NSS

Neutrosophic Sets and Systems, {Special Issue: Advances in SuperHyperStructures and Applied Neutrosophic Theories)}, Vol. 74, 2024

University of New Mexico

NCC: Neutrosophic Control Charts, a didactic way to detect Cardiac Arrhythmias from reading Electrocardiograms

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Abstract: Cardiac arrhythmias are cardiovascular conditions caused by irregularities in the formation or transmission of electrical impulses. To identify these arrhythmias and determine their origin, an electrocardiogram (ECG) is used, which graphically records the electrical activity responsible for each heartbeat over a short period. This analysis can reveal stochastic changes, introducing a degree of uncertainty. To detect these changes, neutrosophic control charts provide an appropriate statistical tool to assess the stability of the ECG, anticipate potential heart failures, reduce variability in measurements, and, in some cases, make predictions. The results indicate that the proposed model is highly accurate in detecting and classifying arrhythmias and that T^2 control charts are useful for monitoring the quality of the detection process. In conclusion, the proposed hybrid neutrosophic model effectively identifies and classifies cardiac arrhythmias in clinical practice.

Keywords: Uncertainty Control charts, Hotelling's T^2, Neutrosophy, Cardiac arrhythmias.

1. Introduction

Currently, the preventive monitoring of cardiovascular diseases is of high importance, as it reduces the morbidity and mortality associated with these conditions, which are among the leading causes of death worldwide. The significance of monitoring this type of chronic disease lies in its ability to detect cardiac problems such as arrhythmias, heart attacks, or heart failure. It is essential to understand that early detection enables timely interventions, leading to improved clinical outcomes, reducing the need for invasive treatments, and lowering costs across the entire healthcare system. [1].

Early detection of abnormalities in the electrocardiogram (ECG) signal could indicate the development of a cardiac arrhythmia, which may have severe consequences if not properly detected and treated. The early diagnosis of these arrhythmias is essential for timely treatment and for improving the patient's quality of life. [2]

In [3], the ability to handle uncertainty, indeterminacy, and contradiction in medical data—common characteristics in both the diagnosis and monitoring processes of cardiovascular diseases—has been significantly supported by neutrosophy. Neutrosophy manages this uncertainty more effectively than traditional models by incorporating degrees of truth (T), falsehood (F), and indeterminacy (I) into its calculations. [4]. This is particularly useful for making more accurate clinical decisions based on undefined data.

On the other hand, advancements in medical technology have enabled the development of more precise and effective tools and methods for detecting cardiac arrhythmias, resulting in more accurate diagnoses and better patient stratification. This not only optimizes the diagnosis of cardiac arrhythmias but also contributes to a more efficient and proactive healthcare system. Additionally, the use of

statistical techniques, such as heart rate variability (HRV) analysis, and machine learning can aid in the early detection and accurate diagnosis of arrhythmias, thereby improving the management of cardiovascular diseases. Similarly, the use of statistical techniques, such as heart rate variability (HRV) analysis and machine learning, can assist in the early detection and accurate diagnosis of arrhythmias, which can enhance care in the management of cardiovascular diseases.

2. Preliminaries

This section summarizes statistical control charts and the theory of neutrosophic logic

2.1 Statistical Control Charts

In [5] and [6], the authors mention that control charts are valuable tools for improving quality, early detection of process deviations, and analyzing their underlying causes. These charts enable the early identification of process issues, saving time and money in error correction. Additionally, control charts help enhance productivity and efficiency by providing a better understanding of the process and facilitating quicker problem identification.

Hotelling's T^2 chart is a type of multivariate control chart used to monitor the simultaneous behavior of two or more variables in a process. This chart is based on the calculation of a T^2 statistic, which measures the distance between a point in multivariate space and the process mean. It enables the detection of deviations in both the mean and variance of the variables simultaneously, making it particularly useful in processes involving multiple interdependent variables. When a deviation is detected on the T^2 chart, it indicates a change in the process has occurred, and the cause should be investigated to take corrective actions. [7] and [8].

2.2 Neutrosophy

Neutrosophy is a recent philosophical discipline that focuses on the study of neutralities and their interactions with various concepts and entities, including ideas, propositions, theories, events, and entities, among others. Neutrosophy divides these concepts into three categories: A, anti-A, and neut-A, with the latter representing a neutral position between the first two. The term neutrosophy derives from the combination of "neutral" (from the Latin *neuter*, meaning "neutral") and "sophia" (from the Greek *sophia*, meaning "knowledge"). Its main theory posits that every idea tends to be balanced by ideas that are not A (not just anti-A, as Hegel suggested), ultimately achieving a state of equilibrium. Neutrosophy began to develop in 1995 [9].

Neutrosophy is used as a tool to analyze uncertainty and indeterminacy in various fields of knowledge. In the context of cardiovascular disease detection, neutrosophy has been applied to manage uncertainty. Specifically, [10] propose a technique that aids decision-making, assisting both patients and physicians in determining whether a patient has heart failure. Additionally, the technique enables users to handle the uncertainty arising from the imprecision and vagueness of the symmetric priority scales of various disease symptoms, allowing them to better understand the severity of the condition in their body.

2.3 Neutrosophic Control Charts.

Classical control charts, such as $\boldsymbol{X-R}$ o $\boldsymbol{X-S}$, charts, are highly effective for monitoring processes with controlled variability and well-defined data. They work very well if measurements are accurate and there is little doubt about the precision of the data. For this reason, traditional control charts can identify when a process is out of control. Additionally, they are advantageous because they effectively detect variations in stable and well-understood processes. [11] and [12].

However, when the data of variables related to cardiovascular problems contain uncertainty or indeterminacy, or if the data is contaminated with noise or unrecognized errors, the use of classical control charts is not recommended, as it may produce misleading results. On the other hand, integrating neutrosophic logic with control charts allows the model to capture not only the variability in the data but also the uncertainty and indeterminacy, instead of assuming that each piece of data is entirely true or false. This makes it a powerful tool for process monitoring in environments with uncertainty, such as healthcare. [13].

In [14], the authors propose a neutrosophic mean deviation (MD) control chart that can accommodate imprecise observations in the collected quality characteristic variables. The results indicated that the proposed MD chart design outperforms existing counterparts in terms of statistical power. Similarly, in [15], attribute control charts are presented for monitoring blood components under neutrosophic statistics. These are described as highly effective, appropriate, adaptable, and informative for the surveillance of blood components in uncertain environments, as evidenced in various applications. They also mention that the proposed control chart can be applied in medical sciences for monitoring various diseases.

3. Calculation of Neutrosophic Control Limits

The present research proposes a neutrosophic hybrid model to classify cardiac arrhythmias using parameters obtained from electrocardiogram (ECG) signals. The proposed model employs adjusted means and standard deviations for the neutrosophic components. Based on this, upper and lower limits can be calculated, considering the uncertainty and indeterminacy of the data, where μ_T is the mean adjusted by the value of T y σ_T is the standard deviation considering uncertainty. This is achieved using a linear interpretation formula such as:

$$\boldsymbol{Upper\ Control\ Limit\ (UCL)} = \mu_T + Z * \sigma_T$$
$$\boldsymbol{Lower\ Control\ Limit\ (LCL)} = \mu_T - Z * \sigma_T$$

The parameters obtained from the ECG, such as heart rate, P wave, QRS complex, and RR interval, are used to train the neutrosophic hybrid model. [16]

4. Neutrosophic Hybrid Model

Neutrosophy is a mathematical theory that allows processing information that is neither true, nor false, nor indeterminate. In the context of classifying the four types of cardiac arrhythmias, the uncertainty and ambiguity of the detected waves are studied using Hotelling's T^2 control charts and neutrosophic values to calculate the percentage of truth, uncertainty, and falsehood of their characteristics, as shown in (Table 1). [17]

The Neutrosophic Hybrid Model is an advanced approach that combines neutrosophic logic with other statistical, mathematical, or computational methods to address complex problems where uncertainty, indeterminacy, and vagueness are critical factors. This model is particularly useful in areas where data is incomplete, noisy, or ambiguous, such as medical analysis, artificial intelligence, and decision-making.

Table 1: Definition of Linguistic Terms

Linguistic Terms	SNVV
Extremely Important	(1.00, 0.00, 0.00)
Very Very Important	(0.90, 0.10, 0.10)
Very Important	(0.80, 0.15, 0.20)
Important	(0.70, 0.25, 0.30)
Moderately Important	(0.60, 0.35, 0.40)

Linguistic Terms	SNVV
Moderate	(0.50, 0.50, 0.50)
Moderately Insignificant	(0.40, 0.65, 0.60)
Insignificant	(0.30, 0.75, 0.70)
Very Insignificant	(0.20, 0.85, 0.80)
Very Very Insignificant	(0.10, 0.90, 0.90)
Extremely Insignificant	(0.00, 1.00, 1.00)

In a universe E, the truth membership function (Tx), indeterminacy (Ix) and falsehood (Fx) functions determine the neutrosophic set to which an element belongs in E. The notation of these functions allows the following equation to be used to describe the neutrosophic set to which it belongs.

$$\boldsymbol{X} = \frac{(\boldsymbol{T}(\boldsymbol{x}) + \boldsymbol{I}(\boldsymbol{x}) + \boldsymbol{F}(\boldsymbol{x}))}{\mathbf{3}} \quad \textbf{(1)}$$

Donde:
$\boldsymbol{X}$: *The arrhythmia x belongs to the category of arrhythmias y representa y"*
$\boldsymbol{T}(\boldsymbol{x})$: *Represents "arrhythmia x belongs to the category of arrhythmias y"*
$\boldsymbol{F}(\boldsymbol{x})$: *Represents "Arrhythmia x does not belong to the category of arrhythmias y"*
$\boldsymbol{I}(\boldsymbol{x})$: *Represents "arrhythmia x is indeterminate with respect to the category of arrhythmias y"*

The values of the components of the membership function are associated with the linguistic characteristics (Table 1). Table 2 correspond cardiac parameters and values.

Characteristics	Value
Heart rate	0.6
QRS complex duration	0.8
Presence of P wave	0.2
Relationship between QRS complex and RR interval	0.9

Tabla 2: Cardiac Parameters and Values

To analyze the existence of out-of-control processes determined by neutrosophic linguistic characteristics, a matrix is generated with three variables, features that will allow the formula to be used:

$$\boldsymbol{MT^2} = \frac{\boldsymbol{ST^2}}{\boldsymbol{n}} \quad \textbf{(2)}$$

Where MT^2represents the mean T^2, ST^2 the sum T^2, and n is the number of T^2 observations. This formula calculates the arithmetic mean of the data in a set of T^2 observations. For the classification of cardiac arrhythmias, Hotelling's T^2 sample covariance matrix allows the detection of anomalies in electrocardiogram data by implementing the following formula.

$$\boldsymbol{S} = \frac{\mathbf{1}}{\boldsymbol{n-1}} * (\boldsymbol{X} - \bar{\boldsymbol{X}})' * (\boldsymbol{X} - \bar{\boldsymbol{X}}) \quad \textbf{(3)}$$

Where **S** represents the measure of the joint variability of the variables in the dataset to define the upper control limit T^2 using a test called **F** with a significance level of 5%. A neutrosophic composition matrix allows representing the composition of a set of elements and the value of the corresponding degree for each element, enabling classification as either standard or non-standard real subsets by applying the following:

$$\boldsymbol{VT(x,y)} = \sum (\boldsymbol{VT(x)} * \boldsymbol{CF(y)})$$
$$\boldsymbol{VF(x,y)} = \sum (\boldsymbol{VF(x)} * \boldsymbol{CT(y)})$$
$$\boldsymbol{VI(x,y)} = \sum (\boldsymbol{VI(x)} * \boldsymbol{CI(y)})$$

Where, for each degree of element **X**, the summation of the complement for the corresponding degree must be performed, and the summation is carried out over all elements Y in the combination that are not X. Subsequently, the results obtained from the neutrosophic composition matrix are graphed and analyzed, allowing a probabilistic evaluation of whether an arrhythmia belongs to a specific category, even in cases where the classification is unclear, ambiguous, or there is no presence of waves.

5. Results

To determine the accuracy in classifying cardiac arrhythmias, the experimental results showed that the neutrosophic hybrid model achieved an average classification accuracy of 82.99% for detecting four different types of cardiac arrhythmias. These results were comparable to the original values of each dataset, as shown in (Table 3). To evaluate the scalability of the neutrosophic hybrid model, the signal duration was increased from 3500 ms to 5000 ms, and the model's performance was assessed in terms of classification accuracy and processing time. The results demonstrated that the neutrosophic hybrid model was capable of handling ECG datasets with a higher number of signals without significantly reducing classification accuracy.

Table 3: Accuracy Results of the Hybrid Model

Id	Database	Arrhythmia	Records	Hybrid Model	Accuracy
1	MIT-BIH Atrial Fibrillation Database	Atrial fibrillation	14	14	100.00%
2	CU Ventricular Tachyarrhythmia Database	Ventricular tachycardia	18	13	72.22%
3	Norwegian Endurance Athlete ECG Database	Bradycardia	17	24	70.83%
4	MIT-BIH Supraventricular Arrhythmia Database	Supraventricular tachycardia	18	16	88.89%
	Total		***67***	***67***	**82.99%**

To formulate the mathematical model based on Table 3, an approach can be constructed to evaluate the overall accuracy of the hybrid model in classifying arrhythmias. This involves integrating the observations by arrhythmia type and calculating a general metric.

5.1 Mathematics Model

5.1.1 Define Variables:

- $\boldsymbol{n_i}$: Total number of records for the database i.
- $\boldsymbol{r_i}$: Number of correctly classified records for database i using the hybrid model.
- $\boldsymbol{p_i}$: Accuracy of the hybrid model for database i, calculated as:

$$\boldsymbol{p_i = \frac{r_i}{n_i}\, x\, 100} \tag{4}$$

5.1.2 Total Accuracy of the Hybrid Model:

Let $\boldsymbol{N}$ be the total number of records across all databases:

$$N = \sum_{i=1}^{k} n_i \tag{4.1}$$

Let $\boldsymbol{R}$ be the total number of correctly classified records across all databases.

$$R = \sum_{i=1}^{k} r_i \tag{4.2}$$

The total accuracy $\boldsymbol{P}$ of the hybrid model is calculated as:

$$P = \frac{R}{N}\, x\, 100 \tag{4.3}$$

5.1.3 Application with the Data:

For each database:

$$p_1 = \frac{14}{14}\, x\, 100 = 100\%$$

$$p_2 = \frac{13}{18}\, x\, 100 = 72.22\%$$

$$p_3 = \frac{17}{24}\, x\, 100 = 70.83\%$$

$$p_4 = \frac{16}{18}\, x\, 100 = 88.89\%$$

Total records($\boldsymbol{N}$) and correct records($\boldsymbol{R}$)

$$N = 14 + 18 + 24 + 18 = 74$$
$$R = 14 + 13 + 17 + 16 = 60$$

Total Accuracy($\boldsymbol{P}$):

$$P = \frac{60}{74}\, x\, 100 = 82.99\%$$

This model allows calculating the total accuracy of the hybrid model by integrating data from all databases to evaluate its performance in arrhythmia classification. Regarding its efficiency, the obtained result of 82.99% suggests that the model has a solid performance in classifying arrhythmias. This

indicates that the model can correctly handle the majority of cases, accurately identifying the corresponding type of arrhythmia.

Similarly, regarding the margin for improvement, it can be noted that 17.01% of the samples were not correctly classified, reflecting opportunities to optimize the model. Possible areas for improvement include adjustments to the neutrosophic parameters, higher quality training data, or the integration of additional features

Finally, we can conclude that this level of accuracy positions the hybrid model as a viable solution for classifying cardiac arrhythmias, especially in contexts where data uncertainty can hinder the use of traditional methods. However, it is important to continue refining and validating the model to achieve greater accuracy and minimize potential errors.

The robustness of the neutrosophic hybrid model was determined through the generation of neutrosophic triangular scales for each cardiac arrhythmia signal, as observed in (Algorithm_1 and Algorithm_2). Neutrosophic distances were generated, which allowed validating the percentage of divergence from each type of arrhythmia: Bradycardia (Tables 5 and 6), Ventricular Tachycardia (Tables 7 and 8), Supraventricular Tachycardia (Tables 9 and 10), and Atrial Fibrillation (Tables 11 and 12).

5.1.4 Definition of Variables

$\boldsymbol{T_i} =$ Truth degree of the signal i (Neutrosophic component).
$\boldsymbol{I_i} =$ Indeterminacy degree of the signal i
$\boldsymbol{F_i} =$ Falsity degree of the signal i
$\boldsymbol{D_i} =$ Neutrosophic distance of signal **i** to the reference neutrosophic scale

Algorithm 1 classifies data using a covariance measure. For each sample, it evaluates whether the covariance measure is less than 0.25, in which case the label "Ventricular" is assigned to sample iii. If cov_matrix is greater than or equal to 0.25 but less than 0.5, the label "Supraventricular" is assigned. If cov_matrix is greater than or equal to 0.5 but less than 0.75, the label "Bradycardia" is assigned. If cov_matrix is greater than or equal to 0.75, the label "Atrial Fibrillation" is assigned. In other words, the algorithm evaluates each sample iii and determines which class it belongs to base on the comatrix value. The steps are as follows:

The values obtained from (Algorithm 1) are related to heart conditions and are used in the context of classifying cardiac arrhythmias, which are abnormal heart rhythms. In other words, the algorithm classifies cardiac signals into one of four arrhythmia categories based on covariance values and performs a normalization preprocessing step. Although it is a simple approach, it can be useful as a first step in a more advanced classification workflow or as a quick tool for initial evaluations.

Algorithm 1: Training Algorithm for Cardiac Classification

```
# Loop through the sample set
for i in range(n_samples):
    # Classification based on the covariance matrix (cov_matrix)
    if cov_matrix < 0.25:
        y[i] = 1 # Class 1: Ventricular Rhythm
    elif cov_matrix < 0.5:
        y[i] = 2 # Class 2: Supraventricular Rhythm
    elif cov_matrix < 0.75:
        y[i] = 3 # Class 3: Bradycardia
    else:
        y[i] = 4 # Class 4: Atrial Fibrillation
# Data normalization (X)
X_norm = (X - np.mean (X, axis=0)) / np.std (X, axis=0)
```

a. Data normalization

After classifying all the samples, the algorithm normalizes the data in **X** so that they have a mean of zero and a standard deviation of one, resulting in the neutrosophic reference values for each cardiac arrhythmia (Table 4),

$$\mathbf{Xnorm[i,j]} = \frac{\mathbf{X[i,j]} - \boldsymbol{\mu}\mathbf{j}}{\boldsymbol{\sigma}\mathbf{j}} \quad (5)$$

Donde:
X[**i**, **j**]: Value of feature **j** for sample **i**.
μj: Mean of feature **j** for all samples.
σj: Standard deviation of feature **j** for all samples.
Each feature has a mean of 0 and a standard deviation of 1.

b. Sample classification

Each sample is classified into one of the arrhythmia categories based on the value of the covariance matrix (cov_matrix):

$$y[i] = \begin{cases} 1;\ \text{si cov\_matrix} < 0.25 (\text{Ventricular Tachycardia}) \\ 2;\ \text{si } 0.25 \leq \text{cov\_matrix} < 0.5 (\text{Supraventricular Tachycardia}) \\ 3;\ \text{si } 0.5 \leq \text{cov\_matrix} < 0.75 (\text{Atrial Fibrillation}) \\ 4;\ \text{si } \text{cov}_{\text{matrix}} > 0.75 (\text{Bradycardia}) \end{cases}$$

c. Calculation of Neutrosophic Reference Values (NRV)

For each arrhythmia category ($\mathbf{k} \in \{\mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4}\}$ The neutrosophic reference values($(\boldsymbol{T_k}, \boldsymbol{I_k}, \boldsymbol{F_k})$ are calculated as the means of the normalized values of the corresponding features.

Truth Degree ($\boldsymbol{T_k}$): Represents the mean of the features that indicate a direct relationship with the category:

$$\mathbf{T_k} = \frac{1}{n_k} \sum_{i \in k}^{n} X_{norm}[\![\text{i, Truth features}]\!]$$

Indeterminacy Degree ($\boldsymbol{I_k}$): Represents the mean of the features that introduce ambiguity or variability in the category:

$$\boldsymbol{I_k} = \frac{1}{n_k} \sum_{i \in k}^{n} X_{norm}[\![\text{i, Indeterminacy features}]\!]$$

Falsity Degree ($\boldsymbol{F_k}$)**:** Represents the mean of the features that contradict the category**:**

$$\boldsymbol{F_k} = \frac{1}{n_k} \sum_{i \in k}^{n} X_{norm}[\![\text{i, Falsity features}]\!]$$

Donde:
$\mathbf{n_k}$: Number of samples in category k.
$\mathbf{i} \in \mathbf{k}$: Samples classified in the category k.

d. Results for the Categories.

Table 4: Neutrosophic Reference Values

Cardiac arrhythmia	NRV
Ventricular tachycardia	(0.4, 0.6, 0)
Supraventricular tachycardia	(0.3, 0.3, 0.4)

Cardiac arrhythmia	NRV
Atrial fibrillation	(0.3, 0.2, 0.5)
Bradycardia	(0.2, 0.8, 0)

These values reflect the neutrosophic mean calculated for each category after normalization and classification.

e. Interpretation of the Categories According to the Table

Taquicardia Ventricular ($T = 0.4, I = 0.6, F = 0.0$**)**:

- **High Truth (T=0.4):** Indicates a reliable classification based on specific features of the arrhythmia.
- **Moderate Indeterminacy (I=0.6):** The category has some ambiguity, which might be related to features shared with other arrhythmias.
- **No Falsity (F=0.0):** The features do not contradict the classification

Supraventricular tachycardia ($T = 0.3, I = 0.3, F = 0.4$):

- **Moderate Truth** ($T = 0.3$): The classification is supported but not as strong as in other categories.
- **Low Indeterminacy** ($I = 0.3$): The data is clearer and more consistent.
- **High Falsity** ($F = 0.4$): There are significant contradictions in the features, suggesting possible errors in classification or conflicting data.

Atrial fibrillation ($\boldsymbol{T = 0.3, I = 0.2, F = 0.5}$**):**

- **Moderate Truth (T=0.3):** Similar to supraventricular, the data partially support the classification.
- **Low Indeterminacy (I=0.2):** The data is quite clear and well-defined.
- **High Falsity (F=0.5):** Suggests a high degree of conflict, possibly due to similarities with other categories.

Bradycardia ($\boldsymbol{T = 0.2, I = 0.8, F = 0.0}$**):**

- **Low Truth (T=0.2):** The specific features of bradycardia are less defined compared to other arrhythmias.
- **High Indeterminacy (I=0.8):** The data shows significant variability or ambiguity.
- **No Falsity (F=0.0):** There are no clear contradictions in the data, suggesting that the conflicts are due to lack of definition rather than errors.

Robustness of the Hybrid Model

- This NRV-based approach demonstrates that the hybrid model is capable of handling ambiguous and conflicting data by representing the characteristics of arrhythmias in terms of truth, indeterminacy, and falsity.
- The differences in $\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F}$ between categories can help to:

- Identify areas where the data is inconsistent.
- Adjust the model to improve its accuracy.
- Prioritize key features in future optimizations.

In conclusion, we can state that the neutrosophic model based on normalization and $\boldsymbol{NRV}$ provides a more detailed and realistic representation of cardiac arrhythmias, addressing uncertainty and ambiguity in medical data. This is crucial for improving the accuracy and reliability of automated diagnoses and supporting clinical decisions with more interpretable data

On the other hand, (Algorithm 2) creates a transition matrix used in the analysis of discrete time series, particularly in the analysis of electrocardiograms (ECGs). The transition matrix represents the

probability of transitioning from one state to another in a discrete time series. In this case, the matrix represents the transition probabilities between different types of cardiac complexes in an ECG time series. This matrix has four rows (one for each type of cardiac arrhythmia) and three columns (one for each possible subsequent type of cardiac arrhythmia).

Algorithm 2: ENT Algorithm

```
# Creation of the neutrosophic matrix
# Each row corresponds to a specific cardiac signal feature
# Columns represent truth, indeterminacy, and falsehood values
neutro_matrix = np.array([
   [1 - fc, 0, fc],      # Row 1: Feature-based on 'fc'
   [1 - qrs, qrs, 0], # Row 2: Feature-based on 'qrs'
   [p, 1 - p, 0],                # Row 3: Feature-based on 'p'
   [1 - qrs_rr, qrs_rr, 0]       # Row 4: Feature-based on 'qrs_rr'
])
# Explanation:
# The matrix stores neutrosophic values: [truth, indeterminacy, falsehood].
# For each feature, the truth, indeterminacy, and falsehood are computed.
```

This algorithm performs a classification of cardiac arrhythmias by calculating the Euclidean distance between the neutrosophic matrix obtained from Algorithm 2.

General Mathematical Model

Neutrosophic Matrix:

$$\mathbf{neutro_{matrix}} = \begin{bmatrix} \mathbf{1-fc} & \mathbf{0} & \mathbf{fc} \\ \mathbf{1-qrs} & \mathbf{qrs} & \mathbf{0} \\ \boldsymbol{p} & \mathbf{1-}\boldsymbol{p} & \mathbf{0} \\ \mathbf{1-}\boldsymbol{qrs\_rr} & \boldsymbol{qrs\_rr} & \mathbf{0} \end{bmatrix} \quad (6)$$

Euclidean Distance: For any pair of states $\boldsymbol{i}$ y $\boldsymbol{j}$:

$$\mathbf{D}_{ij} = \sqrt{\sum_{k=1}^{3} (\boldsymbol{neutro\_matrix}[i,k] - \boldsymbol{neutro\_matrix}[j,k])^2} \quad (7)$$

This model allows calculating the distance between different states in a discrete ECG time series, representing how much one type of cardiac complex differs from another in terms of neutrosophic dimensions (truth, indeterminacy, and falsity). Higher values of $\boldsymbol{D_{ij}}$ indicate greater dissimilarity between states, which can aid in analyzing transitions and patterns in cardiac signals.

The elements of the matrix represent the transition probabilities from one type of cardiac arrhythmia to another. For an ECG signal with an arrhythmia of the bradycardia type, its parameters are: $\boldsymbol{fc = 0.3}$, $\boldsymbol{qrs = 0.7}$, $\boldsymbol{p = 0}$, $\boldsymbol{qrs\_rr = 1}$ resulting in the values shown in Table 5. For ventricular tachycardia, its parameters are $\boldsymbol{fc = 0.7, qrs = 0.3, p = 0.7, qrs\_rr = 1}$ resulting in the values shown in Table 7, for supraventricular tachycardia its parameters are: $\boldsymbol{fc = 0.8, qrs = 0.5, p = 0.3, qrs\_rr = 0.3}$ resulting in the values shown in Table 9 and finally for atrial fibrillation its parameters are: $\boldsymbol{fc = 1}$, $\boldsymbol{qrs = 0, p = 1, qrs\_rr = 0.2}$ resulting in the values shown in Table 11.

In Table 5 we can identify the three different measures (truth, uncertainty, and falsehood) for each of the three possible states of the variable (present, uncertain and absent). Where, the first row of values shows has a truth measure of 0.4, suggesting that the patient is likely to have bradycardia. The uncertainty measure is 0, indicating that there is no uncertainty in the statement, and the falsehood measure is 0.6, suggesting that it is unlikely that the patient does not have bradycardia.

Table 5: Neutrosophic scale pertaining to Bradycardia

Neutrosophic Triangular Scale		
True	**Uncertainty**	**Falsehood**
0.4	0	0.6
0.2	0.8	0
0.2	0.8	0
0.1	0.9	0

Table 6: Neutrosophic distances pertaining to Bradycardia

Neutrosophic distances			
Ventricular	**Supraventricular**	**Fibrillation**	**Bradycardia**
1.178	1.241	1.442	1.037

The results obtained in Algorithm 3 show that the neutrosophic matrix is more like the reference matrices for Bradycardia, as its Neutrosophic distance is equal to 1.037. The longest distance is for Fibrillation, suggesting that the neutrosophic matrix is less like the Fibrillation reference matrix.

Table 7: Neutrosophic scale for ventricular tachycardia

Neutrosophic Triangular Scale		
True	**Uncertainty**	**Falsehood**
0.1	0	0.9
0.1	0.9	0
0.5	0.5	0
0.1	0.9	0

In Table 7 we can identify the three different measures (truth, uncertainty, and falsehood) for each of the three possible states of the variable (present, uncertain and absent). Where, the third row of values (0.5, 0.5, 0) indicates a balanced measure of truth and uncertainty, suggesting that we are not sure whether the patient has ventricular tachycardia. The falsehood measure is 0, suggesting that it is unlikely that the patient does not have ventricular tachycardia.

Table 8: Neutrosophic distances pertaining to ventricular tachycardia

Neutrosophic distances			
Ventricular	**Supraventricular**	**Fibrillation**	**Bradycardia**
1.281	1.319	1.476	1.396

The results obtained in Algorithm 3 show that the neutrosophic matrix is more like the reference matrices for Ventricular Tachycardia, as its Neutrosophic distance is equal to 1.281. The longest distance is for Fibrillation, suggesting that the neutrosophic matrix is less like the Fibrillation reference matrix.

Table 9: Neutrosophic scale pertaining to supraventricular tachycardia

Neutrosophic Triangular Scale		
True	**Uncertainty**	**Falsehood**
0.1	0	0.9

Neutrosophic Triangular Scale		
True	**Uncertainty**	**Falsehood**
0	1	0
0.8	0.2	0
0.8	0.2	0

In Table 9 we can identify the three different measures (truth, uncertainty, and falsity) for each of the three possible states of the variable (present, uncertain and absent). Where, the third and fourth sets of values, the measure of belief in truth is high (0.8) and the measure of falsity is low (0), suggesting that the statement is believed to be probably true. However, there is also some uncertainty (0.2) associated with this belief.

Table 10: Neutrosophic distances pertaining to supraventricular tachycardia

Neutrosophic distances			
Ventricular	**Supraventricular**	**Fibrillation**	**Bradycardia**
1.49	1.2	1.49	1.726

The results obtained in Algorithm 3 show that the neutrosophic matrix is more like the reference matrices for Supraventricular Tachycardia, since its Neutrosophic distance is equal to 1.2. The longest distance is for Bradycardia, suggesting that the neutrosophic matrix is less like the Bradycardia reference matrix.

Table 11: Neutrosophic scale pertaining to atrial fibrillation

Neutrosophic Triangular Scale		
True	**Uncertainty**	**Falsehood**
0.1	0	0.9
1	0	0
1	0	0
1	0	0

In Table 11 we can identify the three different measures (truth, uncertainty, and falsehood) for each of the three possible states of the variable (present, uncertain and absent). Where, the fourth set of values, the measure of belief in truth is high (1), while the measure of falsity is low (0). This could be interpreted as an opinion that the statement is true. There is no uncertainty associated with this statement.

Table 12: Neutrosophic distances belonging to atrial fibrillation

Neutrosophic distances			
Ventricular	**Supraventricular**	**Fibrillation**	**Bradycardia**
1.849	1.612	1.606	2.302

The results obtained in Algorithm 3 show that the Neutrosophic matrix is more like the reference matrices for Arterial Fibrillation as its Neutrosophic distance is equal to 1.606. The longest distance is

for Bradycardia, suggesting that the Neutrosophic matrix is less similar to the reference matrix for Bradycardia.

To evaluate how interpretable the results obtained from the Neutrosophic hybrid model are, the visualization of the Neutrosophic distance process was used to verify its behavior for each type of cardiac arrhythmia (Figure 2 and Figure 3) using the Neutrosophic triangular function where the sets of classification rules and the most important features for the classification of cardiac arrhythmias were shown to be consistent with basic clinical knowledge.

Algorithm 3: Neutrosophic Rule Generation Algorithm

```
# Generate a sawtooth wave as the base for the triangular membership functions
tri = sawtooth(x * np.pi, 0.5)
# Calculate Euclidean distances for Ventricular classification
ventricular_dist = np.linalg.norm(neutro_matrix - ventricular_ref, axis=1)
tri_ventricular = np.zeros_like(tri)  # Initialize triangular function for Ventricular
for d in ventricular_dist:
    # Update triangular function with Ventricular distances
    tri_ventricular += np.maximum(0, 1 - 2 * np.abs(x - d))
# Calculate Euclidean distances for Supraventricular classification
supraventricular_dist = np.linalg.norm(neutro_matrix - supraventricular_ref, axis=1)
tri_supraventricular = np.zeros_like(tri)  # Initialize triangular function for Supraventricular
for d in supraventricular_dist:
    # Update triangular function with Supraventricular distances
    tri_supraventricular += np.maximum(0, 1 - 2 * np.abs(x - d))
# Calculate Euclidean distances for Bradycardia classification
bradycardia_dist = np.linalg.norm(neutro_matrix - bradycardia_ref, axis=1)
tri_bradycardia = np.zeros_like(tri)  # Initialize triangular function for Bradycardia
for d in bradycardia_dist:
    # Update triangular function with Bradycardia distances
    tri_bradycardia += np.maximum(0, 1 - 2 * np.abs(x - d))
# Calculate Euclidean distances for Atrial Fibrillation classification
fibrillation_dist = np. linalg.norm(neutro_matrix - fibrillation_ref, axis=1)
tri_fibrillation = np. zeros_like(tri)  # Initialize triangular function for Atrial Fibrillation
for d in fibrillation_dist:
    # Update triangular function with Atrial Fibrillation distances
    tri_fibrillation += np.maximum(0, 1 - 2 * np.abs(x - d))
```

Algorithm 3: Neutrosophic Rule Generation Algorithm generates neutrosophic rules to classify different types of cardiac arrhythmias (ventricular, supraventricular, bradycardia and fibrillation). This is achieved by calculating Euclidean distances from a Neutrosophic matrix to the corresponding references and constructing triangular membership functions for each type of arrhythmia and for each distance in the reference matrix. The construction of the triangular signal is performed by calculating the triangular wave function with the time variable x multiplied by pi and a factor of 0.5, at the end, the resulting triangular signals are used to determine the type of arrhythmia that best correlates with the input signal which returns the graph to review the behavior taken by each rule.

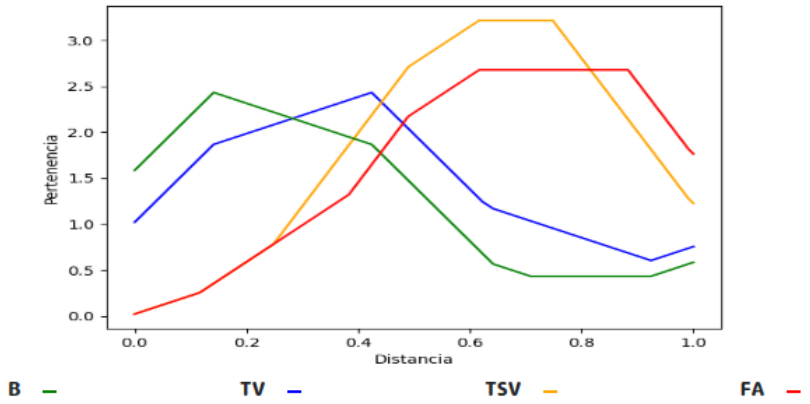

Figure 2: Behavior of neutrosophic distances for each type of cardiac arrhythmia

The results of the application of Algorithm 3 show the behavior of each neutrosophic rule generated from the ECG signal for each type of arrhythmia where B represents bradycardia, VT represents ventricular tachycardia, SVT represents supraventricular tachycardia and AF represents atrial fibrillation.

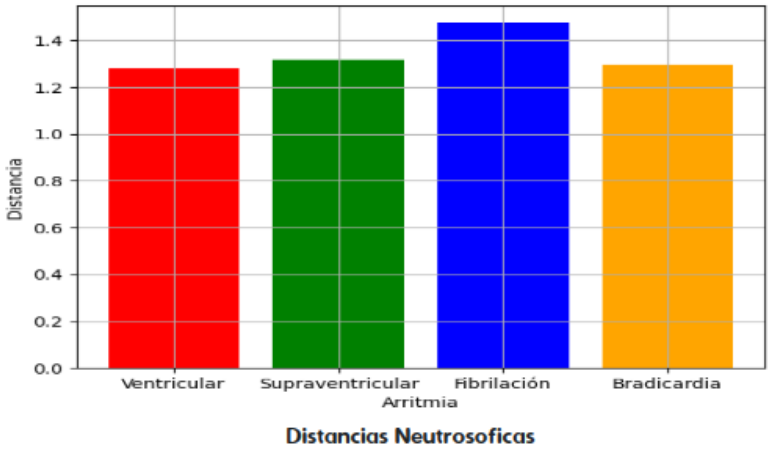

Figure 3: Results of the neutrosophic distances

Figure 3 is another way of representing the values obtained from the neutrosophic rules (Algorithm 3) and their neutrosophic distances where it is possible to interpret for each type of arrhythmia the percentage of remoteness or distance they have taking as a result the minimum value, that is, the closest as the type of arrhythmia classified.

6. Conclusión

This research work was carried out with the purpose of verifying the accuracy of the application of a hybrid model between neutrosophy and T^2 Hotelling control charts to detect and classify cardiac arrhythmias, concluding that the model has a reliable accuracy and is completely scalable by means of its important components, such as the extraction and selection of features that in fusion of the T^2 Hotelling control charts, allow an accurate classification of cardiac arrhythmias even in situations of high variability and noise in the ECG signals..

Neutrosophy offers a unique and effective way to address uncertainty and errors in medical data. While process control charts allow you to monitor process variables, classify and identify unwanted deviations. Successful implementation of such a model requires a careful approach to data selection and

preprocessing, proper identification and measurement of variables, and the establishment of appropriate thresholds and limits for control charts.
This model is also capable of handling large ECG datasets without decreasing classification accuracy, making it scalable and suitable for use in clinical settings. Interpretation of results is also accessible to the end user, increasing confidence in cardiac arrhythmia classification.

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Received: July 28, 2024. Accepted: September 27, 2024