophic attributes for a tuple gives the tolerance value of the tuple.

Neutrosophic SQL: Here, decision maker is responsible to provide a threshold or α-cut value based on which an SQL is generated to select the tuples whose tolerance values are greater than or equal to α-cut value. Neutrosophic α-cut conversion is shown in Figure 2.

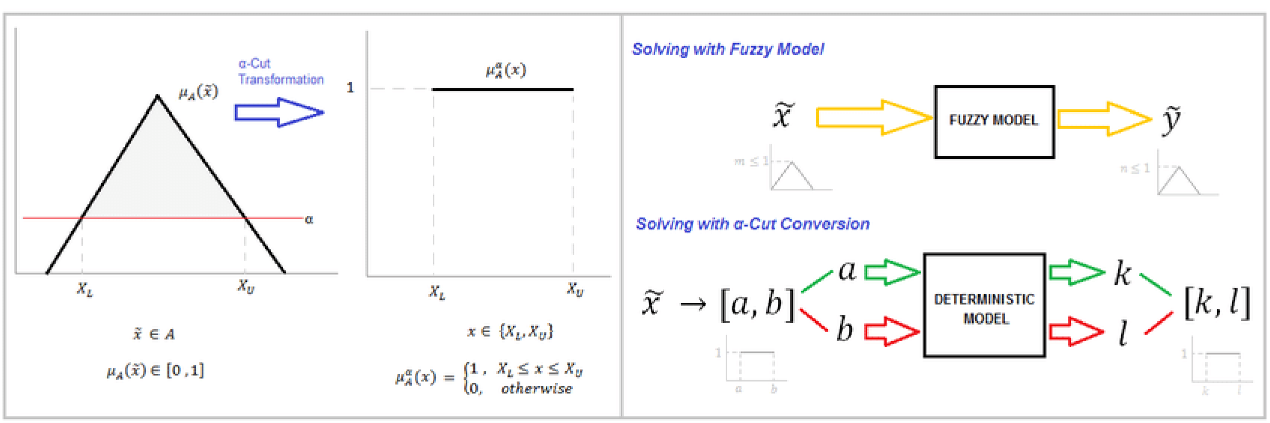

Fig 2. Neutrosophic SQL for the decision makers with α-cut value

Output: Finally, above neutrosophic SQL is submitted to the database as shown in Figure 3 to get the desired tuples as output corresponding to the inputted uncertain query.

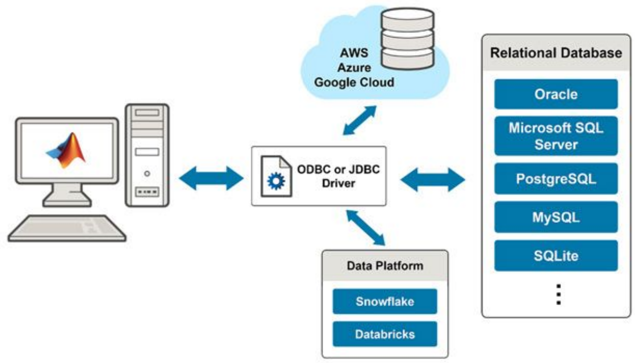

Fig 3. Relational Database Structure for processing queries

3.2. Truth Membership Algorithm

This algorithm will work on domain value of attributes with respect to imprecise data given in the uncertain query.

Input: vague or neutrosophic data for the vague or neutrosophic attributes of imprecise query.
Output: Return truth membership value in the interval [0,1] for each tuple of the relation.
Method: find vague or neutrosophic attributes from the uncertain query.
for each **vauge** or **neutrosophic** attribute **do begin**
$f_{data} \leftarrow$ imprecise data on vague or neutrosophic attribute of the given uncertain query
$RANGE_{value} = MAX_{Dvalue} - MIN_{Dvalue}$
$VALUE_{avg} \leftarrow$ mean of the domain of vague or neutrosophic attribute
$A \leftarrow VALUE_{avg}$
While $(VALUE_{avg} \leq RANGE_{value})$ **do**
$VALUE_{avg} = VALUE_{avg} + A$
end while loop
for each tuple of the table **do**
begin
$TUPLE_{value} \leftarrow$ corresponding tuple value of vague or neutrosophic attribute
$TRUTH_{value} = 1- (|f_{data} - TUPLE_{value}| / VALUE_{avg})$
end for loop of **tuple**
end for loop of **attribute**

3.3. Complexity Analysis of Truth Membership Algorithm

While processing any uncertain query from a relation r having m attributes and n tuples, the proposed algorithm 3.2 finds the membership values for each tuple of the relation w. r. t fuzzy attributes present in the uncertain query. In the worst case any uncertain query may contain all the attributes as fuzzy. Here the authors compute the worst case time complexity of the algorithm 3.2.

In the worst case any uncertain query contains all m attributes as fuzzy. In such a situation the outer loop will run m times. Again for each iteration of the outer loop there are some statesman which run in constant time i.e., $O(1)$ and it also contains an inner loop which runs for n tuples with complexity $O(n)$. So, each iteration, outer loop takes $O(n)$ +$O(1)$ i.e., $O(n)$. Hence, for m iterations time complexity of the proposed algorithm is $O(mn)$.

4 Result and Discussion

To process uncertain query using either vague or neutrosophic set authors have considered the above PATIENT relation given in Table 1. Authors have considered the following imprecise query (IQ-1) to process using either vague and neutrosophic logic with the help of truth membership algorithm explained in section 3.2 and similarity measures formula explained in Definition 3 and Definition 5. Finally, the output obtained using vague and neutrosophic set are compared to establish neutrosophic set provides better outcome compared to vague set.

4.1. In this section authors have considered the case where the uncertain query contains one fuzzy attribute:

IMPRECISE QUERY-1 (IQ-1): "Find the details of the Patients whose weight (**PWeight**) is **around 40**".

In the above query the attribute **PWeight** consist the uncertain data weight **around 40**. Truth membership values of each tuple of the PATIENT relation with respect to uncertain data given in the imprecise query (**IQ-1**) for both vague and neutrosophic logic are calculated using algorithm defined in **section 3.2**.

Method: dom (PWeight) = {28, 51, 37, 41, 38, 40, 43, 39, 47, 53}

f_{data} = 40

$RANGE_{value}$ = 53 - 28 = 25

$VALUE_{avg}$ = 41.7

A = 41.7

$VALUE_{avg} \geq RANGE_{value}$, then $VALUE_{avg}$ is same i.e., $VALUE_{avg}$ = 41.7

for 1st tuple : truth membership value = $1 - (|40 - 28|/41.7) = 0.71$

for 2nd tuple : truth membership value = $1 - (|40 - 51|/41.7) = 0.73$

for 3rd tuple : truth membership value = $1 - (|40 - 35|/41.7) = 0.88$

for 4th tuple : truth membership value = $1 - (|40 - 41|/41.7) = 0.98$

for 5th tuple : truth membership value = $1 - (|40 - 38|/41.7) = 0.95$

for 6th tuple : truth membership value = $1 - (|40 - 40|/41.7) = 1$

for 7th tuple : truth membership value = $1 - (|40 - 44|/41.7) = 0.90$

for 8th tuple : truth membership value = $1 - (|40 - 39|/41.7) = 0.98$

for 9th tuple : truth membership value = $1 - (|40 - 47|/41.7) = 0.83$

for 10th tuple : truth membership value = $1 - (|40 - 53|/41.7) = 0.69$

Next to find closeness of each tuple of the PATIENT relation with respect to imprecise query **IQ-1** for vague as well as neutrosophic set is depicted below:

4.1.1. Vague set based solution:

With respect to uncertain query (**IQ-1**) vague attribute is **PWeight** and vague data is **weight around 40**. Vague representation of all domain values of vague attribute **PWeight** and vague data 40 using **Definition 2** is shown in Table 2. Using similarity measures formula for vague data as defined in **Definition 3**, the tolerance value of all tuples of PATIENT relation are also shown in the following Table 2. Calculation of tolerance value of each tuple PATIENT relation using similarity measure formula defined in **Definition 3** for vague set are as follows:

Similarity measure of neutrosophic data p = <40, [1, 1]> and q = <28, [.71, .76]>

where t_p=1, f_p = 1-1= 0 and t_q = .71, f_q = 1-.76 = .24

$$SM(p,q) = \sqrt{\left(1 - \frac{|(1-.71)-(0-.24)|}{2}\right)(1 - |(1-.71)+(0-.24)|)} = \sqrt{.698} = 0.83$$

Similarly, for vague data p = <40, [1, 1] and q = <51, [.73, .75]>

where t_p=1, f_p = 0, t_q = .73, f_q=1-.75= .25

$$SM(p,q) = \sqrt{\left(1 - \frac{|(1-.73)-(0-.25)|}{2}\right)(1 - |(1-.73)+(0-.25)|)} = \sqrt{0.725} = 0.85$$

and so on.

Table 2. Vague representation of of Patients whose weight (PWeight) is around 40

PName (PK)	PWeight (kg)	Vague representation of domain (PWeight) w.r.t IQ-1	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)	Tuple tolerance value
Sania	28	<28, [.71, .76]>	100	80	85	**0.83**
Bell	51	<51, [.73, .75]>	99	98	83	**0.85**
Jackson	37	<35, [.93, .94]>	98	112	90	**0.96**
Bishop	41	<41, [.98, .99]>	101.5	100	95	**0.98**
Ritesh	38	<38, [.95, .96]>	99.5	102	98	**0.97**

Continued on next page

Table 2 continued

Frank	40	<40, [1,1]>	101	99	80	**1**
Virat	44	<44, [.90, .93]>	102	97	88	**0.93**
Rose	39	<39, [.98, .99]>	98.4	90	92	**0.99**
David	47	<47, [.83, .85]>	99.7	103	87	**0.90**
Smriti	53	<53, [.69, .75]>	98.5	101	86	**0.82**

4.1.2. Neutrosophic set based solution:

PWeight is the neutrosophic attribute and neutrosophic data is **weight around 40** when the imprecise query (**IQ-1**) has processed using neutrosophic set. Neutrosophic representation of the domain of **PWeight** for the uncertain query **IQ-1** using truth membership algorithm given in **section3.2** and **Definition 4** is shown in Table 3. Similarity measures of neutrosophic data as defined in **Definition 5** is used to get the tolerance value of each tuple of PATIENT relation for imprecise query (**IQ-1**) in neutrosophic set are also shown in Table 3. Tuple tolerance value calculation using similarity measure formula in **Definition 5** for each tuple of PATIENT relation using **neutrosophic logic** is as follows:

Similarity measure of neutrosophic data p = <40, [1, 0, 0] [1]> and q = <28, [.71, .8, .24]> are calculated by using Definition 5. Here t_p =1, i_p = 0, f_p = 0, t_q = .71, i_p = .8, f_q = .24

$$SM(p,q)=\sqrt{\left(1-\frac{|(1-.71)-(0-.8)-(0-.24)|}{3}\right)(1-|(1-.71)+(0-.8)+(0-.24)|)}$$

$$=\sqrt{.556\times .25}=\sqrt{.139}=0.37$$

Similarly for neutrosophic data p = <40, [1, 0, 0][1]> and q = <51, [.73, .72, .25]> where t_p =1, i_p = 0, f_p = 0, t_q = .73, i_p = .72, f_q = .25 is

$$SM(p,q)=\sqrt{\left(1-\frac{|(1-.73)-(0-.7)-(0-.25)|}{3}\right)(1-|(1-.73)+(0-.7)+(0-.25)|)}$$

$$=\sqrt{.593\times 0.32}=\sqrt{0.1897}=0.43$$

and so on.

Table 3. Neutrosophic representation of Patients whose weight (PWeight) is around 40

PName (PK)	PWeight (kg)	Neutrosophic representation of domain (PWeight) w.r.t IQ-1	Fever (centi-grade)	FSugar (mg/dl)	Pulse (bpm)	Tuple tolerance value
Sania	28	<28, [.71, .8, .24]>	100	80	85	**0.37**
Bell	51	<51, [.73, .7, .25]>	99	98	83	**0.43**
Jackson	37	<35, [.93, .35, .06]>	98	112	90	**0.74**
Bishop	41	<41, [.98, .02, .01]>	101.5	100	95	**0.98**
Ritesh	38	<38, [.95, .15, .04]>	99.5	102	98	**.88**
Frank	40	<40, [1, 0, 0]>	101	99	80	**1**
Virat	44	<44, [.90, .3, .07]>	102	97	88	**0.78**
Rose	39	<39, [.98, .015, .01]>	98.4	90	92	**0.99**
David	47	<47, [.83, .5, .15]>	99.7	103	87	**0.61**
Smriti	53	<53, [.69, .75, .25]>	98.5	101	86	**0.41**

Finally, authors have generated following SQL to process uncertain query **IQ-1**: "Find the detail report of the Patients whose weight (**PWeight**) is around 40".

SELECT * FROM **PATIENT** WHERE **Tuple tolerance value** $\geq \alpha$

Where α is the α-**cut** or threshold value provided by the decision maker. Accuracy of the above SQL is more appropriate if α-**cut** is closed to **1**. Now for α-**cut** value **0.95**, above SQL has processed for vague and neutrosophic representation of PATIENT table as defined in Table 2 and Table 3 respectively. Hence the SQL statement **SELECT** * FROM **PATIENT** WHERE **Tuple tolerance value** $\geq$ **0.95** has fetched the following resultant **Table-4** from vague representation Table 2 for uncertain query **IQ-1**.

Table 4. Vague accuracy after processing IQ-1

PName (PK)	PWeight (kg)	Vague representation of domain (PWeight) w.r.t IQ-1	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)	Tuple tolerance value
Jackson	37	<35, [.93, .94]>	98	112	90	**0.96**
Bishop	41	<41, [.98, .99]>	101.5	100	95	**0.98**
Ritesh	38	<38, [.95, .96]>	99.5	102	98	**0.97**
Frank	40	<40, [1,1]>	101	99	80	**1**
Rose	39	<39, [.98, .99]>	98.4	90	92	**0.99**

And, the SQL statement **SELECT** * FROM **PATIENT** WHERE **Tuple tolerance value** $\geq$ **0.95** when processed in neutrosophic representation table**Table 3** has fetched the following resultant Table 5 for the uncertain query **IQ-1**.

Table 5. Neutrosophic accuracy after processing IQ-1

PName (PK)	PWeight (kg)	Neutrosophic representation of domain (PWeight) w.r.t IQ-1	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)	Tuple tolerance value
Bishop	41	<41, [.98, .02, .01]>	101.5	100	95	**0.98**
Frank	40	<40, [1, 0, 0]>	101	99	80	**1**
Rose	39	<39, [.98, .015, .01]>	98.4	90	92	**0.99**

Hence, from the output of Table 4 and Table 5 it is clear that the neutrosophic set gives better accuracy compare to vague set while processing uncertain query.

4.2. In this section authors have considered the case where the uncertain query contains two fuzzy attribute:

IMPRECISE QUERY-2 (IQ-2): "Find the details of the Patients whose weight (**PWeight**) is **around 40** and sugar level (**FSugar**) is **more or less 100**".

The above query (**IQ-2**) contains two fuzzy attributes **PWeight** and **FSugar** with uncertain data **around 40** and **more or less 100** respectively. Truth membership values of each tuple of the PATIENT relation with respect to the imprecise query (**IQ-2**) is the **intersection** of the truth membership value for uncertain data **around 40** of fuzzy attribute **PWeight** and the truth membership value for uncertain data **more or less 100** of fuzzy attribute **FSugar**. Truth membership values are calculated using algorithm defined in **section 3.2**.

4.2.1. Vague set based solution:

For vague set using **Definition 2**, **Algorithm 3.2** and **Definition 3**, the tolerance value of each tuple of PATIENT relation for imprecise query (**IQ-2**) is shown in Table 6.

4.2.2. Neutrosophic set based solution:

For neutrosophic set using **Definition 4**, **Algorithm 3.2** and **Definition 5**, the tolerance value of each tuple of PATIENT relation for imprecise query (**IQ-2**) is shown in Table 7.

Decision maker generates following SQL corresponding to imprecise query-2(**IQ-2**) for α-**cut** value **0.95**

SELECT * FROM **PATIENT** WHERE **Final Tuple tolerance value** $\geq$ **0.95**

After processing above SQL in both the above tables Tables 6 and 7, the resultant tables of **IQ-2** w.r.to vague and neutrosophic sets are listed below in the Table 8 and Table 9 espectively.

Table 6. Vague representation of Patients whose weight (PWeight) is around 40 and sugar level (FSugar) more or less 100

PName (PK)	PWeight (kg)	Vague representation of domain (PWeight) w.r.t IQ-1	Tuple tolerance value w.r.t PWeight (μ_1)	FSugar (mg/dl)	Vague representation of domain (FSugar) w.r.t IQ-2	Tuple tolerance w.r.t FSugar (μ_2)	Final Tuple tolerance value $\mu = \mu_1 \cap \mu_2$
Sania	28	<28, [.71, .76]>	**0.83**	80	<80,[.65,.75]>	**0.79**	**0.79**
Bell	51	<51, [.73, .75]>	**0.85**	98	<98,[.98,.98]>	**0.99**	**0.85**
Jackson	37	<35, [.93, .94]>	**0.96**	112	<112,[.84,.9]>	**0.90**	**0.90**
Bishop	41	<41, [.98, .99]>	**0.98**	100	<100,[1,1]>	**1**	**0.98**
Ritesh	38	<38, [.95, .96]>	**0.97**	102	<102,[.98,.99]>	**0.99**	**0.97**
Frank	40	<40, [1,1]>	**1**	99	<99,[.98,.99]>	**0.99**	**0.99**
Virat	44	<44, [.90, .93]>	**0.93**	97	<97,[.96,.96]>	**0.98**	**0.93**
Rose	39	<39, [.98, .99]>	**0.99**	90	<90,[.92,.97]>	**0.95**	**0.95**
David	47	<47, [.83, .85]>	**0.90**	103	<103,[.90,.90]>	**0.95**	**0.90**
Smriti	53	<53, [.69, .75]>	**0.82**	101	<101,[.99,.99]>	**0.93**	**0.82**

Table 7. NeutrosophicrepresentationPatients whose weight(PWeight) is around 40 andsugar level (FSugar) more or less 100

PName (PK)	PWeight (kg)	Neutrosophic representation of domain (PWeight) w.r.t IQ-1	Tuple tolerance value of PWeight (μ_1)	FSugar (mg/dl)	Neutrosophic representation of domain (FSugar) w.r.t IQ-2	Tuple tolerance value of FSugar (μ_2)	Final Tuple tolerance value $\mu = \mu_1 \cap \mu_2$
Sania	28	<28, [.71, .8, .24]>	**0.37**	80	<80,[.65,.25,.28]>	**0.76**	**0.37**
Bell	51	<51, [.73, .7, .25]>	**0.43**	98	<98,[.98,.03,.02]>	**0.97**	**0.43**
Jackson	37	<35, [.93, .35, .06]>	**0.74**	112	<112,[.84,.1,.03]>	**0.91**	**0.74**
Bishop	41	<41, [.98, .02, .01]>	**0.98**	100	**<100,[1,0,0]** [1]>	**1**	**0.98**
Ritesh	38	<38, [.95, .15, .04]>	**.88**	102	<102,[.98,.04,.01]>	**0.96**	**0.88**
Frank	40	<40, [1, 0, 0]>	**1**	99	<99,[.98,.01,.01]>	**0.99**	**0.99**
Virat	44	<44, [.90, .3, .07]>	**0.78**	97	<97,[.96,.04,.03]>	**0.94**	**0.78**
Rose	39	<39, [.98, .015, .01]>	**0.99**	90	<90,[.92,.15,.09]>	**0.86**	**0.86**
David	47	<47, [.83, .5, .15]>	**0.61**	103	<103,[.90,.15,.08]>	**0.88**	**0.61**
Smriti	53	<53, [.69, .75, .25]>	**0.41**	101	<101,[.99,.03,.01]>	**0.98**	**0.41**

Table 8. Vague accuracy after processing IQ-2

PName (PK)	PWeight (kg)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)	Final Tuple Tolerance value $\mu = \mu_1 \cap \mu_2$
Bishop	41	101.5	100	95	**0.98**
Ritesh	38	99.5	102	98	**0.97**
Frank	40	101	99	80	**0.99**
Rose	39	98.4	90	92	**0.95**

Table 9. Neutrosophic accuracy after processing IQ-2

PName (PK)	PWeight (kg)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)	Final Tuple Tolerance value $\mu = \mu_1 \cap \mu_2$
Bishop	41	101.5	100	95	**0.98**
Frank	40	101	99	80	**0.99**

Form the output of the above two resultant table Table 8 and Table 9, it is clear that neutrosophic set provides better output compare to vague set when imprecise query contains more than one fuzzy attributes

5 Conclusion

Imprecise query processing using vague or neutrosophic set is shown through architecture and it has been verified using a real-life example. Authors have discussed an algorithm which is applicable to find closeness between two uncertain data with respect to vague and neutrosophic set. Authors also used PATIENT relation to process uncertain queries using vague as well as neutrosophic set and compare the outcomes obtained by these two soft sets. In uncertain query processing it has been observed that neutrosophic set have produced more accurate result in comparison with vague set. Hence, neutrosophic database model is more accurate in solving our day-to-day activities containing fuzzy data compare to others.

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