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Medical diagnosis based on single-valued neutrosophic information

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Abstract:

Women with heart disease during pregnancy are at higher risk, which can harm the fetus. This risk can be reduced if we diagnose and treat it early. The decision-making system is very helpful in such situations. Many clinical decision-making systems have been proposed, but they are too complicated for medical experts to understand and adapt. Here, we develop a new neutrosophic model for early diagnosis and explain it using explainable artificial techniques. Our model is taking eight symptoms and signs as inputs and determines the diagnosis, type of treatment, and prognosis. Age, obesity, smoking, family pathological history, personal pathological history, electrocardiogram, ultrasound, and functional class are the inputs of this model. Six diagnoses can be made- obstruction at existing, obstruction at entry, rhythm disorder, conduction disorders, congenital diseases, genetic diseases. The types of treatments are- pregnancy interruption, diuretic treatment, anti-arrhythmic treatment, treatment with beta-blockers and anticoagulants treatment. The prognosis is- eutectic delivery, dystocic delivery, the child with complications, child without complications, mother with complications, and mother without complications. The main parts of this system are neutrosophication, knowledge base, inference engine, de-neutrosophication, and explainability. To present the entire execution of the proposed system, we design an algorithm and compute its time complexity to demonstrate the working of the entire system. We compared the results of different methods to gain confidence in our model.

Keywords: Neutrosophic sets, decision-making, heart diseases, algorithm, explainable articial intelligence.

1 Introduction

In medical, computer-aided medical diagnosing applications facilitates doctors to take decisions swiftly. Many models and applications have been designed for this purpose but the major drawback of such models is their complexity and a lot of mathematical work. Their complex models make it difficult for doctors to adopt. Explainable artificial intelligence (XAI) is an approach that makes such a model understandable for doctors and they feel comfortable adopting them. XAI also helps doctors to check the accuracy of the decisions as well.

The medical data is very much sensitive and contains a lot of ambiguities because each doctor has his own opinion, and using these opinions it becomes difficult to take one exact decision. In such environments, fuzzy logic plays an important role to make human-like decisions among multiple decisions. The concept of fuzzy sets was introduced by Zadeh in 1965 after that many extensions of fuzzy sets were proposed, intuitionistic fuzzy is also one of them which works with membership and non-membership [1]. But the restriction on sum of membership and non-membership restricts the selection of membership and nonmembership values.

In 1995, Smarandache introduced a novel branch of philosophy known as neutrosophy to eliminate this issue [2]. Neutrosophy is the essence of the neutrosophic set (NS) and neutrosophic logic (NL). NS concurrently considers true membership, falsity membership, and indeterminacy membership, which are more effective and consistent as compare to fuzzy systems and intuitionistic fuzzy systems. The single-valued neutrosophic set (SVNS) is an extension of the NS [3]-[4]. There are many applications of fuzzy and its extensions are discussed in literature, some of them are [5]-[11].

Abdel-Basset et al. proposed a novel neutrosophic multi-criteria decision-making (MCDM) model that used the neutrosophic analytical network process (ANP), and the TOPSIS method for deciding on the election of an appropriate candidate for job [12]. They using this MCDM technique selection of Chief executive officer (CEO) vacancy. The proposed MCDM procedure combined quantitative and qualitative information for personnel selection.

In 2019, Hashmi et al. proposed a new concept of m-polar neutrosophic set (MPNS) and topological structure on m-polar neutrosophic set by fusing polar fuzzy set (MPFS) and neutrosophic set [13]. They proposed a score function for the estimate of m-polar neutrosophic numbers (MPNNs). m-polar neutrosophic topology is established and defined the interior, exterior, and frontier for m-polar neutrosophic sets (MPNs).

In 2020, Pamucar et al. introduced a neutrosophic decision-making model for the selection of supplier [14]. Their target was to decrease the risk and disruptions to the supply chain and to preserve the stability of the supply-chain system. Also, the unpredictable situations in a supply chain force decisionmakers and authorities to choose a fuzzybased evaluation platform to guarantee safe and secure outcomes. They proposed a new weight aggregator that uses a pairwise comparison.

In 2020, Pamucar et al. evaluated and prioritized the energy storage technology alternatives (methods) by considering technical cost, and environmental and social criteria. They proposed a hybrid trapezoidal neutrosophic fuzzy numbers based Dombi weighted geometric averaging operator and MultiAtributive Ideal-Real Comparative Analysis (MAIRCA) model [15]. They employed a case study in Romania is carried out to illustrate the applicability of the proposed model.

In 2020, Chakraborty et al. suggested the notion of cylindrical neutrosophic single-valued numbers from a different perspective and aspects to obtained its true result [16]. This concept is based on score and accuracy functions that are used to convert fuzzy numbers into a crisp number to make decisions on different problems. This technique was applied to real-life examples like networking and obtain the result that it is a better choice for decision making instead of neutrosophic numbers when falsity and indeterminacy function are dependent. The technique introduced in this paper is helpful in engineering and science-related field for diagnosis purposes.

In 2020, Aslan et al. presented the notion of neutrosociology [17]. It is a more effective way to find out uncertainties in social theories as it is impossible to find out with classical maths. The researchers used similarity measures of single-valued neutrosophic numbers for sociology-related decision-making problems. By using neutrosophic numbers and sets related to other social theories, new similarity measures introduced, and checked the appropriateness of these formulas.

In 2020, Tan et al. proposed a multi-attribute decision-making method for the decision-making problems where the attribute weight is unknown. Using information of entropy evaluation is performed [18]. They defined new formulas of single-valued neutrosophic similarities and single-valued neutrosophic entropy. Moreover, the connection between them is also discussed. Karabasevic et al. introduced a unique type of the TOPSIS method applicable for the use of single-valued neutrosophic sets [19]. The motivations of this study are described below:

1. Women with heart disease during pregnancy are at higher risk, which can have a negative effect on the fetus.
2. Medical data may contain unclear information. Using such data may lead to a wrong diagnosis if not managed efficiently.
3. Modern decision-making systems are very much complicated, and due to non-transparency, it becomes difficult for medical professionals to adopt them.

Our contributions to this research are as follows:

1. We developed a novel decision-making model to facilitate doctors to early predict diagnosis, type of treatment, and prognosis.
2. Single-valued neutrosophic sets are used for decision-making because they are very close to human reasoning. SVNS focuses on the degree of truth, the degree of indeterminacy, and the degree of falsity simultaneously. Also, there is no restriction on its sum of membership and non-membership.
3. We combine the theory of explainable AI to form our system adaptable for medical experts. The degree of explanation is estimated using causability. Explainable AI and causability AI systems support building the trust of medical experts.
4. We have designed an algorithm to explain the entire functioning of the model, as well as to measure its time complexity.
5. We compared our results with the rest of the techniques.

The rest of this article has been designed subsequently: Section 2 concisely reconsiders essential concepts of neutrosophic sets, explainable AI, and causability measures. Section 3 reviews the explainable neutrosophic clinical decision-making systems for the treatment of pregnant women with heart diseases. Section 4 offers a case study to present the effectiveness of the system. Section 5 matches the values of the proposed model with other theories. Section 6 ends this article and presents possible future research directions.

2 Preliminaries

This part recalls some of the preparatory notions that require to be read to completely benefit from this study.

2.1. Explainability [20]: In artificial intelligence (AI), explainability is the extent to which the internal mechanism of the algorithm can be explained in humans terms. Two explainable models have been found in the literature; the post-hoc explainability, and ante-hoc explaining models. The scope of the post-hoc model is local, in which it explains only the specific component of the algorithm, not the complete system. Its examples are LIME and BETA models. Whereas, the ante-hoc system are interpretable by design. Its examples are linear regression, decision trees, and

fuzzy inference systems.

2.2. Causability [20]: Causability measures the quality of explainable. This means that the provided explanation is how much effective and understandable to humans.

2.3. Single-valued neutrosophic set (SVNS) [3]: Let A be a sample space. A SVNS B on a non-empty set A is described by a truth membership function $T_B : A \to [0,1]$, indeterminacy membership function $I_B : A \to [0,1]$ and a falsity membership function $F_B : A \to [0,1]$. Thus, $B = \{< w, T_B(w), I_B(w), F_B(w) > | w \in A\}$. There is no restraint on the sum of $T_B(w)$, $I_B(w)$ and $F_B(w)$ for all $w \in A$.

2.4. Neutrosophic logic [21]: Neutrosophic logic (NL) was bestowed by Smarandache as an extension of fuzzy logic, intuitionistic logic, and para-consistent logic. This logic contains three basic parts, that is, truth membership, indeterminacy membership, and falsity membership.

2.5. Single-valued neutrosophic number [22]: Let V be a SVNN which is defined as $V = ([(u_1, v_1, w_1, x_1); \rho], [(u_2, v_2, w_2, x_2); \sigma], [(u_3, v_3, w_3, x_3); \omega])$ where $\rho, \sigma, \omega \in [0,1]$, the truth membership function $(\mu_V) : \mathbb{R} \to [0, \rho]$, indeterminacy membership function $(\nu_V) : \mathbb{R} \to [\sigma, 1]$, and falsity membership function $(\lambda_V) : \mathbb{R} \to [\omega, 1]$ are represented as follows:

$$\mu_V(w) = \begin{cases} \mu_{Al}(w), & \text{if } u_1 \le w \le v_1, \\ \rho, & \text{if } v_1 \le w \le w_1, \\ \mu_{Au}(w), & \text{if } w_1 \le w \le x_1, \\ 0, & \text{otherwise.} \end{cases}$$

$$\nu_V(w) = \begin{cases} \nu_{Al}(w), & \text{if } u_2 \le w \le v_2, \\ \sigma, & \text{if } v_2 \le w \le w_2, \\ \nu_{Au}(w), & \text{if } w_2 \le w \le x_2, \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_V(w) = \begin{cases} \lambda_{Al}(w), & \text{if } u_3 \le w \le v_3, \\ \omega, & \text{if } v_3 \le w \le w_3, \\ \lambda_{Au}(w), & \text{if } w_3 \le w \le x_3, \\ 1, & \text{otherwise.} \end{cases}$$

2.6. Operations of SVNS [3]: Let A be a space of points and V_1 and V_2 are the two SVNSs and V_3 contains their result.

Intersection: The intersection of V_1 and V_2 is represented as follows:

$$\begin{aligned} T_{V_3}(w) &= \min(T_{V_1}(w), T_{V_2}(w)), \\ I_{V_3}(w) &= \max(I_{V_1}(w), I_{V_2}(w)), \\ F_{V_3}(w) &= \max(F_{V_1}(w), F_{V_2}(w)), \end{aligned}$$

for all w in A.

Union: The union of V_1 and V_2 is represented as follows:

$$\begin{aligned} T_{V_3}(w) &= \max(T_{V_1}(w), T_{V_2}(w)), \\ I_{V_3}(w) &= \min(I_{V_1}(w), I_{V_2}(w)), \\ F_{V_3}(w) &= \min(F_{V_1}(w), F_{V_2}(w)), \end{aligned}$$

for all w in A.

2.7. Major factors :

There are following major factors that can increase the risks during pregnancy.

Age (S1): The length of time that a person has lived or a thing has existed.

Obesity (S2): Obesity is a complicated condition including an unnecessary volume of body fat.

Smoking (S3): Smoking is a habit of gasping smoke of tobacco or a drug.

Family pathological history (S4): Pathology includes investigating the cause of sickness, how it occurs, the impact of the sickness on cells, and the consequence of the sickness. If this sickness comes from family, then it is called family pathological history.

Personal pathological history (S6): If the sufferer itself has an own record of sickness.

Electrocardiogram (S7): An electrocardiogram shows the electrical signals in your heart.

Ultrasound (S8): An ultrasound scan is a medical examination that employs high-frequency sound waves to take live pictures from the inside of your body.

Functional class (S9) [23]: The World Health Organisation (WHO) functional class system was designed to determine the rigor of somebodys manifestations and how they influence day-to-day actions.

2.8 Diagnosis:

Obstruction at exit (OEX) [24]: It is a procedure used to deliver babies who have airway compression due to certain blockage.

Obstruction at entry (OEN) [24]: In pregnancy obstruction at entry is rare and is most generally created by adhesions from past abdominal surgery.

Rhythm disorders (RD) [25]: A biological cycle present in the human body gets upset when the sleep-wake cycle dis-coordinate with the environment and hinder a daily routine.

Conduction disorder (CD) [26]: The heart relies on electrical signals that originate the heartbeat in rhythm, when certain signals obstruct it results in conduction disorder.

Congenital disease (CD) [27]: A medical condition present in babies by birth occurs during the fetal stage of development or is acquired from parents or produced by environmental factors. It is also known as birth defects.

Genetic disease (GD) [27]: A change in DNA sequence from normal sequence results in Genetic disorder. It can be produced in the whole body or a particular part of the body by a mutation in one gene, mutation in multiple genes, or change in the sequence of genes.

2.9 Treatments:

Pregnancy interruption (PI) [28]: Discontinued Pregnancy is recognized as Pregnancy interruption. It can either be done artificially called abortion or naturally due to fetal aberration.

Diuretic treatment (DT) [29]: These are medications cause a net impairment of sodium and water in urine. It is also called water pills.

Anti-arrhythmic treatment (AAT) [29]: These medications are used when the heart rate goes fast or have an extra heart beat. This condition is called tachycardia. This pill helps to restore the regular beat of the heart.

Treatment with beta-blockers (TBB): These medicines are used to decrease high blood pressure by opening up the nerves and arteries to recover blood flow.

Anticoagulants treatment (ACT) [29]: This medicine is utilized to block blood clots and also stopping them from growing big. It also decreases the risks of heart attack and strokes.

Eutectic delivery (ED) [30]: Delivery performs mixing certain drugs.

Dystocic delivery (PD) [30]: Slow cervix dilation during delivery.

Mother with complication (MC): Any health problems a mother ought during or before pregnancy such as blood pressure, anemia, infections, etc.

The following matrices show the relation connecting symptoms and diagnosis. treatment, and prognosis. The following matrices help to examine the correctness of the nal diagnosis, treatment, and prognosis.

$$\begin{array}{c} \\ A \\ OB \\ TAB \\ FPH \\ PPH \\ ECG \\ ECO \\ FC \end{array} \begin{array}{c} OEX \\ \begin{pmatrix} (0.9,0.2,0.3) \\ (0.2,0.6,0.4) \\ (0.9,0.1,0.3) \\ (0.2,0.2,0.3) \\ (0.9,0.1,0.2) \\ (0.8,0.2,0.3) \\ (0.7,0.2,0.2) \\ (0.9,0.2,0.1) \end{pmatrix} \end{array} \begin{array}{c} OEN \\ \begin{pmatrix} (0.2,0.2,0.4) \\ (0.3,0.5,0.6) \\ (0.8,0.1,0.2) \\ (0.2,0.4,0.1) \\ (0.8,0.2,0.3) \\ (0.7,0.2,0.3) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} RD \\ \begin{pmatrix} (0.8,0.3,0.2) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.2,0.1,0.1) \\ (0.9,0.2,0.3) \\ (0.2,0.2,0.4) \\ (0.2,0.8,0.5) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} CDS \\ \begin{pmatrix} (0.9,0.2,0.3) \\ (0.8,0.2,0.1) \\ (0.9,0.2,0.3) \\ (0.3,0.6,0.5) \\ (0.9,0.2,0.2) \\ (0.2,0.5,0.6) \\ (0.9,0.2,0.2) \\ (0.9,0.1,0.3) \end{pmatrix} \end{array} \begin{array}{c} CD \\ \begin{pmatrix} (0.9,0.1,0.3) \\ (0.9,0.2,0.2) \\ (0.8,0.1,0.2) \\ (0.2,0.8,0.1) \\ (0.2,0.5,0.5) \\ (0.9,0.2,0.2) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.2) \end{pmatrix} \end{array} \begin{array}{c} GD \\ \begin{pmatrix} (0.9,0.2,0.3) \\ (0.8,0.2,0.3) \\ (0.2,0.1,0.4) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.3,0.8,0.6) \\ (0.2,0.1,0.5) \\ (0.8,0.2,0.3) \end{pmatrix} \end{array},$$

$$\begin{array}{c} \\ A \\ OB \\ TAB \\ FPH \\ PPH \\ ECG \\ ECO \\ FC \end{array} \begin{array}{c} PI \\ \begin{pmatrix} (0.9,0.2,0.3) \\ (0.8,0.4,0.2) \\ (0.2,0.2,0.5) \\ (0.2,0.1,0.5) \\ (0.9,0.2,0.3) \\ (0.2,0.4,0.1) \\ (0.8,0.1,0.3) \\ (0.7,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} DT \\ \begin{pmatrix} (0.2,0.1,0.5) \\ (0.2,0.1,0.5) \\ (0.2,0.3,0.4) \\ (0.3,0.1,0.5) \\ (0.9,0.2,0.3) \\ (0.2,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} AAT \\ \begin{pmatrix} (0.9,0.4,0.3) \\ (0.7,0.3,0.3) \\ (0.2,0.1,0.5) \\ (0.2,0.5,0.5) \\ (0.2,0.1,0.5) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.8,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} TBB \\ \begin{pmatrix} (0.8,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.2,0.4,0.5) \\ (0.8,0.4,0.2) \\ (0.7,0.2,0.3) \\ (0.2,0.1,0.3) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} ACT \\ \begin{pmatrix} (0.7,0.1,0.1) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.7,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.9,0.2,0.1) \end{pmatrix} \end{array},$$

$$\begin{array}{c} \\ A \\ OB \\ TAB \\ FPH \\ PPH \\ ECG \\ ECO \\ FC \end{array} \begin{array}{c} ED \\ \begin{pmatrix} (0.1,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.1,0.1,0.2) \\ (0.9,0.2,0.4) \\ (0.9,0.2,0.2) \\ (0.7,0.2,0.3) \\ (0.7,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} PD \\ \begin{pmatrix} (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.3,0.1,0.2) \\ (0.2,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array} \begin{array}{c} CHC \\ \begin{pmatrix} (0.1,0.1,0.2) \\ (0.3,0.1,0.2) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.2) \\ (0.9,0.2,0.3) \\ (0.3,0.1,0.2) \\ (0.7,0.2,0.3) \\ (0.8,0.2,0.2) \end{pmatrix} \end{array} \begin{array}{c} NOCHC \\ \begin{pmatrix} (0.1,0.3,0.2) \\ (0.1,0.1,0.2) \\ (0.3,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.7,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.1) \end{pmatrix} \end{array} \begin{array}{c} MC \\ \begin{pmatrix} (0.7,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.8,0.2,0.3) \\ (0.1,0.1,0.2) \\ (0.1,0.1,0.2) \\ (0.9,0.5,0.3) \end{pmatrix} \end{array} \begin{array}{c} NOMC \\ \begin{pmatrix} (0.7,0.2,0.2) \\ (0.9,0.1,0.2) \\ (0.1,0.1,0.2) \\ (0.7,0.2,0.3) \\ (0.9,0.2,0.3) \\ (0.3,0.1,0.2) \\ (0.8,0.2,0.3) \\ (0.9,0.2,0.3) \end{pmatrix} \end{array}.$$

3 Explainable single-valued neutrosophic medical decision-making system for the treatment of pregnant women with cardiac diseases

Let's understand the complete working of the decision-making system for the treatment of pregnant women with cardiac problems. We use SVNN for diagnosing, treatment and prognosis. To make this system simple and transparent, we used XAI methods. These methods help to explain the entire working of a particular module. The causality helps to determine the effectiveness of the explanation. Also, We devise an algorithm and calculates its time complexity.

3.1 Basic structure of explainable single-valued neutrosophic medical decision-making system

The proposed system consists of five main parts. The first part is neutrosophication which contains truth membership, indeterminacy memberships, and falsity membership of each input variable. Section parts is a knowledge base that contains all possible rules of the systems. The third part is the inference engine which contains active decision-making rules. The fourth part is de-neutrosophication which contains truth memberships, indeterminacy memberships, and falsity memberships of the output variable. The fifth part is explainability which is integrated with each part of the systems to explain its working. Figure 1 presents the block diagram of the prescribed system.

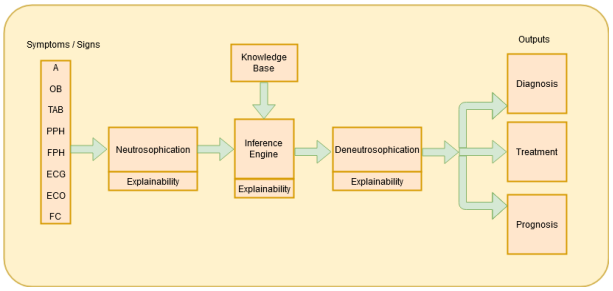

Figure 1: Block Diagram

3.2 Algorithm

The algorithm of the introduced model is as follows:

Algorithm 1 Steps to diagnosis, determine type of treatment, and prognosis by applying single-valued neutrosophic logic.

1: **Inputs:** Take inputs values from user: Age (A), obesity (OB), smoking (TAB), family pathological history (FPH), personal pathological history (PPH), electrocardiogram (ECG), ultrasound (ECO), and functional class (FC).

2: Define truth membership functions, indeterminacy membership functions, and falsity membership functions of each input and output variables.

3: Use these functions to determine degree of truth, degree of indeterminacy, and degree of falsity of each input variable against provided input values in step 1. This process is called neutrosophication process.

4: Defines rules of the system and determine firing strength of each rule using following formulas:

$$T(w) = \min(\mu_A(w), \mu_{OB}(w), \mu_{TAB}(w), \mu_{FPH}(w), \mu_{PPH}(w), \mu_{ECG}(w), \mu_{ECO}(w), \mu_{FC}(w)).$$
$$I(w) = \max(\nu_A(w), \nu_{OB}(w), \nu_{TAB}(w), \nu_{FPH}(w), \nu_{PPH}(w), \nu_{ECG}(w), \nu_{ECO}(w), \nu_{FC}(w)).$$
$$F(w) = \max(\lambda_A(w), \lambda_{OB}(w), \lambda_{TAB}(w), \lambda_{FPH}(w), \lambda_{PPH}(w), \lambda_{ECG}(w)\lambda_{ECO}(w), \lambda_{FC}(w)).$$

5: Use following de-neutrosophication formula to determine the values of each diagnosis, type of treatment, and prognosis. [22]:

$$V = (p + 2q + r + s + 2t + u + v + 2w + x)/12,$$

where, (p, q, r) are three points of truth membership, (s, t, u) are three points of indeterminacy membership, and (v, w, x) are three points of falsity membership.

6: Determine the final values of diagnosis, treatment, and prognosis.

7: Obtained the highest values among all values.

8: **Output:** The maximum value will be the final decision of diagnosis, treatment, and prognosis.

Neutrosophication

		Time Complexity
(i).	Start	
(ii).	Create three linked lists to store values of truth MFs, indeterminacy MFs, and falsity MFs. DF, IF, FF= null;	1
(iii).	Create pointers ptr1= DF; ptr2=IF; ptr3=FF	1
(iv).	for(n=1 to numbers of functions)	n
(v).	newDF.data=truth value of nth MF	n-1
(vi).	ptr1.link=newDF	n-1
(vii).	newIF.data=indeterminacy value of nth MF	n-1

(viii). ptr2.link=newIF n-1

(ix). newFF.data=falsity value of nth MF n-1

(x). ptr3.link=newFF n-1

(xi). end for

(xii). End Time complexity= $O(n)$

Inference Engine

(i). Start

(ii). Create three linked lists to store values of rules
Truth, Indeterminacy, Falsity= null; 1

(iii). Create pointers
ptr1= Truth; ptr2=Indeterminacy; ptr3=Falsity 1

(iv). for(n=1 to numbers of rules) n

(v). newTruth=minimum of truth MFs n-1

(vi). ptr1.link=newTruth n-1

(vii). newInd=maximum of indeterminacy MFs n-1

(viii). ptr2.link=newInd n-1

(ix). newFalsity= maximum falsity MFs n-1

(x). ptr3.ink=newFalsity n-1

(xi). end for

(xii). for(n=1 to numbers of rules) n

(xiii). Truth-value= min from truth values n-1

(xiv). Indeterminacy-value=max if indeterminacy values n-1

(xv). Falsity-value= max of falsity values n-1

(xvi). end for

(xvii). End Time complexity= $O(n)$

Defuzzification

(i). Start

(ii). for(n=1 to numbers of diagnosis) n

(iii). for(k=1 to numbers of output functions) n(n-1)

(iv). W1[n][k]=(p+2q+r+s+2t+u+v+2w+x)/12 (n-1)(n-2)

(v). V1[n]=take max from W1[n][k] (n-1)(n-2)

(vi). end for

(vii). end for

(viii). for(n=1 to number of treatments) n

(ix). for(k=1 to number of output functions) n(n-1)

(x). W2[n][k]=(p+2q+r+s+2t+u+v+2w+x)/12 (n-1)(n-2)

(xi). V2[n]=take max from W2[n][k] (n-1)(n-2)

(xii). end for

(xiii). end for

(xiv). for(n=1 to number of prognosis) n

(xv). for(k=1 to number of output functions) n(n-1)

(xvi). W3[n][k]=(p+2q+r+s+2t+u+v+2w+x)/12 (n-1)(n-2)

(xvii). V3[n]=take max from W3[n][k] (n-1)(n-2)

(xviii). end for

(xix). end for

(xx). for(n=1 to number of diagnosis) n

(xxi). Diagnosis=take max from V1[n] n-1

(xxii). end for

(xxiii). for(n=1 to no. of treatment) n

(xxiv). Treatment=take max from V2[n] n-1

(xxv). end for

(xxvi). for(n=1 to no. of prognosis) n

(xxvii). Prognosis=take max from V3[n] n-1

(xxviii). end for

(xxix). End Time complexity= $O(n^2)$

Let's compute the total time taken by this algorithm. Line 1 takes constant time. Neutrosophication is O(n) time process, therefore, line 2 takes O(n) time. The inference engine is O(n) time process, therefore, line 3 takes O(n) time. The de-neutrosophication process takes $O(n^2)$ time, so, line 4 takes $O(n^2)$. Lines 5, line 6, and line 7 take constant time. Hence, the overall time complexity of Algorithm 1 is $O(n^2)$.

3.3 Working of explainable neutrosophic clinical decision-making system for pregnant women with heart diseases

Our model is taking eight symptoms as inputs and computes the values of diagnosis, treatment, and prognosis. Table 1 shows the scale of each variable.

Table 1: Scale of input variables

Sr. no.	Symptoms	Scale
S1	Age-A (year/s)	0-100
S2	Obesity-OB	0-100
S3	Smoking-TAB	1/2
S4	Family pathological history-FPH	1/2
S5	Personal pathological history-PPH	1/2
S6	Electrocardiogram-ECG	0-100
S7	Ultrasound-ECO	0-100
S8	Functional class-FC	0-100

The scale is divided into three types of MFs. The plot of each symptom is depicted in Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, Figure 12, Figure 13, and Figure 14.

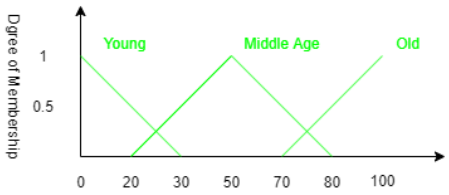

Figure 2: Age-truth MFs

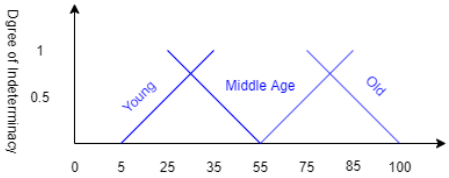

Figure 3: Age-indeterminacy MFs

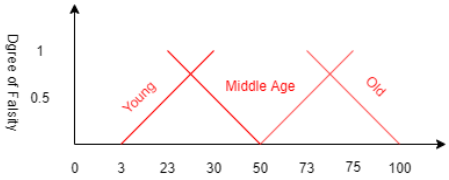

Figure 4: Age-falsity MFs

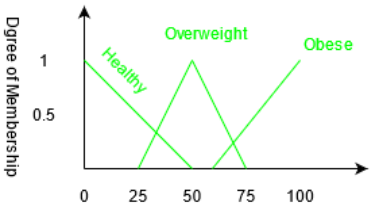

Figure 5: Obesity-truth MFs

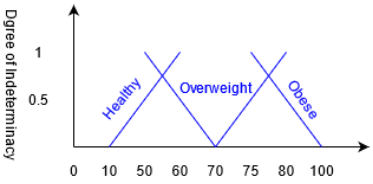

Figure 6: Obesity-indeterminacy MFs

Figure 7: Obesity- falsity MFs

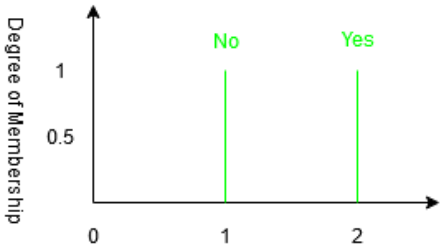

Figure 8: Smoking, personal and family pathological history- truth MFs

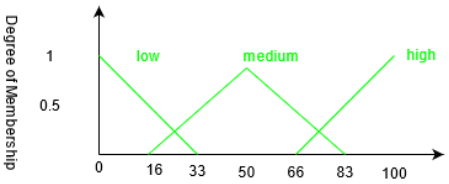

Figure 9: Electrocardiogram-truth MFs

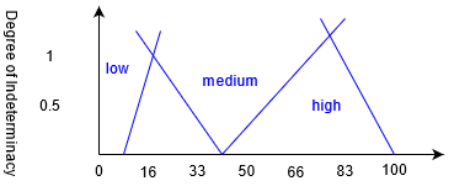

Figure 10: Electrocardiogram-indeterminacy MFs

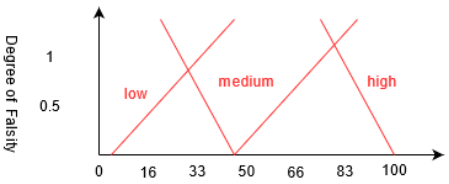

Figure 11: Electrocardiogram-falsity MFs

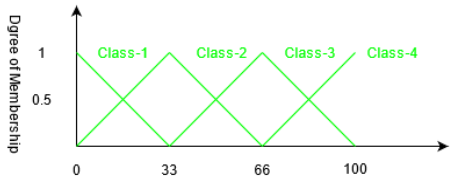

Figure 12: Function class-truth MFs

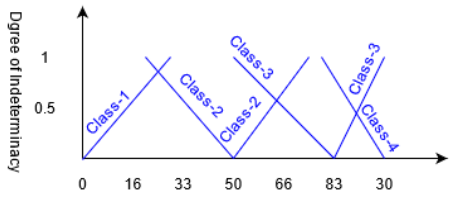

Figure 13: Function class- indeterminacy MFs

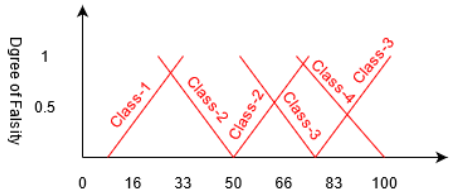

Figure 14: Function class-falsity MFs

The mathematical equations of truth MFs, indeterminacy MFs, and falsity MFs of age are as follows:

$$\mu_{young}(w) = \begin{cases} \frac{30-w}{30}, & \text{if } w \in [0-30], \\ 0, & \text{otherwise.} \end{cases} \qquad \mu_{old}(w) = \begin{cases} \frac{w-70}{30}, & \text{if } w \in [70-100], \\ 0, & \text{otherwise.} \end{cases}$$

$$\mu_{middle-age}(w) = \begin{cases} \frac{w-20}{30}, & \text{if } w \in [20-50], \\ \frac{80-w}{30}, & \text{if } w \in [50-80], \\ 0, & \text{otherwise.} \end{cases}$$

$$\nu_{young}(w) = \begin{cases} \frac{w-5}{30}, & \text{if } w \in [5-35], \\ 1, & \text{otherwise.} \end{cases} \qquad \nu_{old}(w) = \begin{cases} \frac{100-w}{25}, & \text{if } w \in [75-100], \\ 1, & \text{otherwise.} \end{cases}$$

$$\nu_{middle-age}(w) = \begin{cases} \frac{55-w}{30}, & \text{if } w \in [25-55], \\ \frac{w-55}{30}, & \text{if } w \in [55-85], \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_{young}(w) = \begin{cases} \frac{w-3}{27}, & \text{if } w \in [3-30], \\ 1, & \text{otherwise.} \end{cases} \qquad \lambda_{old}(w) = \begin{cases} \frac{100-w}{27}, & \text{if } w \in [73-100], \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_{middle-age}(w) = \begin{cases} \frac{50-w}{27}, & \text{if } w \in [23-50], \\ \frac{w-50}{25}, & \text{if } w \in [50-75], \\ 1, & \text{otherwise.} \end{cases}$$

The mathematical equations of truth MFs, indeterminacy MFs, and falsity MFs of obesity are as follows:

$$\mu_{healthy}(w)=\begin{cases}\dfrac{50-w}{50-0}, & \text{if } w\in[0-50],\\ 0, & \text{otherwise.}\end{cases}\qquad \mu_{obese}(w)=\begin{cases}\dfrac{w-65}{35}, & \text{if } w\in[65-100],\\ 0, & \text{otherwise.}\end{cases}$$

$$\mu_{over-weight}(w)=\begin{cases}\dfrac{w-25}{25}, & \text{if } w\in[25-50],\\ \dfrac{75-w}{25}, & \text{if } w\in[50-75],\\ 0, & \text{otherwise.}\end{cases}$$

$$\nu_{healthy}(w)=\begin{cases}\dfrac{w-10}{50}, & \text{if } w\in[10-60],\\ 1, & \text{otherwise.}\end{cases}\qquad \nu_{obese}(w)=\begin{cases}\dfrac{100-w}{25}, & \text{if } w\in[75-100],\\ 1, & \text{otherwise.}\end{cases}$$

$$\nu_{over-weight}(w)=\begin{cases}\dfrac{70-w}{20}, & \text{if } w\in[50-70],\\ \dfrac{w-70}{20}, & \text{if } w\in[70-90],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{healthy}(w)=\begin{cases}\dfrac{w-5}{50}, & \text{if } w\in[5-55],\\ 1, & \text{otherwise.}\end{cases}\qquad \lambda_{obese}(w)=\begin{cases}\dfrac{100-w}{20}, & \text{if } w\in[80-100],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{over-weight}(w)=\begin{cases}\dfrac{60-w}{15}, & \text{if } w\in[45-60],\\ \dfrac{w-60}{25}, & \text{if } w\in[60-85],\\ 1, & \text{otherwise.}\end{cases}$$

The mathematical equations of truth MFs, indeterminacy MFs, and falsity MFs of smoking, personal pathological history and family pathological history are as follows:

$\mu_{yes}(w)=1.$ $\qquad \mu_{no}(w)=1.$
$\nu_{yes}(w)=0.$ $\qquad \nu_{no}(w)=0.$
$\lambda_{yes}(w)=0.$ $\qquad \lambda_{no}(w)=0.$

The mathematical form of degree of membership, degree of indeterminacy, and degree of falsity of electrocardiogram are as follows:

$$\mu_{low}(w)=\begin{cases}\dfrac{33.33-w}{33.33-0}, & \text{if } w\in[0-33.33],\\ 0, & \text{otherwise.}\end{cases}\qquad \mu_{high}(w)=\begin{cases}\dfrac{w-43.33}{23.33}, & \text{if } w\in[43.33-66.67],\\ 0, & \text{otherwise.}\end{cases}$$

$$\mu_{medium}(w)=\begin{cases}\dfrac{w-16.67}{16.67}, & \text{if } w\in[16.67-33.33],\\ \dfrac{50-w}{16.67}, & \text{if } w\in[33.33-50],\\ 0, & \text{otherwise.}\end{cases}$$

$$\nu_{low}(w)=\begin{cases}\dfrac{w-6.67}{33.33}, & \text{if } w\in[6.67-40],\\ 1, & \text{otherwise.}\end{cases}\qquad \nu_{high}(w)=\begin{cases}\dfrac{66.67-w}{16.67}, & \text{if } w\in[50-66.67],\\ 1, & \text{otherwise.}\end{cases}$$

$$\nu_{medium}(w)=\begin{cases}\dfrac{46.67-w}{13.33}, & \text{if } w\in[33.33-46.67],\\ \dfrac{w-46.67}{13.33}, & \text{if } w\in[46.67-60],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{low}(w)=\begin{cases}\dfrac{w-3.33}{33.33}, & \text{if } w\in[3.33-36.67],\\ 1, & \text{otherwise.}\end{cases}\qquad \lambda_{high}(w)=\begin{cases}\dfrac{66.67-w}{13.33}, & \text{if } w\in[53.33-66.67],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{medium}(w)=\begin{cases}\dfrac{40-w}{10}, & \text{if } w\in[30-40],\\ \dfrac{w-40}{16.67}, & \text{if } w\in[40-56.67],\\ 1, & \text{otherwise.}\end{cases}$$

The mathematical form of degree of membership, degree of indeterminacy, and degree of falsity of ultrasound are as follows:

$$\mu_{low}(w)=\begin{cases}\dfrac{33.33-w}{33.33-0}, & \text{if } w\in[0-33.33],\\ 0, & \text{otherwise.}\end{cases}\qquad \mu_{high}(w)=\begin{cases}\dfrac{w-43.33}{23.33}, & \text{if } w\in[43.33-66.67],\\ 0, & \text{otherwise.}\end{cases}$$

$$\mu_{medium}(w)=\begin{cases}\dfrac{w-16.67}{16.67}, & \text{if } w\in[16.67-33.33],\\ \dfrac{50-w}{16.67}, & \text{if } w\in[33.33-50],\\ 0, & \text{otherwise.}\end{cases}$$

$$\nu_{low}(w)=\begin{cases}\dfrac{w-6.67}{33.33}, & \text{if } w\in[6.67-40],\\ 1, & \text{otherwise.}\end{cases}\qquad \nu_{high}(w)=\begin{cases}\dfrac{66.67-w}{16.67}, & \text{if } w\in[50-66.67],\\ 1, & \text{otherwise.}\end{cases}$$

$$\nu_{medium}(w)=\begin{cases}\dfrac{46.67-w}{13.33}, & \text{if } w\in[33.33-46.67],\\ \dfrac{w-46.67}{13.33}, & \text{if } w\in[46.67-60],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{low}(w)=\begin{cases}\dfrac{w-3.33}{33.33}, & \text{if } w\in[3.33-36.67],\\ 1, & \text{otherwise.}\end{cases}\qquad \lambda_{high}(w)=\begin{cases}\dfrac{66.67-w}{13.33}, & \text{if } w\in[53.33-66.67],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{medium}(w)=\begin{cases}\dfrac{40-w}{10}, & \text{if } w\in[30-40],\\ \dfrac{w-40}{16.67}, & \text{if } w\in[40-56.67],\\ 1, & \text{otherwise.}\end{cases}$$

The mathematical equations of truth MFs, indeterminacy MFs, and falsity MFs functional class are as follows:

$$\mu_{class-1}(w)=\begin{cases}\dfrac{33.33-w}{33.33}, & \text{if } w\in[0-33.33],\\ 0, & \text{otherwise.}\end{cases}\qquad \mu_{class-3}(w)=\begin{cases}\dfrac{w-33.33}{33.33}, & \text{if } w\in[33.33-66.67],\\ \dfrac{100-w}{33.33}, & \text{if } w\in[66.67-100],\\ 0, & \text{otherwise.}\end{cases}$$

$$\mu_{class-2}(w)=\begin{cases}\dfrac{w-33.33}{33.33}, & \text{if } w\in[0-33.33],\\ \dfrac{66.67-w}{33.33}, & \text{if } w\in[33.33-66.67],\\ 0, & \text{otherwise.}\end{cases}\qquad \mu_{class-4}(w)=\begin{cases}\dfrac{w-66.67}{33.33}, & \text{if } w\in[66.67-100],\\ 0, & \text{otherwise.}\end{cases}$$

$$\nu_{class-1}(w)=\begin{cases}\dfrac{w-0}{26.67}, & \text{if } w\in[0-26.67],\\ 1, & \text{otherwise.}\end{cases}\qquad \nu_{class-3}(w)=\begin{cases}\dfrac{83.33-w}{43.33}, & \text{if } w\in[40-83.33],\\ \dfrac{w-83.33}{16.67}, & \text{if } w\in[83.33-100],\\ 1, & \text{otherwise.}\end{cases}$$

$$\nu_{class-2}(w)=\begin{cases}\dfrac{50-w}{30}, & \text{if } w\in[20-50],\\ \dfrac{w-50}{26.67}, & \text{if } w\in[50-76.67],\\ 1, & \text{otherwise.}\end{cases}\qquad \nu_{class-4}(w)=\begin{cases}\dfrac{100-w}{20}, & \text{if } w\in[80-100],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{class-1}(w)=\begin{cases}\dfrac{w-10}{23.33}, & \text{if } w\in[10-33.33],\\ 1, & \text{otherwise.}\end{cases}\qquad \lambda_{class-3}(w)=\begin{cases}\dfrac{76.67-w}{36.67}, & \text{if } w\in[40-76.67],\\ \dfrac{w-76.67}{23.33}, & \text{if } w\in[76.67-100],\\ 1, & \text{otherwise.}\end{cases}$$

$$\lambda_{class-2}(w)=\begin{cases}\dfrac{50-w}{20}, & \text{if } w\in[30-50],\\ \dfrac{w-50}{23.33}, & \text{if } w\in[50-73.33],\\ 1, & \text{otherwise.}\end{cases}\qquad \lambda_{class-4}(w)=\begin{cases}\dfrac{100-w}{30}, & \text{if } w\in[70-100],\\ 1, & \text{otherwise.}\end{cases}$$

3.3.1 Ante-hoc explanation

In this section, we dene mathematical equations of truth MFs, indeterminacy MFs, and falsity MFs. These equations help to convert crisp input into linguistics values. We also draw the plots of each input variable. The value of these functions extends between 0 to 1. The value of each linguistic variable is the output of the neutrosophication module.

3.4 Inference engine

The inference engine is the main part of the system which contains the firing strength of all active rules. There are 330 rules in the system, some of them are written here:

R1−**IF** (age=middle-age, obesity=obese, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heartbeat=low, ultrasound=no-complications, functional class=class-3) **THEN** (obstruction at exist=medium, obstruction at entry=low, rhythm disorder=high, conduction disorders=medium, congenital diseases=medium, genetic diseases=medium) **AND** (pregnancy interruption=low, diuretic treatment=low, anti-arrhythmic treatment=low, treatment with beta blockers=high and anticoagulants treatment=medium) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=medium, child without complications=low, mother with complications=high, mother without complications=medium).

R2−**IF** (age=middle-age, obesity=overweight, smoking=yes, personal pathological history=no, family pathological history=yes, electrocardiogram/heartbeat=low, ultrasound=complications, functional class=class-2) **THEN** (obstruction at exist=low, obstruction at entry=low, rhythm disorder=low, conduction disorders=low, congenital diseases=medium, genetic diseases=high) **AND** (pregnancy interruption=low, diuretic treatment=low, anti-arrhythmic treatment=low, treatment with beta blockers=medium and anticoagulants treatment=high) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=high, child without complications=low, mother with complications=medium, mother without complications=low).

R3 − **IF** (age=old, obesity=obese, smoking=no, personal pathological history=no, family pathological history=yes, electrocardiogram/heartbeat=high, ultrasound=complications functional class=class-4) **THEN** (obstruction at exist=high, obstruction at entry=medium, rhythm disorder=low, conduction disorders=low, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=low, diuretic treatment=low, anti-arrhythmic treatment=high, treatment with beta blockers=medium and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=high, child with complications=medium, child without complications=low, mother with complications=medium, mother without complications=low).

R4 − **IF** (age=young, obesity=healthy, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heartbeat=high, ultrasound=complications, functional class=class-3) **THEN** (obstruction at exist=medium, obstruction at entry=high, rhythm disorder=low, conduction disorders=low, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=medium, diuretic treatment=high, anti-arrhythmic treatment=low, treatment with beta blockers=low and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=high, child without complications=low, mother with complications=medium, mother without complications=low).

3.4.1 Ante-hoc Explanation

The knowledgebase is a vital part of our system. It contains all possible rules which are highlighted against the provided inputs. These rules are IF-THEN statements, which describe how to associate inputs with desired outputs. This module receives input from the neutrosophication module and the knowledge base, it is determined that which rules are currently triggered, and their firing strength is computed in the inference engine. To compute the firing strengths of rules, we take the minimum value out of all values of truth memberships, the maximum value of all indeterminacy membership functions, and the maximum value of all falsity membership functions.

3.5 De-Neutrosophication

The last phase of our system is de-neutrosophication We used de-neutrosophication formula to covert linguistic values into crisp values discussed in [22].

$$V=(p+2q+r+s+2t+u+v+2w+x)/12,$$

where, (p,q,r) are the points of truth MF, (s,t,u) are the points of indeterminacy MF, and (v,w,x) are the points of falsity MFs. The plots of truth MFs, indeterminacy MFs, and falsity MFs for output parameter are depicted in Figure 15, Figure 16, and Figure 17.

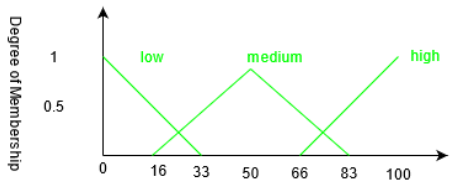

Figure 15: Diagnosis, treatment, prognosis-truth MFs

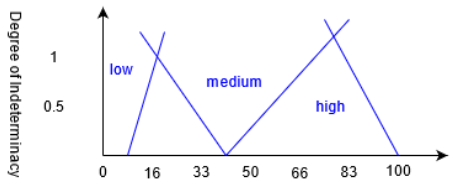

Figure 16: Diagnosis, treatment, prognosis- indeterminacy MFs

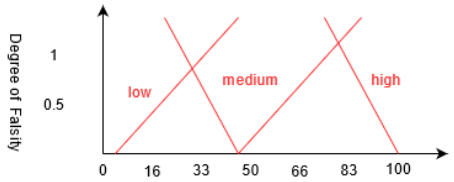

Figure 17: Diagnosis, treatment, prognosis- falsity MFs

The mathematical equation of truth MFs, indeterminacy MFs, and falsity MFs of outputs are as follows:

$$\mu_{low}(w) = \begin{cases} \frac{33.33 - w}{33.33 - 0}, & \text{if } w \in [0 - 33.33], \\ 0, & \text{otherwise.} \end{cases}$$

$$\mu_{high}(w) = \begin{cases} \frac{w - 43.33}{23.33}, & \text{if } w \in [43.33 - 66.67], \\ 0, & \text{otherwise.} \end{cases}$$

$$\mu_{medium}(w) = \begin{cases} \frac{w - 16.67}{16.67}, & \text{if } w \in [16.67 - 33.33], \\ \frac{50 - w}{16.67}, & \text{if } w \in [33.33 - 50], \\ 0, & \text{otherwise.} \end{cases}$$

$$\nu_{low}(w) = \begin{cases} \frac{w - 6.67}{33.33}, & \text{if } w \in [6.67 - 40], \\ 1, & \text{otherwise.} \end{cases}$$

$$\nu_{high}(w) = \begin{cases} \frac{66.67 - w}{16.67}, & \text{if } w \in [50 - 66.67], \\ 1, & \text{otherwise.} \end{cases}$$

$$\nu_{medium}(w) = \begin{cases} \frac{46.67 - w}{13.33}, & \text{if } w \in [33.33 - 46.67], \\ \frac{w - 46.67}{13.33}, & \text{if } w \in [46.67 - 60], \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_{low}(w) = \begin{cases} \frac{w - 3.33}{33.33}, & \text{if } w \in [3.33 - 36.67], \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_{high}(w) = \begin{cases} \frac{66.67 - w}{13.33}, & \text{if } w \in [53.33 - 66.67], \\ 1, & \text{otherwise.} \end{cases}$$

$$\lambda_{medium}(w) = \begin{cases} \frac{40 - w}{10}, & \text{if } w \in [30 - 40], \\ \frac{w - 40}{16.67}, & \text{if } w \in [40 - 56.67], \\ 1, & \text{otherwise.} \end{cases}$$

3.5.1 Ante-hoc Explanation

De-neutrosophication is the last phase of our model. The input of part is the weight of active rules. It contains truth MFs, indeterminacy MFs, and falsity MFs of each output variable. It converts linguistic values to crisp values by using de-neutrosophication formulas. Its crisp values help to determine diagnosis, treatment, and prognosis.

4 Case study

This section demonstrate a numerical example of our system to explain its entire working to the readers. For this purpose, consider an input: (age, obesity, smoking, personal pathological history, family pathological history, electrocardiogram/heart-beat, ultrasound, functional class)=(40, 75, 2, 2, 1, 16.67, 16.6, 76.67). Lets see the execution of each module of the proposed system.

4.1 Neutrosophication

The first step is neutrosophication. We obtained the following linguistic values against the provided inputs.

Age(40)= $(\mu_{yng}, \mu_{m-a}, \mu_{ol})$=(0,0.67,0), $(\nu_{yng}, \nu_{m-a}, \nu_{ol})$=(1,0.5,1), $(\lambda_{yng}, \lambda_{m-a}, \lambda_{ol})$=(1,0.37,1).

Obesity(75)= $(\mu_{healthy}, \mu_{over-weight}, \mu obese)$ =(1,1,0.29), $(\nu_{healthy}, \nu_{over-weight}, \nu_{obese})$ =(1,0.25,1), $(\lambda_{male}, \lambda_{female})$ =(1,0.6,1).

Smoking(2)= (μ_y, μ_n) =(1,0), (ν_y, ν_n) =(0,1), (λ_y, λ_n) =(0,1).

Personal pathological history(2)= (μ_y, μ_n) =(1,0), (ν_y, ν_n) =(0,1), (λ_y, λ_n) =(0,1).

Family pathological history(1)= (μ_y, μ_n) =(0,1), (ν_y, ν_n) =(1,0), (λ_y, λ_n) =(1,0).

Electrocardiogram(16.67)= $(\mu_{lo}, \mu_{med}, \mu_{hi})$ =(0.5,0,0), $(\nu_{lo}, \nu_{med}, \nu_{hi})$ =(0.3,1,1), $(\lambda_{lo}, \lambda_{med}, \lambda_{hi})$ =(0.4,1,1).

Ultrasound(16.67)= $(\mu_{lo}, \mu_{med}, \mu hi)$ =(0.5,0,0), $(\nu_{lo}, \nu_{med}, \nu_{hi})$ =(0.3,1,1), $(\lambda_{lo}, \lambda_{med}, \lambda_{hi})$ =(0.4,1,1).

Function class(76.67)= $(\mu_{c1}, \mu_{c2}, \mu c3), \mu c4$ =(0,0,0.7,0.3), $(\nu_{c1}, \nu_{c2}, \nu_{c3}, \nu_{c4})$ =(1,1,0.15,1), $(\lambda_{c1}, \lambda_{c2}, \lambda_{c3}, \lambda_{c4})$ =(1,1,1,0.78).

4.1.1 Explanation

In this module, we take exemplary values of inputs to understand the complete working of the proposed model. We passed the input values from truth MFs, indeterminacy MFs, and falsity MFs of each input and find out the degree of each function. The degree of each function can lies between 0 to 1.

4.2 Inference Engine

The next phase is the inference engine. Let's pass linguistic values to the inference engine to get the active rules. **R1** − **IF** (age=middle-age, obesity=over-weight, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heart-beat=low, ultrasound=no-complications, functional class=class-3) **THEN** (obstruction at exist=medium, obstruction at entry=high, rhythm disorder=low, conduction disorders=low, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=medium, diuretic treatment=high, anti-arrhythmic treatment=low, treatment with beta blockers=low and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=high, child without complications=low, mother with complications=medium, mother without complications=low).

R2−**IF** (age=middle-age, obesity=over-weight, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heart-beat=low, ultrasound=no-complications, functional class=class-4) **THEN** (obstruction at exist=medium, obstruction at entry=medium, rhythm disorder=medium, conduction disorders=low, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=medium, diuretic treatment=high, anti-arrhythmic treatment=low, treatment with beta blockers=low and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=medium, child without complications=low, mother with complications=low, mother without complications=low).

R3−**IF** (age=middle-age, obesity=obese, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heart-beat=low, ultrasound=no-complications, functional class=class-3) **THEN** (obstruction at exist=low, obstruction at entry=high, rhythm disorder=low, conduction disorders=low, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=low, diuretic treatment=high, anti-arrhythmic treatment=low, treatment with beta blockers=low and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=high, child without complications=low, mother with complications=medium, mother without complications=low).

R4−**IF** (age=middle-age, obesity=obese, smoking=yes, personal pathological history=yes, family pathological history=no, electrocardiogram/heart-beat=low, ultrasound=no-complications, functional class=class-4) **THEN** (obstruction at exist=medium, obstruction at entry=high, rhythm disorder=low, conduction disorders=medium, congenital diseases=low, genetic diseases=low) **AND** (pregnancy interruption=medium, diuretic treatment=medium, anti-arrhythmic treatment=low, treatment with beta blockers=low and anticoagulants treatment=low) **AND** (eutectic delivery=low, dystocic delivery=low, child with complications=high, child without complications=low, mother with complications=medium, mother without complications=low).

The output generated from inference engine is shown in Table 2. The abbreviations used in the table are as follows: MA=middle-age, OB=obese, OW=over-weight, Y=yes, N=no, L=low, C1=class-1, C2-class-2, C3=class-3, and C4=class-4.

Table 2: Active rules in inference engine

Input	R60	R61	R62	R63
A	MA(0.67, 0.5 ,0.37)	MA (0.67, 0.5 ,0.37)	MA (0.67, 0.5, 0.37)	MA(0.67, 0.5 ,0.37)
OB	OW(1, 0.25, 0.6)	OW(1, 0.25, 0.6)	OB(0.29, 0.25, 0.6)	OB(0.29, 0.25, 0.6)
TAB	Y(1, 0 ,0)	Y(1, 0, 0)	Y(1, 0, 0)	Y(1, 0, 0)
FPH	N(1, 0, 0)	N(1 ,0, 0)	N(1, 0, 0)	N(1 ,0 ,0)
PPH	Y(1 ,0 ,0)	Y (1, 0, 0)	Y(1, 0, 0)	Y(1 ,0 ,0)
ECG	L(0.5, 0.3, 0.4)	L (0.5, 0.3 ,0.4)	L(0.5, 0.3 ,0.4)	L(0.5, 0.3 ,0.4)
ECO	L (0.5, 0.3 ,0.4)	L(0.5, 0.3, 0.4)	L (0.5, 0.3, 0.4)	L(0.5, 0.3 ,0.4)
FC	C3(0.7, 0.15, 1)	C4(0.3, 1 ,0.78)	C3(0.7, 0.15, 1)	C4(0.3, 1, 0.78)
(min,max,max)	(0.5 ,0.5, 1)	(0.3, 1, 0.78)	(0.29, 0.5, 1)	(0.29, 1, 0.78)

4.2.1 Explanation

The linguistic values obtained from the neutrosophication section are passed to the inference engine. Inference engine gets all rules from the knowledge base and against these linguistic values determines the active rules and computes their firing strengths. In our example, R60, R61, R62, and R63 are fired.

4.3 De-neutrosophication

The last phase of the proposed model is de-neutrosophication to get the final findings. Let's see the de-neutrosophication process and determines the final findings.

OEX:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

OEN:

$$high = \frac{2 + 2 \times 3 + 3 + 1.9 + 2 \times 3 + 3 + 2.2 + 2 \times 3 + 3}{12},$$

$$high = 2.8.$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

RD:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

CDS:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

CD:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

GD

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

The maximum value is of OEN. Now we will perform de-neutrosophication for treatment using de-neutrosophication method proposed in [22]:

PI:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

DT

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$$medium = 1.57.$$

$$high = \frac{2 + 2 \times 3 + 3 + 1.9 + 2 \times 3 + 3 + 2.2 + 2 \times 3 + 3}{12},$$

$$high = 2.8.$$

AAT:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

TBB:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$$low = 0.341.$$

ACT:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

The maximum value is of DT. Now we will perform de-neutrosophication for prognosis using de-neutrosophication method proposed in [22]:

ED:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

PD:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

CHC

$$high = \frac{2 + 2 \times 3 + 3 + 1.9 + 2 \times 3 + 3 + 2.2 + 2 \times 3 + 3}{12},$$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$medium = 1.57.$

$high = 2.8.$

NOCHC:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

MC:

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

$$medium = \frac{0.5 + 2 \times 1.5 + 2.5 + 0.4 + 2 \times 1.2 + 2.4 + 1.6 + 2 \times 1.4 + 2.6}{12},$$

$medium = 1.57.$

NOMC

$$low = \frac{0 + 2 \times 0 + 1 + 0.2 + 2 \times 0.2 + 1.2 + 0.1 + 2 \times 0.1 + 1.1}{12},$$

$low = 0.341.$

The maximum value is of CHC.

4.3.1 Explanation

The final step of the proposed model is de-neutrosophication. Here, we used a de-neutrosophication formula to obtain the value of each diagnosis, treatment, and prognosis. The among all values of diagnosis, we pick the maximum value which is considered as the final decision about the diagnosis. The same procedure is adopted for treatment and prognosis.

4.4 Three-layered causal hierarchy

Now we will determine the quality of our explanation using Peral et al method [31]-[32]:

Level 1: Association- How many considered symptoms and signs relate to the particularized diagnosis, treatment, and prognosis? This inquiry is investigated by medical specialists and decided that all the specified symptoms and signs are almost associated with diagnosis, treatment, and prognosis.
Level 2: Intervention- What will happen if the doctor adopted the recommended method will the patient get diagnosed earlier? According to the specialists, the recommended model encourages doctors to diagnose, treatment, and prognosis pregnant women at the earliest.
Level 3: Counterfactuals- Was the diagnosis, treatment, and prognosis that influences the specified symptoms? After analyzing the outcomes of diagnosis, treatment, and prognosis with symptoms, it is inferred that diagnosis, treatment, and prognosis cause most of the signs. The diagnosis, treatment, and prognosis are firmly linked with specified symptoms.

5 Comparison Analysis

This segment presents a contrastive examination of the outcomes achieved from our model and with the present decision-making methods using different data sets [22], [6]-[7]. In the research, various schemes of decision-making are presented. Here we analyzed fuzzy soft sets and fuzzy cognitive maps to analyze the recommended model. We have considered eighteen data sets for testing purposes. The outcomes achieved by these techniques are quite alike to the final findings as we obtained from our method. All approaches recognized the similar diagnosis, treatment, and prognosis. The terminal values achieved by these models are reviewed in Figure 18, Figure 19, and Figure 20.

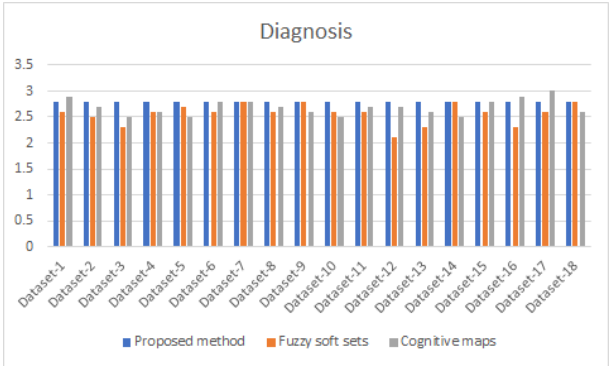

Figure 18: Diagnosis-Comparison Analysis

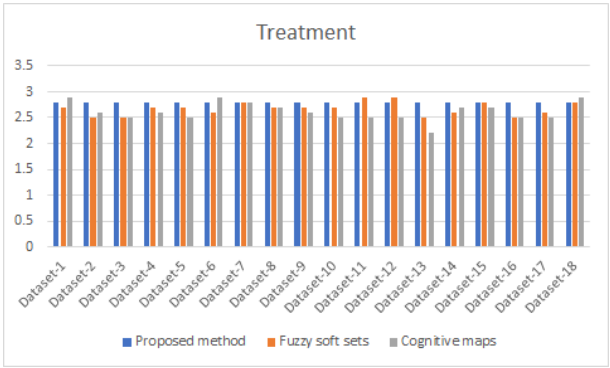

Figure 19: Treatment-Comparison Analysis

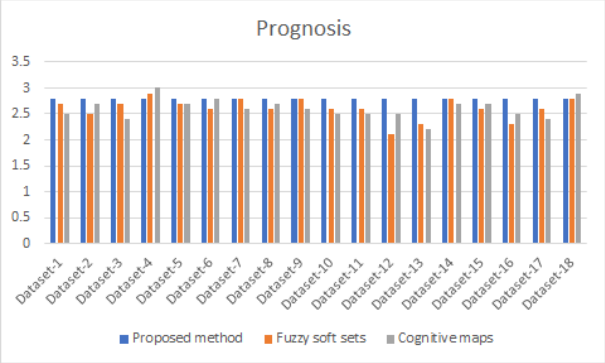

Figure 20: Prognosis-Comparison analysis

After comparing, we conclude that the proposed system is the best alternative to the existing model which offers explainability part as well.

6 Conclusion and future directions

This study presented a novel explainable single-valued neutrosophic decision-making model for the treatment of pregnant women with cardiac diseases. To make this system more effective and understandable to medical experts, we used XAI techniques and measures the quality of explanation as well. The principal contributions and advantages of our research are as follows:

1. Our methods help medical specialists to early diagnosis, identify the type of treatment, and prognosis so that prudent actions can be brought timely. The system considered eight parameters as inputs and computes the value of each diagnosis, type of treatment, and prognosis. The proposed system consists of five main parts, neutrosophication, knowledge base, inference engine, de-neutrosophication, and explainability.
2. In this study ante-hoc explanation is used to make the systems more understandable to the medical experts, and its quality is also measured.
3. To demonstrate the working of the system we devise an algorithm and computed its time complexity as well.
4. Also, a comparative analysis is performed to get the precision of the system and concluded that all decision-making methods highlighted the same diagnosis, treatment, and prognosis.

The recommended model can be applied in many other problems where we need to decide uncertain situations. Examples of such problems are diagnosis and treatment of cancers and other diseases, irrigation in agriculture, any industrial decision-making problems, and many more.

References

[1] Zadeh, L.A., *Fuzzy sets*, Information and Control, **8**(3)(1965), 338-353.

[2] Smarandache, F., *A unifying field in logics. neutrosophy: neutrosophic probability, set and logic*, (1999), 1-141.

[3] Akram, M., *Single-valued neutrosophic graphs*, Infosys Science Foundation Series in Mathematical Sciences, Springer, (2018).

[4] Wang, H., Smarandache, F., Zhang, Y., and Sunderraman, R., *Single-valued neutrosophic sets*, Multispace Multistruct, **4**(2010), 410-413.

[5] Habib, S., and Akram, M., and Ashraf, A., *Fuzzy climate decision support systems for tomatoes in high tunnels*, International Journal of Fuzzy Systems, **19**(3)(2017), 751-775.

[6] Habib, S., and Akram, M., *Diagnostic methods and risk analysis based on fuzzy soft information*, International Journal of Biomathematics, **11**(8)(2018), 1850096.

[7] Habib, S., and Akram, M., *Medical decision support systems based on fuzzy cognitive maps*, International Journal of Biomathematics, **12**(6)(2019), 1950069.

[8] Habib, S., us Salam, W., Butt, M. A., Akram, M., and Smarandache, F., *A neutrosophic clinical decision-making system for cardiovascular diseases risk analysis*, Journal of Intelligent & Fuzzy Systems, (Preprint)(2020), 1-23.

[9] Ye, J., *Improved cosine similarity measures of simplified neutrosophic sets for medical diagnoses*, Artificial intelligence in medicine, **63**(3)(2015), 171-179.

[10] Singh, P. K., *Medical diagnoses using three-way fuzzy concept lattice and their Euclidean distance*, Computational and Applied Mathematics, **37**(3)(2018), 3282-3306.

[11] Singh, P. K., *Three-way fuzzy concept lattice representation using neutrosophic set*, International Journal of Machine Learning and Cybernetics, **8**(1)(2017), 69-79.

[12] Abdel-Basset, M., Gamal, A., Son, L. H., and Smarandache, F., *A bipolar neutrosophic multi criteria decision making framework for professional selection*, Applied Sciences, **10**(4)(2020), 1202.

[13] Hashmi, M. R., Riaz, M., and Smarandache, F., *m-Polar neutrosophic topology with applications to multi-criteria decision-making in medical diagnosis and clustering analysis*, International Journal of Fuzzy Systems, **22**(1)(2019), 273-292.

[14] Pamucar, D., Yazdani, M., Obradovic, R., Kumar, A., and TorresJimenez, M., *A novel fuzzy hybrid neutrosophic decisionmaking approach for the resilient supplier selection problem*, International Journal of Intelligent Systems, **35**(12)(2020), 1934-1986.

[15] Pamucar, D., Deveci, M., Schitea, D., Erikin, L., Iordache, M., and Iordache, I., *Developing a novel fuzzy neutrosophic numbers based decision making analysis for prioritizing the energy storage technologies*, International Journal of Hydrogen Energy, **45**(43)(2020), 23027-23047.

[16] Chakraborty, A., Mondal, S. P., Alam, S., and Mahata, A., *Cylindrical neutrosophic single-valued number and its application in networking problem, multi-criterion group decision-making problem and graph theory*, CAAI Transactions on Intelligence Technology, **5**(2)(2020), 68-77.

[17] Aslan, C., Kargn, A., and ahin, M., *Neutrosophic modeling of talcott parsonss action and decision-making applications for it*, Symmetry, **12**(7)(2020), 1166.

[18] Tan, R. P., *Decision-making method based on new entropy and refined single-valued neutrosophic sets and its application in typhoon disaster assessment* Applied Intelligence, (2020), 1-25.

[19] Karabasevic, D., Stanujkic, D., Zavadskas, E. K., Stanimirovic, P., Popovic, G., Predic, B., and Ulutas, A., *A novel extension of the TOPSIS method adapted for the use of single-valued neutrosophic sets and hamming distance for e-commerce development strategies selection*, Symmetry, *12*(8)(2020), 1263.

[20] Holzinger, A., Langs, G., Denk, H., Zatloukal, K., and Mller, H., *Causability and explainability of artificial intelligence in medicine*, Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, **9**(4)(2019), p. e1312.

[21] Smarandache, F., *A unifying field in Logics: neutrosophic logic philosophy*, American Research Press, (1999), 1-141.

[22] Chakraborty, A., Mondal, S.P., Ahmadian, A., Senu, N., Alam, S., and Salahshour, S. *Different forms of triangular neutrosophic numbers, de-neutrosophication techniques, and their applications*, Symmetry, **10**(8)(2018), 327.

[23] https://www.phaeurope.org/about-ph/classification-and-who-functional-class/.

[24] Daimon, A., Terai, Y., Nagayasu, Y., Okamoto, A., Sano, T., Suzuki, Y., and Ohmichi, M, . *A case of intestinal obstruction in pregnancy diagnosed by MRI and treated by intravenous hyperalimentation*, Case reports in obstetrics and gynecology, 2016.

[25] https://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/symptoms-causes/syc-20350668.

[26] https://www.nhlbi.nih.gov/health-topics/conduction-disorders

[27] https://www.spine-health.com/glossary/congenital-disorder

[28] https://www.health.harvard.edu/medical-tests-and-procedures/abortion-termination-of-pregnancy-a-to-z.

[29] https://www.mayoclinic.org/diseases-conditions/high-blood-pressure/in-depth/diuretics/art-20048129.

[30] Udigwe, G. O., Eleje, G. U., Ihekwoaba, E. C., Udegbunam, O. I., Egeonu, R. O., and Okwuosa, A. O., *Acute intestinal obstruction complicating abdominal pregnancy: conservative management and successful outcome*, Case reports in obstetrics and gynecology, 2016.

[31] Pearl, J., *Theoretical impediments to machine learning with seven sparks from the causal revolution*, (2018), arXiv preprint arXiv:1801.04016.

[32] Pearl, J., and Mackenzie, D., *The book of why: the new science of cause and effect*, Basic Books, (2018).

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