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A Neutrosophic Soft Set-Based Approach for Anemia Diagnosis: Managing Uncertainty in Medical Decision-Making

Ümit Karabıyık [1]*, Metin Bağcı [2]

[1] Department of Mathematics and Computer Sciences, Faculty of Science, Necmettin Erbakan University, Konya, Turkey; ukarabiyik@erbakan.edu.tr
[2] Department of Hematology, Ministry of Health Konya City Research Hospital, Konya, Turkey; metin.bagci@saglik.gov.tr

* Correspondence: ukarabiyik@erbakan.edu.tr

Abstract: Fuzzy sets, introduced by Lotfi A. Zadeh in 1965, have been widely used to solve real-world problems involving uncertainty and ambiguous situations. However, traditional fuzzy sets and interval-valued fuzzy sets are insufficient to fully capture uncertainty. To address this problem, intuitionistic fuzzy sets and neutrosophic sets have been proposed. Neutrosophic sets, especially neutrosophic soft sets, provide an effective framework for dealing with uncertain, conflicting, and incomplete information, especially in medical decision making. In this study, a model for the diagnosis of anemia is developed using the Neutrosophic Soft Set (NSS) method. The model scores female patients according to age groups (15-44, 45-59, 60+) and several hematological parameters such as hemoglobin level (Hb), hematocrit (Hct), mean corpuscular volume (MCV), serum iron level, ferritin, and total iron binding capacity (TIBC). A more robust and accurate decision-making process is created by assigning neutrosophic values to each parameter, including accuracy, uncertainty, and inaccuracy values. Data for the model were obtained from patients treated in the hematology clinic of a full-fledged hospital in Turkey. Smarandache stated that neutrosophic clusters have a superior ability to deal with uncertainty, inconsistency, and missing data. This approach offers significant advantages, especially in medical decision-making processes, where uncertainty and contradiction are intense. Maji's method, based on the theory of neutrosophic soft sets, has yielded effective results in increasing the accuracy and consistency of medical diagnoses. Used in the diagnosis of anemia and similar diseases, this approach is a valuable tool in the evaluation of uncertain data. This paper aims to provide a guide to the application of neutrosophic soft sets in medical decision-making. It also highlights the potential of these approaches to improve decision support systems in medical diagnostics and provides recommendations for future research.

Keywords: Neutrosophic Soft Sets; Anemia Diagnosis; Medical Decision-Making; Uncertainty Management; Neutrosophic Set Theory

1. Introduction

Fuzzy sets, introduced by Lotfi A. Zadeh in 1965 [1], have been widely used to solve real-world problems in uncertain and ambiguous situations. Traditional fuzzy sets are defined by a membership value, but it is sometimes difficult to assign an exact membership. To address this, interval-valued fuzzy sets have been introduced [2], which better capture uncertainty in membership. In problems such as expert systems and belief systems, it is important to consider both the true and false membership of an object to describe it accurately. However, traditional fuzzy sets and interval-valued fuzzy sets are not sufficient for this. Intuitionistic fuzzy sets, introduced by Atanassov [3], provide a better solution by considering both truth-membership and falsity-membership. However, they still struggle to deal with indeterminate or inconsistent information in belief systems. To further address such challenges, Smarandache [4] introduced the concept of neutrosophic sets, a mathematical approach designed to deal with problems involving unclear, uncertain, and contradictory data, thus providing a more advanced tool for dealing with complex situations where both truth and falsity are difficult to determine.

Medical decision-making often involves navigating complex and uncertain information. Conditions such as overlapping symptoms, incomplete medical histories and variable patient responses pose challenges for healthcare professionals. In this context, mathematical frameworks that explicitly account for uncertainty and indeterminacy have received increasing attention. Among these, neutrosophic soft sets have emerged as a promising tool.

Neutrosophic soft sets integrate two powerful theories: neutrosophy and soft set theory. Neutrosophy, introduced by Florentin Smarandache [4], [5], [6], generalizes fuzzy logic by including indeterminacy as an explicit component alongside truth and falsity. This framework is particularly well suited to medical scenarios where uncertainty and vagueness are inherent. For example, a patient's symptoms may only partially match the characteristics of a known disease, or test results may be inconclusive.

Soft set theory, on the other hand, was developed by Molodtsov [7] to deal with uncertainty through a parameterised approach. It describes objects that are characterized by attributes or parameters, allowing flexibility in the definition of membership. This attribute-focused perspective complements the generality of neutrosophy, making the combination of the two neutrosophic soft sets an ideal candidate for dealing with diverse medical data.

Neutrosophic soft sets provide an effective way of representing medical data that contains uncertainty and indeterminacy. For example, a patient's symptoms, laboratory results and medical history can be encoded as a neutrosophic soft set. Here the parameters correspond to medical attributes, and the value of each attribute is expressed as a triad of degrees of truth, indeterminacy and falsity. This nuanced representation allows physicians to capture the complexity of medical data. The diagnosis of a disease often involves analyzing incomplete or ambiguous patient data. By encoding patient profiles as neutrosophic soft sets, healthcare professionals can employ algorithms and similarity measures to compare these profiles with known disease patterns. The explicit inclusion of indeterminacy enhances the robustness of these comparisons, accommodating cases where traditional deterministic approaches might fail. Selecting an optimal treatment plan is a multifaceted decision influenced by factors such as effectiveness, side effects, cost, and patient preferences. Neutrosophic soft sets allow each treatment option to be evaluated as a multi-criteria entity. Decision-makers can apply comparison methods within the neutrosophic framework to identify treatments that best align with patient needs and medical priorities.

In recent years, soft set theory and its extensions have been increasingly utilized to address uncertain and complex problems, particularly in the field of medical decision-making. Neutrosophic set theory, as an advanced extension, has emerged as a powerful tool for managing uncertain, ambiguous, and contradictory information in such processes. For example, the neutrosophic soft set theory, applied using the Maji approach, has been used effectively to diagnose Type 2 diabetes mellitus (DM2) by incorporating relevant variables, improving precision and consistency in decision making [8]. Similarly, neutrosophic models have been applied to various medical decision-making problems, highlighting their advantages in handling uncertainty [9]. Moreover, research on physician selection utilizing neutrosophic multi-criteria decision-making methods has demonstrated its practical utility in healthcare settings [10]. The application of single-valued neutrosophic sets for similarity measures has further improved decision-making and pattern recognition processes [11]. Refined neutrosophic fuzzy logic has shown significant potential in managing ambiguous medical data [12]. Additionally, a recommendation system based on algebraic neutrosophic measures has been developed to address incomplete or uncertain information effectively [13]. These studies collectively underscore the growing interest in neutrosophic set theory and its expanding potential to provide robust solutions in medical decision-making under uncertainty.

In this study, a model for anemia diagnosis is developed using the Neutrosophic Soft Set (NSS) method, incorporating age groups and hematological parameters. The model evaluates In this study, a model for anemia diagnosis is developed using the Neutrosophic Soft Set (NSS) method, incorporating age groups and hematological parameters. The model evaluates female patients based on their age groups (15--44, 45--59, 60+) and hematological parameters, such as hemoglobin (Hb) level, hematocrit (Hct), mean corpuscular volume (MCV), serum iron level, ferritin, and total iron-binding capacity (TIBC). Neutrosophic values $(\mathcal{T}, \mathcal{I}, \mathcal{F})$ are assigned to facilitate the decision-making process for diagnosis. The data used in the model are obtained from patients $(p_1, p_2, p_3, p_4, p_5)$ at the hematology clinic of a large-scale, fully equipped hospital in Turkey. To the best of our knowledge, this is the first study applying this method for anemia diagnosis.

The key advantages of the proposed method are highlighted below:

1) It effectively captures and represents both uncertainty and indeterminacy, providing a robust framework for decision-making in complex scenarios;
2) The study offers a comprehensive resource for researchers interested in exploring this methodology and its applications.

The structure of the paper is as follows: Section 2 provides an overview of neutrosophic sets. Section 3 outlines the main steps of the NSS methodology. In Section 4, the application of the proposed model to anemia diagnosis is demonstrated, and the results are discussed in detail. Finally, Section 5 presents conclusions and directions for future research.

2. Neutrosophic Sets

Let $\boldsymbol{\mathcal{U}}$ be a universal set of objects, with each element denoted by $\boldsymbol{u} \subseteq \boldsymbol{\mathcal{U}}$. For a subset $\boldsymbol{B} \subseteq \boldsymbol{\mathcal{U}}$, the membership functions related to truth, indeterminacy, and falsity are defined as $\boldsymbol{\mathcal{T}_B(u)}, \boldsymbol{\mathcal{I}_B(u)}$ and $\boldsymbol{\mathcal{F}_B(u)}$, respectively. These functions are expressed as follows:

$$\boldsymbol{\mathcal{T}_B(u)}: \boldsymbol{\mathcal{U}} \to]\mathbf{0}^-, \mathbf{1}^+[,\ \boldsymbol{\mathcal{I}_B(u)}: \boldsymbol{\mathcal{U}} \to]\mathbf{0}^-, \mathbf{1}^+[,\ \boldsymbol{\mathcal{F}_B(u)}: \boldsymbol{\mathcal{U}} \to]\mathbf{0}^-, \mathbf{1}^+[$$

There are no restrictions on the sum of these functions. Hence:

$$\mathbf{0}^- \leq \boldsymbol{sup\mathcal{T}_B(u)} + \boldsymbol{sup\mathcal{I}_B(u)} + \boldsymbol{sup\mathcal{F}_B(u)} \leq \mathbf{3}^+.$$

A subset $\boldsymbol{B}$ of $\boldsymbol{\mathcal{U}}$ characterized by these functions is called a neutrosophic set (NS) and can be represented as:

$$\boldsymbol{B} = \{\langle \boldsymbol{u}, \boldsymbol{\mathcal{T}_B(u)}, \boldsymbol{\mathcal{I}_B(u)}, \boldsymbol{\mathcal{F}_B(u)} \rangle : \boldsymbol{u} \in \boldsymbol{\mathcal{U}}\}.$$

In this definition, $\mathbf{0}^- = \mathbf{0} - \boldsymbol{\varepsilon}$ and $\mathbf{1}^+ = \mathbf{1} + \boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon}$ is a non-standard infinitesimal component.

For practical purposes in technical and engineering applications, the interval $[\mathbf{0}, \mathbf{1}]$ is commonly used instead of $]\mathbf{0}^-, \mathbf{1}^+[$ as the latter is challenging to apply in real-world scenarios. This adaptation leads to the concept of simplified neutrosophic sets SNSs [14], where the membership functions are redefined as:

$$\boldsymbol{\mathcal{T}_B(u)}: \boldsymbol{\mathcal{U}} \to [\mathbf{0}, \mathbf{1}],\ \boldsymbol{\mathcal{I}_B(u)}: \boldsymbol{\mathcal{U}} \to [\mathbf{0}, \mathbf{1}],\ \boldsymbol{\mathcal{F}_B(u)}: \boldsymbol{\mathcal{U}} \to [\mathbf{0}, \mathbf{1}].$$

An SNS can be written as:

$$\boldsymbol{B} = \{\langle \boldsymbol{u}, \boldsymbol{\mathcal{T}_B(u)}, \boldsymbol{\mathcal{I}_B(u)}, \boldsymbol{\mathcal{F}_B(u)} \rangle : \boldsymbol{u} \in \boldsymbol{\mathcal{U}}\}.$$

Furthermore, let $\boldsymbol{M}$ represent a set of parameters and $\boldsymbol{\mathcal{U}}$ be a universal set. If $\boldsymbol{A} \subseteq \boldsymbol{M}$ and $\boldsymbol{F}: \boldsymbol{A} \rightarrow \boldsymbol{\mathcal{P}}(\boldsymbol{\mathcal{U}})$ is a mapping, the pair $(\boldsymbol{F}, \boldsymbol{A})$ is called a soft set (SS) over $\boldsymbol{\mathcal{U}}$ [7]. Extending this concept, a neutrosophic soft set (NSS) over $\boldsymbol{\mathcal{U}}$ is defined as follows [15]:

Let $\boldsymbol{F}: \boldsymbol{A} \rightarrow \boldsymbol{\mathcal{P}}(\boldsymbol{\mathcal{U}})$ and $\boldsymbol{A} \subseteq \boldsymbol{M}$. The pair $(\boldsymbol{F}, \boldsymbol{A})$ is termed a neutrosophic soft set if:

$$\boldsymbol{F}(\boldsymbol{e}) = \{\langle \boldsymbol{n}, \boldsymbol{\mathcal{T}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n}), \boldsymbol{\mathcal{I}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n}), \boldsymbol{\mathcal{F}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n})\rangle : \boldsymbol{n} \in \boldsymbol{\mathcal{U}}\}, \forall \boldsymbol{e} \in \boldsymbol{A}.$$

Here, $\boldsymbol{\mathcal{T}}_{\boldsymbol{B}}(\boldsymbol{u})$, $\boldsymbol{\mathcal{I}}_{\boldsymbol{B}}(\boldsymbol{u})$ and $\boldsymbol{\mathcal{F}}_{\boldsymbol{B}}(\boldsymbol{u})$ represent the truth, indeterminacy, and falsity membership functions for the parameter **e**.

The value-class of a Neutrosophic Soft Set (NSS) is defined as the collection of all value sets associated with an NSS $(\boldsymbol{F}, \boldsymbol{M})$. This collection is denoted by $\boldsymbol{C}(\boldsymbol{F}, \boldsymbol{A})$, and it is clear that $\boldsymbol{C}(\boldsymbol{F}, \boldsymbol{M}) \subseteq \boldsymbol{\mathcal{P}}(\boldsymbol{\mathcal{U}})$, where $\boldsymbol{\mathcal{P}}(\boldsymbol{\mathcal{U}})$ represents the power set of the universal set $\boldsymbol{\mathcal{U}}$.

Consider two neutrosophic soft sets $(\boldsymbol{F}, \boldsymbol{A})$ and $(\boldsymbol{J}, \boldsymbol{B})$ over the universal set $\boldsymbol{\mathcal{U}}$, where $\boldsymbol{A}, \boldsymbol{B} \subseteq \boldsymbol{M}$ and $\boldsymbol{A} \subseteq \boldsymbol{B}$. If $\mathbf{A}$ is a subset of $\boldsymbol{B}$ then $(\boldsymbol{F}, \boldsymbol{A})$ is termed a neutrosophic soft subset of $(\boldsymbol{J}, \boldsymbol{B})$. This relationship is denoted by $(\boldsymbol{F}, \boldsymbol{A}) \subseteq (\boldsymbol{J}, \boldsymbol{B})$, and it satisfies the following conditions for every $\boldsymbol{e} \in \boldsymbol{A}$ and $\boldsymbol{n} \in \boldsymbol{\mathcal{U}}$:

$$\boldsymbol{\mathcal{T}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n}) \leq \boldsymbol{\mathcal{T}}_{\boldsymbol{J}(\boldsymbol{e})}(\boldsymbol{n}),\ \boldsymbol{\mathcal{I}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n}) \leq \boldsymbol{\mathcal{I}}_{\boldsymbol{J}(\boldsymbol{e})}(\boldsymbol{n}),\ \boldsymbol{\mathcal{F}}_{\boldsymbol{F}(\boldsymbol{e})}(\boldsymbol{n}) \leq \boldsymbol{\mathcal{F}}_{\boldsymbol{J}(\boldsymbol{e})}(\boldsymbol{n}).$$

The concept of neutrosophic soft subsets provides a foundation for comparing different neutrosophic soft sets based on their respective membership functions. It ensures that the truth-membership, indeterminacy-membership, and falsity-membership values of one soft set do not exceed those of another within the subset relationship. This property is crucial for hierarchical evaluations and applications where parameters and their relationships need to be consistently structured. This framework is particularly valuable in decision-making scenarios, allowing the representation of uncertainty, indeterminacy, and contradiction within a structured and mathematically rigorous context.

3. Steps of the NSS Method

In this study, a model has been developed for the diagnosis of anemia using the Neutrosophic Soft Set (NSS) method. The model allows for the evaluation of patients by considering age groups and hematological parameters. Female patients are assessed based on their age groups (15–44, 45–59, 60+) as well as hematological parameters such as hemoglobin (Hb) level, hematocrit (Hct), mean corpuscular volume (MCV), serum iron levels, ferritin, and total iron-binding capacity (TIBC). Neutrosophic values $\mathcal{T}, \mathcal{I}$ and $\mathcal{F}$ are assigned to simplify the diagnostic process. The data used in the model were obtained from a large-scale, fully equipped hospital's hematology clinic in Turkey, including patient data $(p_1,\ p_2,\ p_3,\ p_4,\ p_5)$.

In this model, Maji's Neutrosophic Soft Set theory [15] and the algorithm proposed by Maji will be used.

For the diagnosis of anemia, let there be n patients $p_1, p_2, \dots, p_n$ *and* m selection parameters $e_1, e_2, \dots, e_m$. For each selection parameter e_j $(j = 1,2, \dots, m)$, the evaluation or performance value of patient p_i $(i = 1,2, \dots, n)$ is represented as a triplet:

$$t_{ij} = (\mathcal{T}_{F(e_j)}(p_i), \mathcal{I}_{F(e_j)}(p_i), \mathcal{F}_{F(e_j)}(p_i)),$$

where:

- $\mathcal{T}_{F(e_j)}(p_i)$: The truth value representing the correct diagnosis of patient p_i for parameter e_j (e.g., positive anemia diagnosis).

- $\mathcal{I}_{F(e_j)}(p_i)$: The indeterminacy value representing the uncertainty in the diagnosis of patient p_i for parameter e_j.
- $\mathcal{F}_{F(e_j)}(p_i)$: The falsity value representing the incorrect diagnosis of patient p_i for parameter e_j (e.g., negative anemia diagnosis).

For a fixed i, the values t_{ij} $(j = 1,2, \ldots, m)$ represent the Neutrosophic Soft Set of all patients. These performance values can be organized into a matrix known as the $criteria\,matrix$. As the number of criteria increases, the suitability of a given patient for diagnosis also increases.

This study aims to identify the most suitable patient who dominates all others within the spectrum of parameters e_j, i.e., the patient with the highest accuracy and the lowest uncertainty in terms of anemia diagnosis. However, as the data is not precise and involves Neutrosophic Soft Data, direct selection is not possible.

The problem is to determine the most appropriate patient for anemia diagnosis based on the selection parameters. For instance, one patient (p_1) may be evaluated as having anemia under certain parameters, while other patients (p_2, p_3,…., p_n) may not satisfy the criteria. The selection varies depending on each patient's hematological parameters, age group, and other clinical factors. In this study, a technique based on Neutrosophic Soft Sets has been employed to calculate the performance scores of patients and facilitate the diagnosis process.

Comparison Matrix: A matrix where rows represent objects (p_1, p_2,…., p_n), and columns correspond to parameters (e_1, e_2,…., e_n). The entry c_{ij} in the matrix is determined using the formula:

$$c_{ij} = a + b - c,$$

where:
'a' is the integer calculated as 'how many times $T_{p_i}(e_j)$ exceeds or equal to $T_{p_k}(e_j)$', for $p_i \neq p_k$, $\forall p_k \in \mathcal{U}$,
'b' is the integer calculated as 'how many times $I_{p_i}(e_j)$ exceeds or equal to $I_{p_k}(e_j)$', for $p_i \neq p_k$, $\forall p_k \in \mathcal{U}$,
'c' is the integer 'how many times $F_{p_i}(e_j)$ exceeds or equal to $F_{p_k}(e_j)$', for $p_i \neq p_k$, $\forall p_k \in \mathcal{U}$.

Object Score: The score of each object p_i, denoted as S_i, is calculated by summing the entries of its corresponding row in the comparison matrix:

$$S_i = \sum_j c_{ij}\,.$$

Algorithm for Optimal Object Selection:

1) Input the Neutrosophic Soft Set (F, A).
2) Specify P, the subset of parameters relevant to the decision-maker's preferences.
3) Extract $(F, P)$and organize it in tabular form.
4) Compute the comparison matrix for (F, P).
5) Calculate the score S_i for each p_i.
6) Identify $S_k = \max_i S_i$.
7) If multiple p_i share the maximum score, any one of them can be selected as the optimal choice.

4. Medical Applications and Results

Anemia is a condition in which the body lacks sufficient oxygen-carrying red blood cells and is typically diagnosed using a series of hematological parameters. The World Health Organization (WHO) highlights the importance of hemoglobin level, hematocrit, mean corpuscular volume (MCV), serum iron levels, ferritin, and total iron-binding capacity (TIBC) in the diagnosis of anemia [16]. These parameters play a critical role in determining the type and severity of anemia. Hemoglobin and hematocrit are often considered primary indicators of anemia, as they directly affect the body's oxygen-carrying capacity. Other parameters provide insights into the status of iron metabolism and the adequacy of iron stores in the body. Ferritin is frequently used to assess iron deficiency anemia, while TIBC measures the body's capacity to transport iron, both of which are essential in the evaluation of anemia [17]. These parameters provide essential information for the treatment and management of anemia in clinical practice.

In this section, we will apply the algorithm introduced in the previous section. The set $\boldsymbol{P}$ consists of independent variables from the dataset, which are:

$$\boldsymbol{P}=\left\{\begin{array}{c}\text{Age }(\boldsymbol{A}),\\ \text{Hemoglobin }(\boldsymbol{HB}),\\ \text{Hematocrit }(\boldsymbol{HCT}),\\ \text{Mean Corpuscular Volume }(\boldsymbol{MCV}),\\ \text{Serum Iron},\\ \text{Ferritin},\\ \text{Total Iron-Binding Capacity }(\boldsymbol{TIBC})\end{array}\right\}$$

These variables represent important factors for diagnosing anemia. They are used to assess patients' health status, taking into account both demographic information (such as age) and hematological parameters . This comprehensive evaluation allows for a more accurate diagnosis of anemia.

Biochemical parameters that vary with age play a critical role in assessing an individual's health. These parameters provide essential insight into the body's iron levels, the oxygen-carrying capacity of the blood, and the health of the red blood cells. Values such as hemoglobin levels, hematocrit and MCV are key indicators, particularly in the diagnosis of blood disorders such as anemia, while serum iron levels, ferritin and TIBC are critical for understanding iron deficiency or iron overload. In addition, these parameters are essential for early diagnosis of disease and treatment planning. Table 1 provides a detailed overview of these parameters, highlighting their definitions, variations between categories, and health implications.

Table 1. Key biochemical parameters and their descriptions.

Parameter	Definition	Significance
Age Groups	Classification by age.	Highlights health variations.
Hemoglobin (Hb)	Amount of hemoglobin in blood.	Diagnoses anemia and hypoxia.
Hematocrit (Hct)	Proportion of red blood cells.	Linked to anemia, dehydration.
MCV	Average volume of red blood cells.	Identifies anemia types.
Serum Iron	Iron level in blood serum.	Detects deficiency or overload.
Ferritin	Stored iron levels in the body.	Indicates ironrelated conditions.
TIBC	Capacity to bind iron in serum.	Reflects anemia or liver issues.

The World Health Organization (WHO) recommends the evaluation of specific hematological parameters for the diagnosis of anemia. These parameters play a crucial role in determining the diagnosis, severity, and type of anemia, especially in female patients. The criteria established by the WHO facilitate the accurate diagnosis of the condition and the selection of appropriate treatment methods. Common hematological parameters and reference values for female patients are shown in Table 2.

Table 2. Parameters, categories, and reference ranges for anemia diagnosis

Parameter	Category	Reference Range
Age Groups	Y1: 15-44 years,	-
	Y2: 45-59 years,	-
	Y3:60+ years	-
Hemoglobin (Hb)	Normal	≥ 12.0 g/dL
	Mild Anemia	11.0 – 11.9 g/dL
	Moderate Anemia	8.0 – 10.9 g/dL
	Severe Anemia	< 8.0 g/dL
Hematocrit (Hct)	Normal	35 – 45% (varies with age)
	Mildly Low	30 – 35%
	Very Low	< 30%
MCV	Microcytic	< 80 fL
	Normocytic	80 – 100 fL
	Macrocytic	> 100 fL
Serum Iron	Normal	37 – 145 μg/dL
	Low	< 37 μg/dL
Ferritin	Normal	15 – 150 ng/mL
	Low	< 15 ng/mL
TIBC	Normal	240 – 450 μg/dL
	Low	> 450 μg/dL

The Table 3 below shows the age, hemoglobin (Hb) level, hematocrit (Hct), mean corpuscular volume (MCV), serum iron level, ferritin, and total iron-binding capacity (TIBC) of 5 different patients. These data provide information about the biochemical changes occurring in their bodies and the health status of the patients.

Table 3. Patient Data

Patient	Age (Y)	Hb (g/dL)	Hct(%)	MCV(fL)	Serum Iron (μg/dL)	Ferritin (ng/mL)	TIBC (μg/dL)
P1	33	10.5	36.5	73	36	5	416
P2	43	10.6	32.9	79	34	10	320
P3	38	9.9	33.3	79	22	4	334
P4	51	3.4	14.7	63	14	2	606
P5	40	10.2	33.6	80	47	4	441

After this stage, we will follow the steps outlined below. First, we will generate the NSS (H,P) values, which will be shown in Table 4. Next, we will prepare the comparison matrix in the format provided in Table 5. Then, we will calculate the score for each $\boldsymbol{p_i}$, and the results will be displayed in Table 6. Finally, we will make a decision based on the highest score from Table 6. Each step is crucial to ensure the correct evaluation and ultimate decision-making process.

The Neutrosophic Soft Set values are assigned for each patient as follows:

- $\mathcal{T}$: The degree of suitability for the patient regarding the parameter.
- $\mathcal{I}$: The degree of uncertainty (borderline or missing information).
- $\mathcal{F}$: The degree of non-suitability for the parameter.

Table 4. Neutrosophic soft set values for each patient

Parameter	P1	P2	P3	P4	P5
Age Groups	(0.4, 0.0, 0.8)	(0.6, 0.0, 0.7)	(0.5, 0.0, 0.4)	(0.7, 0.0, 0.5)	(0.9, 0.0, 0.2)
Hemoglobin	(0.8, 0.2, 0.4)	(0.8, 0.2, 0.5)	(0.7, 0.2, 0.3)	(0.9, 0.0, 0.1)	(0.8, 0.1, 0.3)
Hematocrit	(0.6, 0.1, 0.6)	(0.7, 0.1, 0.4)	(0.7, 0.1, 0.5)	(0.9, 0.0, 0.2)	(0.7, 0.1, 0.5)
MCV	(0.4, 0.1, 0.5)	(0.3, 0.3, 0.7)	(0.3, 0.3, 0.7)	(0.6, 0.0, 0.4)	(0.3, 0.3, 0.8)
Serum Iron	(0.5, 0.3, 0.6)	(0.6, 0.3, 0.5)	(0.7, 0.1, 0.4)	(0.8, 0.0, 0.3)	(0.2, 0.1, 0.8)
Ferritin	(0.3, 0.1, 0.6)	(0.1, 0.1, 0.7)	(0.3, 0.1, 0.6)	(0.4, 0.0, 0.5)	(0.3, 0.0, 0.6)
TIBC	(0.7, 0.1, 0.4)	(0.4, 0.0, 0.5)	(0.4, 0.0, 0.5)	(0.9, 0.0, 0.2)	(0.8, 0.1, 0.3)

Table 5. Comparison matrix of the NSS (H,P)

Patient	Age (Y)	Hb (g/dL)	Hct(%)	MCV(fL)	Serum Iron (µg/dL)	Ferritin (ng/mL)	TIBC (µg/dL)
P1	-4	4	0	3	2	4	4
P2	-1	3	5	3	4	0	-1
P3	0	2	3	3	4	4	-1
P4	1	4	4	4	4	5	6
P5	4	2	3	2	-2	1	5

In this section, we will calculate the total scores for each patient based on the comparison of various parameters. The score for each patient will be computed using the formula:

$$\boldsymbol{c_{ij} = a + b - c}$$

where $\boldsymbol{a}, \boldsymbol{b}$ and $\boldsymbol{c}$ represent the respective values for the parameters under consideration. This formula will help us quantify the relationship between the selected factors and provide a comprehensive evaluation of each patient's condition. The calculated scores will be summarized in

Table 6 below, which will offer an overview of the relative health status of the patients based on these biochemical parameters.

Table 6. Total scores of each patient

Patient	Score
P1	13
P2	13
P3	15
P4	28
P5	15

Decision: Table 6, which we presented, shows that the highest score is 28, measured for the *fourth patient (p4).* According to the evaluation based on the neutrosophic soft set approach, *(p4)* appears to be the patient most severely affected by anemia. This indicates that the biochemical parameters in her body are significantly more negatively impacted, and the severity of her condition is higher compared to the other patients.

Following *(p4),* the patients *(p3)* and *(p5),* both with scores of 15, are moderately affected by anemia. Subsequently, *(p1)* and *(p2),* both with scores of 13, show relatively milder impacts. These findings suggest that while all patients are affected by anemia to varying degrees, the severity differs significantly among them.

The neutrosophic soft set method provides a clear differentiation between the patients based on their health condition. It highlights which patients may require more urgent or intensive intervention, particularly *(p4),* who is in the most critical condition.

These results allow for a more in-depth evaluation of the patients' health status and offer insights into prioritizing clinical interventions. This study contributes to a better understanding of the effects of anemia on female patients and presents an innovative approach for making more informed decisions in clinical settings.

5. Conclusion and Suggestions for Future Studies

In this study, the concept of neutrosophic set developed by Smarandache has been studied and its applicability in the context of soft sets has been investigated. The study is based on an approach that considers parameters as neutrosophic sets. In addition, the integration of the neutrosophic soft set (NSS) method with Maji's approach to medical diagnostic problems has been addressed.

A case study based on real data shows that Maji's approach is both simple and effective. This approach has significant potential for supporting decision making, especially in problems characterized by uncertainty and complexity, such as medical diagnosis. The results of the study clearly demonstrate the effectiveness and applicability of NSS in decision-making problems. NSS stands out as an effective tool, especially in situations with uncertain or incomplete information.

In this context, the operations defined in the study and the theoretical insights obtained contribute to a better understanding of NSS and demonstrate its potential use in decision-making processes in various domains. However, it should be noted that this research has certain limitations in its scope. Applications on larger datasets and in different problem domains are crucial to assess the general validity and impact of the method.

Future studies should focus on exploring how NSS can be adapted to decision-making problems in different disciplines. The relationship between Maji's approach and other neutrosophic and soft sets should be further explored. Beyond medical diagnosis, research evaluating the applicability of

NSS in fields such as engineering, economics, and education will further highlight the potential of this method in a broader framework.

In conclusion, this study demonstrates that the neutrosophic soft set approach is an effective tool in situations involving uncertainty and incomplete information. The study sheds light not only on the theoretical foundations of NSS, but also on its potential in practical problems, opening new avenues of research that can contribute to more informed and effective decision-making processes.

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